Melting Down: Systemic Financial Instability and the Macroeconomy*

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Abstract

We investigate the role of systemic financial instability in an empirical macro-financial model for the euro area, employing a richly specified Markov-Switching Vector Autoregression model to capture the dynamic relationships between a set of core macroeconomic variables and a novel indicator of systemic financial stress. We find that at times of widespread financial instability the macroeconomy functions fundamentally differently from tranquil times. Not only the variances of the shocks, but also the parameters that capture the transmission of shocks change regime, especially around times of high systemic stress in the financial system. In particular, financial shocks are larger and their effects on real activity propagate

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much more strongly during high-financial-stress regimes than during tranquil times. We find an economically important role of loan growth in the propagation of financial stress to the macroeconomy. We also show that prospects for detecting episodes of what we call financial fragility appear promising, although we argue that more research is required. We conclude that macroprudential and monetary policy makers are well advised to take these non-linearities into account.

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1 Introduction

Economic history has shown that financial crises are a regular, if infrequent occurrence, observed over extended periods of time, across a range of countries, encompassing a variety of economic systems (Kindelberger 1978 and Reinhart and Rogoff 2009). Systemic financial crises - crises that impair the overall functioning of financial systems - tend to have the most devastating effects on economic growth and welfare; the recent financial crisis and the resulting meltdown of the global economy is just the latest example. In a systemic crisis, it tends to happen that an initial adverse shock is propagated and amplified in a way that it eventually affects the entire financial system. When financial instability has become widespread, the financial and the real sector typically enter into a vicious circle with pernicious feedback loops which further aggrevates systemic stress. As a consequence of the presence of large shocks as well as propagation, amplification and feedback effects, financial crises are likely to be characterised by discontinuous, abrupt changes in the economic dynamics which poses great challenges for theoretical and empirical modeling as well as forecasting (see e.g. de Bandt and Hartmann 2000 and Trichet 2011).

Recently, the literature on theoretical models that incorporates financial instability in macroeconomic models allowing for nonlinearities (see e.g. Brunnermeier and Sannikov 2013, He and Krishnamurthy 2014b, Goodhart, Kashyap, Tsomocos and Vardoulakis 2012, Martinez-Miera and Suarez 2012), is growing. Given that the empirical evidence is still rather scarce, we comlement the theoretical literature by providing empirical evidence on the joint dynamics of a core set of macroeconomic variables and a broadly based measure of financial instability for the euro area economy.

The main question we address is whether there is empirical evidence for nonlinearities in the relation between systemic stress and the macroeconomy in the euro area relevant for monetary and macroprudential policy. More specifically, we first investigate whether it is only the size of shocks that is changing in episodes of high systemic stress or whether a more fundamental change is taking place during such episodes, namely a change in the interaction between the financial sector and the macroeconomy and the transmission of shocks through the economy. Second, we analyse whether the resulting nonlinearities are economically relevant, in particular whether the macroeconomy reacts differently to financial stress shocks in high systemic stress than in tranquil episodes, taking into account feedback effects. Third, we investigate whether certain features of the composite systemic stress indicator we employ are important for our results. Fourth, we investigate whether our model is useful for tracking systemic stress episodes in real time.

To investigate those questions, we employ the Composite Indicator of Systemic Stress (CISS) - recently developed at the European Central Bank by Hollo, Kremer and Lo Duca (2012) - a synthetic measure of systemic financial instability of euro area data. Compared to alternative financial stress indices (see e.g. Illing and Liu 2006 and Kliesen, Owyang and Vermann 2012 for overviews), the CISS appears particularly suitable for our purpose. It concentrates on capturing the systemic dimension of financial instability by, first, covering the main classes of financial markets and intermediaries in a systematic fashion and, second, by considering the time-varying dependence of stress between those major segments of the financial system. The systematic inclusion of financial intermediaries may be important in the context of our analysis since we focus on the euro area, a more bank-based financial system in contrast to more market-based systems like the US.[1]

We then embed the CISS – together with a few other major macroeconomic and financial variables – in a richly specified Markov-switching Vector Autoregression (MS-VAR) model estimated with Bayesian methods (see Sims, Waggoner and Zha 2008). The model specification allows both estimated parameters and shock variances to change regime. We can thereby distinguish economic shifts due to fundamental changes in the interaction between the financial sector and the macroeconomy from changes in the size of shocks. Such MS-VAR models have been employed, for instance, by Sims and Zha (2006) to assess structural changes in US monetary policy and more recently by Hubrich and Tetlow (2012) for the US economy with a focus on monetary policy effectiveness.[2]

[1]A number of bank based systemic risk measures based on micro data have been proposed in the literature (see e.g. Archaya, Engle and Richardson, 2012).

[2]For related papers with regime-switching, see Baele, Bekaert, Cho, Inghelbrecht and Moreno (2012) and F. Bianchi (2014).

Our results support the view that the macroeconomy functions fundamentally differently in times of widespread financial instability compared to more tranquil times. Both the coefficients and the variances of the identified shocks change in economically relevant ways across regimes. We date the most fundamental regime change in 2008, in between the Bear Stearns takeover and the Lehman Brothers failure. In general, the effects of financial stress shocks in this regime of high systemic instability are much larger and more persistent than during tranquil times. Other episodes of regime change in coefficients include, for instance, the run-up to the EMS crisis or the burst of the dot-com bubble, but those episodes are characterised by smaller shocks. We also calculate the state probabilities for the regimes in real time, finding few false positives, which suggests the model has some potential for at least identifying current ("nowcasting") systemic instability as an aid to macro-prudential policy.[3] We employ counterfactual analysis to investigate what would have happened according to the model if the economy would not have been in high systemic stress in the Fall of 2008 and Spring 2009, but instead in tranquil times. We find substantial differences in model dynamics with important implications for the real economy, capturing for instance increases in risk aversion, uncertainty and default risk. Also, we show that loan growth has an independent role for real activity in high systemic stress episodes likely reflecting binding loan supply constraints. Finally, we find that alternative measures of financial stress, such as stock market volatility and corporate bond spreads, produce regimes that do not track known systemic stress episodes equally well and render dynamic multipliers that display less severe and less persistent real effects of financial shocks. This underlines the important features of a broadly based systemic stress indicator for modellig the interaction between the financial sector and the macroeconomy. Furthermore, we show that the inclusion of cross-market correlations and the financial intermediation sector are also relevant features of the CISS in our context.

This paper is most closely related to the empirical literature on the real effects of financial distress and crises. Early contributions on the Great Depression and the 1990 US credit crunch include Bernanke (1983) and Bernanke and Lown (1991), respectively. In recent contributions, Barkbu, Eichengreen and Mody (2012) and Schularick and Taylor (2014) measure, inter alia, the output costs of many crises across a broad set of countries taking a long-term historical perspective. Allen, Bali and Tang (2012) derive a measure of aggregate systemic risk from the cross-section of banks' equity returns (CATFIN) and find significant predictive power of the

[3] The European Systemic Risk Board, for example, has a role in identifying situations of systemic instability in which a state of emergency may have to be declared by the European Council (http://www.esrb.europa.eu/about/tasks/html/index.en.html).

CATFIN for different measures of real economic activity up to six months ahead in the US as well in European and Asian countries within standard predictive regressions. Giglio, Kelly, Pruitt and Qiao (2012) run one-month ahead in- and out-of-sample predictive quantile regressions and find particularly strong and signficant predictive power for low quantiles of several economic activity measures when aggregating more than 20 individual measures of systemic risk in the US and Europe into a single index. A few studies embed a financial stress index in macro-financial VAR models and find material adverse effects of financial stress shocks on economic activity. Some of those studies use linear models, only few use models allowing for nonlinearities such as ours. For instance, Dovern and van Roye (2014) estimate such effects jointly for a set of 20 advanced and emerging economies within a standard Global VAR framework.

Recent theoretical approaches to integrate financial instability into macroeconomic models build on features like occasionally binding borrower constraints (Mendoza 2002), borrower default (Dubey, Geanakoplos and Shubik 2005), limited commitment in financial contracts (Lorenzoni 2008), endogenous financial risks, fire sales and pecuniary externalities (Bianchi 2011, Korinek 2012, Brunnermeier and Sannikov 2013 and He and Krishnamurthy 2014a) as drivers of propagation and amplification of shocks. Other recent theoretical approaches emphasize the role of banks (and other financial intermediaries) and their incentives in expaining financial instability (Boissay 2011, Aoki and Nikolov 2012, Goodhart, Kashyap, Tsomocos and Vardoulakis 2012, Martinez-Miera and Suarez 2012, Boissay, Smets and Collard 2013 and He and Krishnamurthy 2014b). Some of those features are able to theoretically explain the occurrance of regime changes in response to the emergence of systemic stress. Regime changes may furthermore reflect run-like equilibrium phenomena as in Diamond and Dybvig (1983), Morris and Shin (2012), Allen and Gale (2000), Diamond and Rajan (2005), Brunnermeier and Pedersen (2008) and Gorton and Metrick (forthcoming). Our model complements the theoretical literature by providing empirical evidence of nonlinearities in the interaction between systemic financial stress and the macroeoconomy, contributing to the debate of whether it is just large shocks or more fundamental changes in economic dynamics characterising episodes of high systemic stress, while we do not attempt to model specific origins of systemic stress.

The remainder of the paper is structured as follows. Section 2 describes the econometric methodology employed and the main features of the systemic stress indicator as well as the macroeconomic variables used. Section 3 presents the empirical results, interpreting the smoothed probabilities of high systemic stress, impulse responses to a financial stress shock, counterfactual analyses investigating the impact of the regime change to high systemic stress in 2008 as well as the role of loan growth in the episodes of systemic stress. We also show the real-time probabilities of the model. Section 4 compares our main results with those obtained with alternative measures of financial stress such as aggregate stock market volatility and corporate spreads. We also present results for models that exclude correlation across stress in different financial sectors and financial intermediation, respectively, from our measure of systemic stress. Section 5 draws some conclusions, relevant from a monetary and macro-prudential policy perspective.

2 Model setup and measurement of systemic financial instability

Several choices have to be taken at the initial stage of model specification. First, we need a flexible econometric model framework that can accommodate the (infrequent) occurrence of systemic stress episodes which typically bring about swift changes in the economic dynamics. Second, we need a measure of systemic financial instability that ably captures the spreading of financial stress across markets. Third, the remaining model variables have to ensure a sufficient representation of the macroeconomic dynamics in general and interactions between key macro variables and our financial stability measure in particular. Fourth, the model needs to be identified to achieve a structural interpretation of shocks. We discuss each of these topics, in turn, in the next four subsections.

2.1 Non-linear multivariate model framework

An important feature of our analysis is the application of an econometric framework that allows to investigate empirically whether the macroeconomy fundamentally changes its functioning when systemic financial stress emerges or disappears. In particular, we ask whether specific non-linearities in the form of regime switches in the dynamics of and the relationships between key macroeconomic variables can be identified empirically, notably in terms of the role of systemic financial stress and related amplification effects and feedback mechanisms. For this purpose we apply a richly specified Markov-switching VAR model that can estimate abrupt, discrete changes in the economic dynamics. Our specific MS-VAR framework furthermore distinguishes between two different types of regime switches, namely shifts in the volatility of shocks and changes in the structure of the shock transmission.

Estimation of and statistical inference from the MS-VAR model rests on recent Bayesian methods developed in Sims and Zha (2006) and Sims, Waggoner and Zha (2008). Some details on the relevant techniques are provided in the Appendix B.[4]

We consider (possibly) non-linear vector stochastic processes of the following form:

$$y_t^{'} A_0(s_t^c) = \sum_{j=1}^{l} y_{t-l}^{'} A_j(s_t^c) + z_t^{'} C(s_t^c) + \varepsilon_t' \Xi^{-1}(s_t^v), \qquad t = 1, 2...T. \tag{1}$$

where y_t is an $n \times 1$ vector of endogenous variables; s_t^m, $m = v, c$ are unobservable (latent) state variables, defining different regimes for error $v$ariances, v, and for intercepts and slope $c$oefficients, c. l is the VAR's lag length. z_t is a matrix of exogenous variables, which we are setting to a column vector of constants 1_n, i.e. one intercept per equation. $A_0(s_t^c)$ is an $n \times n$ matrix of parameters describing contemporaneous relationships between the elements of y_t, $C(s_t^c)$ is an $1 \times n$ vector of parameters of the exogenous variables and $A_j(s_t^c)$ is a $n \times n$ matrix of parameters of the endogenous variables and T is the sample size. ε_t is the $n \times 1$ vector of the random shocks. The diagonal $n \times n$ matrix $\Xi^{-1}(s_t^v)$ contains the standard deviations of ε_t. $\varepsilon_t' \Xi^{-1}(s_t^v)$ represents the structural shocks. The values of s_t^m are elements of $\{1, 2, ...h^m\}$ and evolve according to a first-order Markov process with the following state probabilities:

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

Let us designate $Y_t = \{y_0, y_1, ...y_t\}$ as the vector y stacked in the time dimension. We assume that ε_t is conditionally standard normal:

$$p(\varepsilon_t | Y_{t-1}, S_t, A_j) \sim N(0_{n \times 1}, I_n).$$

The variance-covariance matrix $\Sigma(s_t^m)$ of the correlated reduced-form regression errors can be recovered as follows:[5]

$$\Sigma(s_t^m) = (A_0(s_t^c) \Xi^2(s_t^v) A_0'(s_t^c))^{-1}. \tag{2}$$

Since the matrix A_0 varies across coefficient regimes s_t^c, the number of regimes of the correlated shocks obtains as a multiple of the number of variance regimes of the structural shocks s_t^v since coefficients and variances are assumed to switch stochastically independently of each other.

[4] These recent developments in Bayesian econometrics have facilitated the estimation of and inference for such richly parameterised models like ours.

[5] See Sims, Waggoner and Zha (2008), p. 265.

2.2 Systemic stress indicator

A suitable systemic stress indicator must have several features. First, as the word *stress* suggests, it needs to capture not just activity or even disruption in the financial sector, but stress that might be of concern to market participants and policy makers. Second, as the word *systemic* indicates, it should ideally distinguish between stress that are germane to a single or small subset of markets–and thus not of concern to the system as a whole or its' regulators–and stress that has the potential to infect the entire system. It is presumably when stress is widespread that they have implications for the broader macroeconomy. Indeed, a conventional definition of systemic risk is that it is "the risk that financial instability becomes so widespread that it impairs the functioning of a financial system to the point where economic growth and welfare suffer materially" (ECB 2009). Third, the word *indicator* points to the need for the candidate measure of systemic stress to be timely in the marking of stress episodes, reliably identifying events of potential concern to market participants and policy makers, preferably in real time.

We will argue that the Composite Indicator of Systemic Stress (CISS) developed by Hollo, Kremer and Lo Duca (2012) ably fulfills the roles of a good systemic stress indicator, as just described. Our discussion of the CISS will be brief by necessity; readers interested in more details are invited to consult Appendix A or Hollo, Kremer and Do Luca (2012).

First of all, the scope of the CISS is broad, comprising five aggregate market segments covering the main channels by which the funds of savers are reallocated to borrowers, whether those funds are channeled indirectly through financial intermediaries or directly via short-term and long-term markets. These segments include: (1) financial intermediaries; (2) money markets; (3) bond markets; (4) equity markets; and (5) foreign exchange markets. Each of the five market segments is populated with three representative stress indicators that are generally recognized as excellent proxies of fundamental risks and market disruptions, such as spreads, volatilities and market return correlations (see Table 4 in Appendix A for a precise description of the input data). Aggregation of each set of three constituent stress measures - after appropriate transformation to harmonise their scale and probability distribution - results in five segment-specfic subindexes of financial stress.

The way how the subindexes are aggregated into a composite indicator is the main innovative feature of the CISS. In the same way that portfolio risk is computed from individual asset risks, the subindexes are aggregated by taking into account the time-varying (rank)-correlations between them. The time variation in the correlations means that relatively more weight is applied during periods in which stress prevails in several market segments at the same time. In

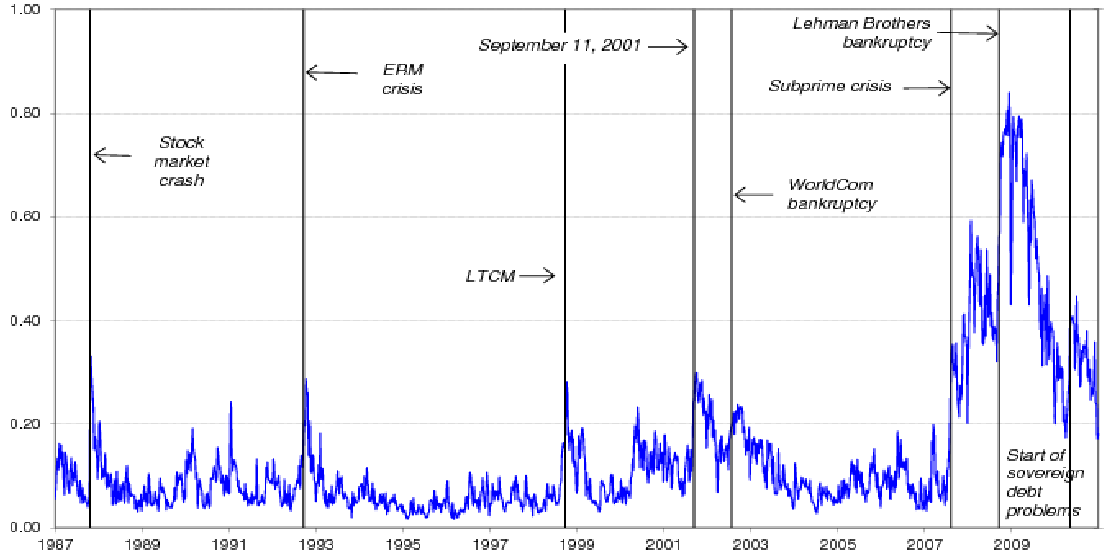

Figure 1: Composite Indicator of Systemic Stress ("CISS") for the euro area and specific financial stress episodes, January 1987 to December 2010

this way, the CISS is specifically designed to describe how widespread and severe instability in the financial system has become at any one time.

As we noted in the Introduction, our approach in this paper is agnostic when it comes to the origins of financial instability. Regardless of the origins, for financial stress to be consequential, it must eventually be widespread. Thus, we regard it as an advantage of our approach that we can start the analysis from what systemic crises have in common, namely their breadth across markets and institutions.

The final index, as constructed from euro area data, is plotted in Figure 1. As can be seen, the largest spikes in the indicator coincide with well-known financial stress episodes, such as the 1987 stock market crash, the 1992 crisis of the European exchange rate mechanism, the 1998 Russian debt default and associated Long Term Capital Management crisis, as well as the financial stress around the terrorist attacks on 11 September 2001.[6] More recently, the financial crisis stands out in comparison with previous stress events in terms of both the level reached, in the wake of the September 2008 bankruptcy of Lehman Brothers, and in the duration of high readings.

[6] See Hollo, Kremer and Lo Duca (2012) for a more extensive coverage of historical stress events which coincide with peaks in the CISS.

2.3 Other variables and data sources

Since MS-VAR models allowing for regime changes in all coefficients and shock variances even with a moderate number of different regimes require estimation of a large number of parameters, we opt for a model with five endogeneous variables. Three of them represent standard variables in the macro VAR literature, namely industrial production growth as a measure of economic activity, consumer price inflation and a short-term interest rate, where the latter may capture short-term funding costs in the economy but also proxies for conventional monetary policy. These variables form the backbone of any stylised empirical representation of standard macroeconomic models (for an overview see, e.g., Christiano, Eichenbaum and Evans, 1999).

The set of endogenous variables is completed by adding the CISS and the growth rate in nominal bank loans to the private sector. The latter choice can be generally motivated by the strong role that bank lending played in the most severe financial crises in history (e.g. Schularick and Taylor 2012). It is also justified by the relatively large share of bank loans in the overall financing of the euro area economy.

The data sample runs from January 1987 to December 2010. Industrial production, consumer price inflation (based on the Harmonised Index of Consumer Prices, HICP) and nominal bank loans to the private sector are expressed in year-on-year percentage log changes of seasonally-adjusted monthly data for the euro area as a whole. The short-term interest rate is represented by the three-month Euribor (Euro InterBank Offered Rate) and measured as monthly averages of daily data. All four series are taken from ECB data bases. The CISS data are monthly averages of weekly data and is taken from Hollo, Kremer and Lo Duca (2012).

2.4 Structural model identification

The contemporaneous relationships between the endogenous variables - as reflected in the Matrix A_0 - are identified on the basis of a triangular representation analogue to the well-known Choleski decomposition often used in structural VAR applications (see, e.g., Hamilton 1994). In triangular identification schemes the ordering of the variables determines the contemporaneous causality structure. For instance, the variable ordered first is assumed to be contemporaneously uncorrelated to all other variables.

The conventional ordering in the macro VAR literature places the short-term interest rate last, implicitly assuming that monetary policy may react instantaneously (i.e., within the time unit of the data sampling frequency) to shocks in the other variables while no other variable is allowed to respond contemporaneously to monetary policy shocks.[7] In our structural identification setup, we maintain this basic assumption and place the short-term interest rate right after industrial production growth and inflation. However, we order the short-term rate before loan growth assuming that banks can adjust their lending activity quickly to monetary policy innovations. Finally, we order the CISS last such that output, inflation, interest rate and loan shocks can all have contemporaneous effects on financial stress, while systemic financial instability (CISS) shocks are restricted to impact on the rest of the economy only with a lag. This ordering reflects the conventional practice in the recent VAR literature to allow asset price variables to respond instantaneously to shocks in usually more sluggish macro variables such as output and inflation. The variables thus enter the model in the following order: output growth (ΔIP), inflation (ΔP), interest rate (R), loans (ΔLn) and the CISS (S). Our main results turn out to be qualitatively robust to different variable orderings, however.[8] In what follows we thus present results only for the above ordering which constitutes the most conservative estimates for the issue we are most interested in, namely the link between systemic financial instability and the real economy.[9]

3 Systemic stress, macroeconomic regimes and the role of financial crises

3.1 Model estimation and evaluation

The five-variable structural MS-VAR model in equation (1) is estimated with a lag order of three using Bayesian methods.[10] We employ a blockwise optimization algorithm to estimate

[7] See e.g. Christiano, Eichenbaum and Evans (1999).

[8] In particular, when placing the CISS first in the order (followed by interest rates, output growth, inflation and loan growth) such that all shocks in financial stress become exogenous to the contemporaneous shocks in the other model variables (assuming, e.g., that output and monetary policy can react simultaneously to surging financial stress), the impulse response functions still convey the same basic messages. The same robustness result holds true when switching the order between bank loan growth and the interest rate (allowing short-term rates to react immediately to lending innovations).

[9] We also carried out several other sensitivity analyses, which again turned out immaterial for our main findings. For instance, we replaced the three-month Euribor by the monthly average EONIA (Euro OverNight Index Average) rate, where the latter substitution takes account of the fact that banks' liquidity and counterparty risk considerations drove a large wedge between both rates during certain episodes of the recent crisis. Results not displayed in the paper are available from the authors upon request.

[10] A model with a lag length of 12 provides similar results in terms of the real effects of a financial stress shock reported later.

the posterior mode. In a first step, parameters are divided into blocks and the resulting initial guesses for the parameters are used in a hill-climbing quasi-Newton routine. At candidate maximum points, we subject the estimator to random perturbations thus generating starting values from which the optimization process is restarted in order to assure that the estimated posterior mode we obtain is indeed the most likely estimate.[11]

Our modeling framework allows for two independent Markov chains, one governing the structural error variances, and the other determining the dynamic interactions between the model variables as reflected in the model parameters. To assess alternative specifications, we compute the logarithm of marginal data densities (MDDs) for each candidate specification and compare goodness of fit.

The standard modified harmonic mean (MHM) method for computing MDDs of Gelfand and Dey (1994) has been found to be unreliable when the posterior distributions are very non-Gaussian as is likely to be the case here. To overcome numerical problems that arise in this context, and to better approximate the posterior density function, we are using an elliptical distribution as a weighting function to calculate MDDs (see Waggoner and Zha 2012, Appendix C3).[12]

We employ two sets of priors for estimating our model, One for the VAR parameters, the other for the transition matrix. Following Sims, Waggoner and Zha (2008) we use standard Minnesota priors for the VAR parameters; for the transition matrix, we use the Dirichlet prior.[13]

3.2 Determining and interpreting regimes

3.2.1 Model selection

The Bayesian counterpart to frequentist hypothesis testing is to compare MDDs, or equivalently, to assess Bayes factors, across models.[14] In accordance with the suggestion of Jeffreys (1961), differences in log MDDs of 10 or more are normally taken as strong evidence that one model is more supported by the data than the other. Before turning to the results, a few words on notation are useful in order to interpret the table. In table headings and elsewhere, a v indicates the Markov chain associated with switching in shock $v$ariances, while a c refers to the

[11] We use 5 large random perturbations and 5 random perturbations in the neighbourhood of each of the resulting peaks.

[12] In the Markov Chain Monte Carlo (MCMC) algorithm we use 10000 proposal draws and 5 million posterior draws with a thinning factor of 10, so retaining 500000 posterior draws. The burn-in period is 10%.

[13] For more details on the priors, see Appendix B.

[14] Log(mdd) differences can be considered as posterior odds ratios assuming equal weights for the models as priors.

Table 1: Marginal data densities, selected model regime specifications

	[1]	[2]	[3]	[4]	[5]
Regime combination	$1v1c$	$2v1c$	$3v1c$	$2v2c$	$3v2c$
log of marginal data density	-6.05	92.4	131.9	126.1	147.4
- *difference from* $1v1c$ *model*	0	98.4	138.0	132.1	153.4

Notes: Log MDDs are calculated as in Sims, Waggoner and Zha (2008)
$ivjc$ where i = number of variance and j = number of coefficient regimes.

chain governing model *c*oefficients. A number preceding either v or c indicates the number of regimes allowed in the Markov chain governing shock variances or coefficients, as applicable. So, for example, $3v2c$ indicates a specification that allows for three regimes in the variances of shocks and two regimes in coefficients.

Table 1 presents the log MDDs for several combinations of the two types of regimes. For ease in interpretation, the log MDDs are shown both in absolute terms in the first row of numbers and relative to a standard constant-coefficient Gaussian VAR model—that is, the $1v1c$ specification—as a benchmark, in the second row.

As can be seen, the results provide strong evidence against a constant-coefficient ($1v1c$) model. The difference between the constant-coefficient model, column [1], and any of the models with regime switching is at least 98 in terms of log MDDs, and in most cases much above 100. Restricting the number of coefficient regimes to one, and allowing for two or three regimes in shock variances, as in columns [2] and [3], shows that the models with several regimes in shock variances outperform the constant coefficient model: the $3v1c$ specification is the preferred one among the three specifications that allow only switching in variances. Consider, however, starting with two regimes in shock variances—that is, the $2v1c$ specification—whether the addition of a third variance state ($3v1c$)or a second coefficient state ($2v2c$) improves the model fit. Columns [3] and [4] suggest that there is no strong reason to prefer one of these models over the other. Lastly, the specification with three variance regimes and two coefficient regimes—$3v2c$, column [5]—is shown to outperform all the other models considered. Not shown in the table are results for more complicated models than the $3v2c$ specification. In fact, on purely statistical grounds, a few models allowing more states in shock variances are favored. However these models were either similar in economic terms to the $3v2c$ specification, or had nonsensical properties from an economic perspective.[15] If for no other reason than parsimony in presentation and based

[15] Marginal data density computations do, at least in principle, penalize non-parsimony of models, employing a Bayesian information criterion.

Table 2: Relative standard deviations of structural shocks by regime

	ΔIP	ΔP	R	ΔLn	S
Variance regime 1 ($v1$)	1.00	1.00	1.00	1.00	1.00
Variance regime 2 ($v2$)	0.91	1.53	0.29	0.74	0.62
Variance regime 3 ($v3$)	0.85	1.99	0.65	0.56	2.98

Notes: Entries are normalized for each variable on the unit std devs of the first regime.

on economic interpretability, we therefore select the $3v2c$ specification as our preferred model. We turn to the economic characterisation of the different regimes of our preferred model in the following.

3.2.2 Economic characterisation of regimes

Table 2 shows the estimated standard deviations of the structural shocks in all variables across the three identified variance regimes ($v1$ to $v3$), relative to the volatilities of the first regime which are normalized to unity. Several noteworthy conclusions arise from the table. First, switching in shock variances is consequential, at least statistically, in that there are substantial differences in standard deviations from regime to regime. Second, there is no uniform pattern in the ranking of standard deviations across all variables in that the standard deviations of shocks do not rise and fall together from regime to regime. Third, for the shock of principal interest for this paper, the magnitude of the CISS (S) shock in the variance regime 3 clearly stands out. Finally, it is also worth noting that while the S shock and also the inflation shock rises substantially, in $v3$ relative to $v1$, the pattern is the opposite for shocks to industrial production (ΔIP), loans (ΔLn) and the interest rate (R). Precisely what to make of this latter observation is not entirely clear, but it does suggest that shocks to financial stress play a more important role in driving dynamics in $v3$ than do shocks to loan supply and real activity, operating independently of financial stress. In short, the suggestion is that in $v3$, it is stress shocks that dominate.

Table 3, which shows descriptive statistics for endogenous variables conditional on each of the six possible combinations of variance and coefficient regimes, sheds some light on the economic characterization of regimes from the viewpoint of financial instability.[16] For ease of comparison, the regimes are ordered such that regimes with $v = v1$ and c varying from $c1$ to $c2$ are presented in the first two rows of the table, while regimes with $v = v2$ and $v = v3$ are displayed in the

[16] These summary statistics compute the conditional moments (conditional on regime) of each variable over all months in which a given regime dominates. The dominant regime is the one with the highest smoothed regime probability in the respective month. As we show below, which regime is dominant is rarely ambigious.

Table 3: Descriptive statistics, by regime

Line	Regime	conditional means					sample
#		ΔIP	ΔP	R	ΔLn	S	shares (%)
[1]	regime 1 $(v1, c1)$	0.54	2.26	5.85	5.97	0.071	16.1
[2]	regime 2 $(v1, c2)$	3.39	3.01	6.13	8.43	0.092	17.8
[3]	regime 3 $(v2, c1)$	2.78	1.96	3.22	6.33	0.081	35.3
[4]	regime 4 $(v2, c2)$	1.16	2.83	5.85	6.11	0.110	18.9
[5]	regime 5 $(v3, c1)$	3.96	2.43	4.18	9.66	0.260	5.2
[6]	regime 6 $(v3, c2)$	-11.3	1.57	2.88	4.66	0.520	6.6

Notes: vi variance regime, $i = 1, 2, 3$. cj coefficient regime, $j = 1, 2$.

subsequent four rows. Several interesting observations with respect to the interpretation arise. First, and most obviously, as one moves down in Table 3 from row [1] to [3] and [5], or from row [2] to [4] and [6], the regime-dependent means of the CISS rise. It would appear, therefore, that at least a portion of elevated levels of stress, when applicable, stem from stress shocks themselves. Second, as demonstrated by lines [5] and [6], regime 5 $(v3, c1)$ and regime 6 $(v3, c2)$ are periods of extremely high levels of financial stress, but represent relatively rare events, as judged by the 5 and 7 percent sample shares of the two regimes, respectively. Third, while growth in loans, ΔLn, and growth in real activity, ΔIP, are positively associated when going from $v1$ to $v3$ when $c = c1$, they both fall sharply and montonically with v when $c = c2$. Evidently, periods of financial stress also feature reduced lending activity and deterioration in real economic performance. And clearly, shifts from regime $c1$ to $c2$ are economically consequential, although in precisely what way depends a great deal on the prevailing variance regime as we will explore in more detail in section 3.2.4.

The remaining regimes display no clear patterns in terms of means and shock volatilities of the CISS. Regimes 1 to 3 are associated with periods of relatively low financial stress in general, a situation which can probably also be regarded as "tranquil" given that these three regimes together prevail in about 70 percent of the sample period (see the last column in Table 3). However, these normal and generally tranquil periods can include episodes with occasional, short-lived spikes in financial stress. Regime 4 might be labelled "medium stress", since it occurs during the first two years of the dot-com bust period – during which financial stress persisted at an elevated, though not extremely high level – and for roughly half a year some time after the Lehman debacle (see Figure 3). A similar pattern to that of the CISS also emerges for the other endogenous variables. While in general no uniform ranking order exists in terms of regime-dependent shock volatilities or conditional means, all series (except for the CISS) assume their lowest readings in terms of means in regime 6.

3.2.3 Smoothed probabilities, regimes and historic events

We next assess the smoothed regime probabilities, first of each variance regime and each coefficient regime in isolation (see Figure 2). In general, the regime probabilities are either very close to one or very close to zero, indicating that the model classifies regimes quite sharply. Each of the five panels in Figure 2 illustrates which observations contribute to estimating the parameters of the respective variance and coefficient regimes. It deserves special mention that the estimation of both coefficient regimes receives support from several elongated periods of time. This appears important given the large number of parameters to be estimated for each of the coefficient regimes. In contrast, variance regime 3 - which is characterised by much higher variances of CISS shocks than in the remaining variance regimes - lasts only for about three years and covers almost exclusively observations from the recent global financial crisis. However, the numbers of paramaters to be estimated for each variance regime is also rather low, namely equal to five, the number of shocks in our system.

Figure 3 plots the smoothed probability of regime 6 $(v3, c2)$ along with that of regime 4 $(v2, c2)$. Both regimes combine a different variance regime with the same coefficient regime $c2$ which, as we will demonstrate in section 3.2.4, features a stronger transmission of financial stress to the macroeconomcy than coefficient regime $c1$. The state probability of the medium-stress variance, high-stress coefficient regime 4 is represented by the blue line. Episodes captured by this regime correspond to the aftermath of the 1987 stock market crash; the Gulf war in 1990; the run-up to the crisis in the European Exchange Rate Mechasim (ERM) in the early 1990s; the "dot-com bubble" bust; and finally a time period in 2009 when the financial crisis was moderating until the euro area sovereign debt crisis took off in early 2010. For instance, the episode before the UK left the European Monetary System (EMS) in September 1992 was characterized by the German reunification leading to a divergence in policy priorities in Germany and those in other EMS countries. In particular, in the first three quarters of 1992 the policy mix in Germany led to tensions in macroeconomic and political conditions, as argued in Buiter, Corsetti and Pesenti (1998).

The smoothed probability of regime 6, which combines the high-stress variance regime with the high-stress coefficient regime, is plotted as the red line in Figure 3. Apart from a blip

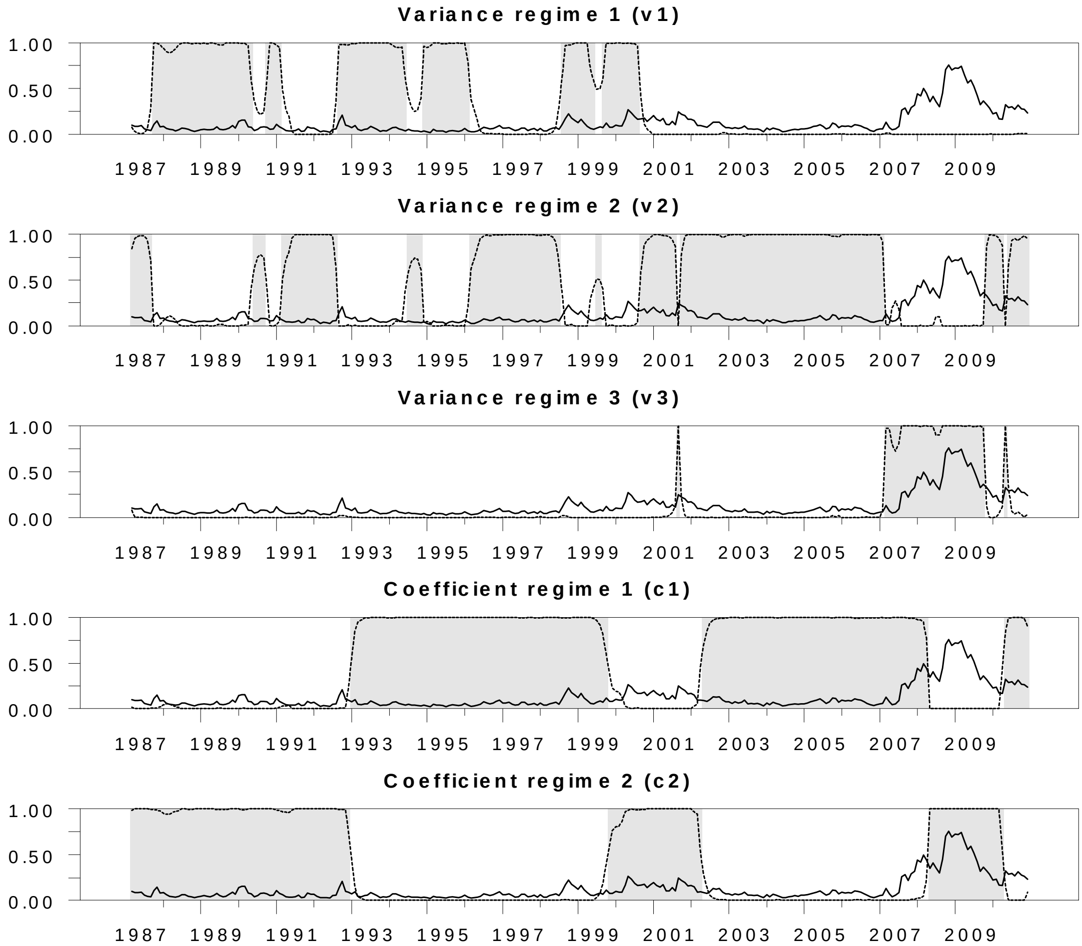

Figure 2: CISS and regime probabilities (dominant regime shaded)

caused by the US terrorist attacks in September 2001, this regime covers the peak times of the Great Financial Crisis including the meltdown of the euro area economy (see line [6] in Table 3). Interestingly, the initial stages of the recent crisis, namely the financial turmoil caused by the subprime mortgage crisis, are covered by regime 5 which combines high-stress variances with coefficient regime $c1$. The next section, after discussing the differences in transmission between high systemic stress and tranquil episodes, will help interpreting the fundamental differences between regimes 5 to 6.

3.2.4 Transmission of financial shocks

We now assess the economic differences between the various regimes in terms of the regime-dependent impulse response functions (IRFs).[17] While the three variance regimes deliver dif-

[17] Note that the impulse responses presented here are based on the posterior mode.

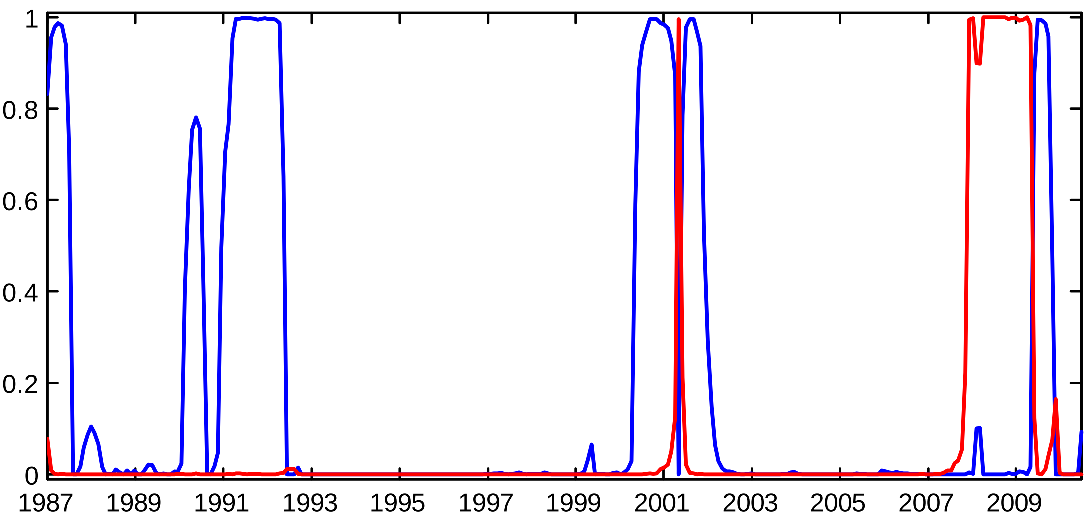

Figure 3: State probabilities, Red: High stress variance high stress coefficients, Blue: Medium stress variance high stress coefficients

ferent typical shock sizes, the two different sets of model coefficients summarize the dynamic structure of the macroeconomy and therefore the transmission of shocks. Since the main purpose of our paper is to study potential state dependencies in the transmission of systemic financial instability to the real sector, we put particular focus on the IRFs describing the dynamic effects caused by structural shocks to the CISS. Figure 4 plots the impulse responses of all model variables to shocks in the CISS (S) for two different regimes, namely regime 6 (solid red lines) and regime 1 (blue dashed lines).[18] Regime 6 represents times of extremely high financial stress and regime 1 tranquil times. The graphs also include the IRFs from a standard linear VAR model (the $1v1c$ specification).

The differences between the IRFs from regime 6 and regime 1 are striking. In tranquil regimes, industrial production growth (as well as all other variables) displays hardly any reaction to a CISS shock. It thus appears that the financial stress shocks become a *quantité négligeable* in tranquil episodes, an observation that accords well with the fact that the CISS aims to measure systemic stress and not general financing conditions. By contrast, in regime 6 a positive shock in financial stress leads to a quick, severe and protracted contraction in economic activity. For example, a positive one standard deviation shock in the CISS by around 0.1 leads to a sharp

[18] The IRFs are calculated for a positive one-standard-deviation shock in the CISS from the high-stress variance regime ($v3$) in the first case and from one of the low-stress variance regimes ($v1$) in the second case, respectively. Alternatively, we could have taken the IRFs from regime 5, the "financial turmoil" regime, with essentially the same implications.

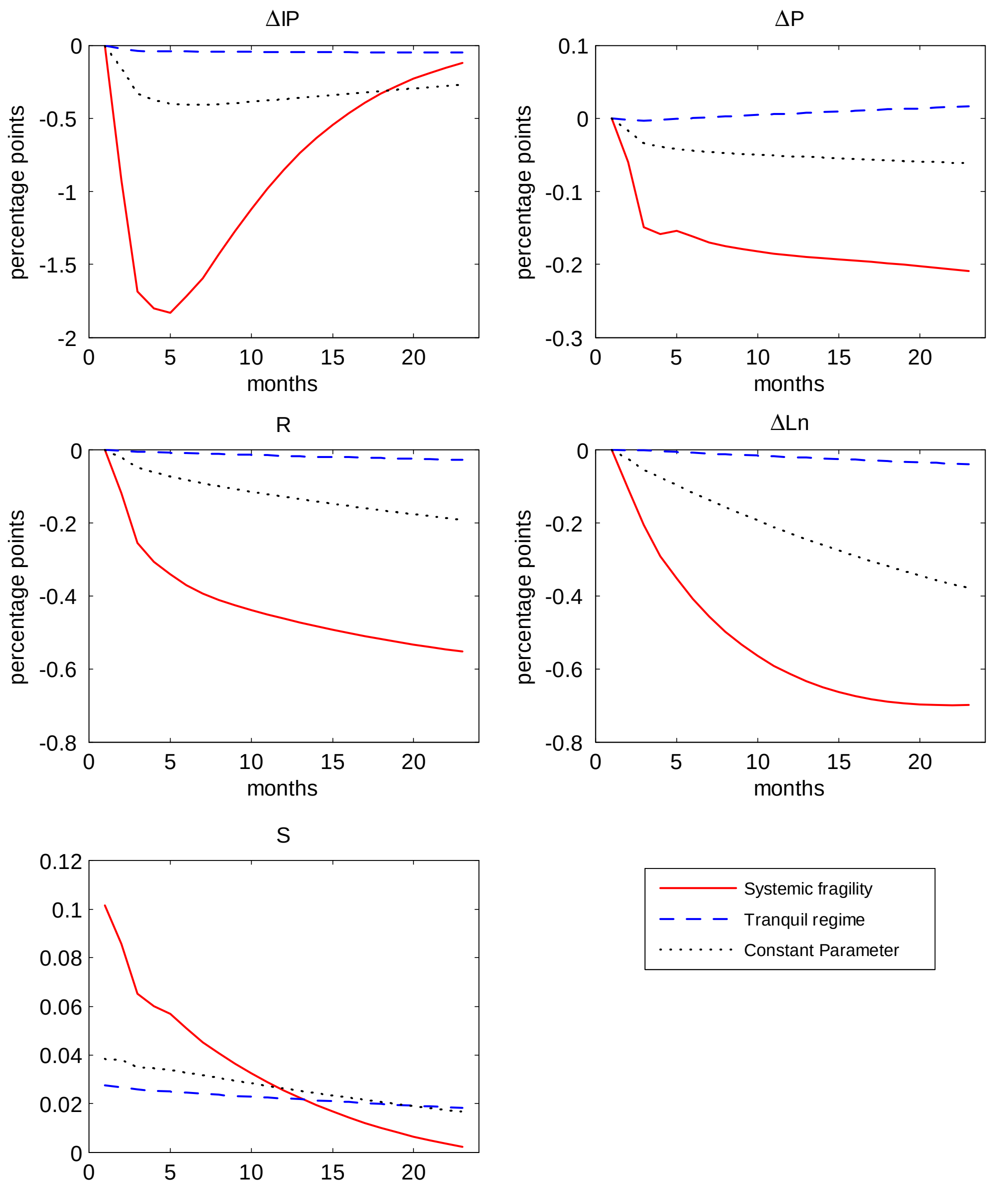

Figure 4: Impulse responses to financial stress shock, one standard deviation shock, comparison constant parameter model and 2 coefficient regime model (3v2c)

decline in output growth by about 2 percentage points over the first five months. By contrast, an identical CISS shock in regime 5 triggers only a moderate reaction in economic activity. Hence, we argue the coefficient regime $c1$ implies very weak financial-real linkages and the coefficient regime $c2$ very strong ones. We accordingly classify regime 6 featuring the largest CISS shock variances and the strongest financial-real linkages—that is, $(v3, c2)$— as a regime of "systemic fragility", in reflection of the vulnerability of the economy under such circumstances. Regime 5, which shares with regime 6 the largest shock variances but with weaker financial-real linkages, $(v3, c1)$, we classify as a regime of "financial turmoil" since it lacks the strong propagation mechanism that results in high costs in terms of output losses.

The lower-right panel of Figure 4 shows also a relatively strong, gradual and persistent effect of a CISS shock on loan growth in regime 6. This suggests that bank lending also plays a role in amplifying the transmission of financial stress to the real economy in times of financial turbulence. The rather gradual decline in loan growth in response to an adverse CISS shock may reflect firms' ability to draw down existing credit lines at the early stages of a financial crisis, mitigating the overall constraints on bank loan supply in the short term.[19] On the other hand, this fact is also in line with a lagged reaction in credit demand following the strong and immediate decline in output growth.

The IRFs from the linear VAR (the black dotted lines) illustrate that estimates based on a constant-parameter VAR model would have clearly underestimated the dynamic impacts of shocks in financial stress on economic activity as well as on the other macro aggregates in episodes of systemic fragility as covered by regime 6 and would have provided seriously misleading policy conclusions in such a situation.

Against the background of these findings, our model offers an interesting view on the different stages of the recent crisis. Figure 5 plots the smoothed probabilities of the "financial turmoil" regime 5 $(v3, c1)$ and the "systemic fragility" regime 6 $(v3, c2)$. The two regimes jointly identify the period from March 2007—when first signs of strains in the subprime mortgage market emerged and caused some peaks of the CISS—until October 2009, as the regime with the highest variances of CISS innovations; that is.a regime characterized by large financial shocks. Initially, however, the large shocks from this high-stress variance regime were only weakly transmitted to the rest of the economy, because the coefficient regime $c1$ was still in place. But as of May 2008, the coefficient regime switched to $c2$—one of very strong financial-real linkages. This timing corresponds with the negative growth rates in industrial production observed since that month

[19] See Ivashina and Scharfstein (2010) for pertinent evidence on this point for the case of the United States.

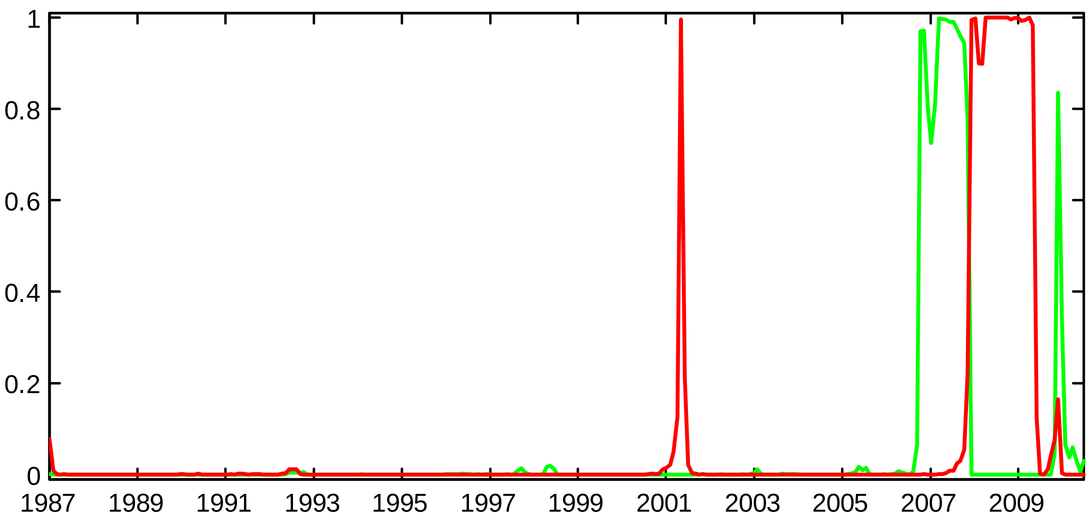

Figure 5: Smoothed probability of the systemic fragility regime (red line) and the financial turmoil regime (green line)

and, in particular, with the subsequent meltdown of the euro area economy in the aftermath of the Lehman debacle.

The particular sequence of regimes 5 and 6, each with its specific economic implications, is arguably an important finding of this study. During the initial stages of the subprime crisis, the associated financial turmoil apparently did not bring about material output losses and thus might not be considered as systemic. However, according to the model, the turmoil transformed into an episode of systemic fragility with strong adverse effects on real economic activity as of Spring 2008, that is, a few months prior to the bankruptcy of Lehman.

3.3 Counterfactual analyses

To illustrate the differential effects of financial shocks during systemic crises and in tranquil times, while providing some historical context, in this subsection we carry out counterfactual analyses.

3.3.1 The role of systemic stress

To illustrate further the fundamental change in the dynamics of the economy during crisis episodes, we consider a counterfactual scenario in which tranquil times are assumed to have persisted from October 2008 to February 2009, instead of undergoing the historical switch to systemic fragility.[20] Figure 6 demonstrates that in this scenario the level of systemic stress would have been substantially lower, by almost 0.2. The impact on output growth here is substantial. The figure shows that industrial production would have declined by only 6 percent per annum, instead of melting down by 21 percent; loan growth and inflation would have remained more or less stable at the rates observed at the outset of the exercise, instead of being 2.5 percentage points and 3 percentage points lower, respectively. Monetary policy would have been less accommodative with short-term interest rates dropping by only 1 percentage point instead of the 3 percentage points that was observed. Additional counterfactual experiments comparing the effects of a different path of financial stress in systemic fragility versus tranquil times are presented in the Appendix. They show that an increase in systemic financial stress has little effect in tranquil times, but substantial effects in episodes of systemic fragility.

3.3.2 The role of loan growth

Our final experiment assesses the real effects of a decrease in loan growth to 0 between October 2001 to March 2002, with the path of financial stress held constant at the average level of the actual path over the counterfactual period,. Thus we run a counterfactual what the effects would have been of a credit reduction as large as during the 2008/2009 financial crisis compared to the historical path during the period of the bursting of the dot-com bubble.[21] Our model characterizes this episode as one of intermediate financial stress and strong shock propagation (regime 4, $v2, c2$). We find that if loan growth would have deteriorated in the high stress episode in 2001 to such an extent, i.e. there would have been zero loan growth during this period, output growth would have been about 5ppt lower, as displayed in Figure 7. Inflation would also have substantially declined by 1ppt as would have the interest rate, the latter possibly reflecting a monetary policy reaction to loan reduction and output losses. These results suggest that loans play a material role for macroeconomic dynamics during regimes in which financial-real linkages are strong, and the macroeconomic effects of loan growth are independent of the effects

[20] This counterfactual employs the estimated coefficients and the parameters of the shock variances of the counterfactual regime to compute the counterfactual path of the variables during the counterfactual period. See also Sims and Zha (2006) for a similar counterfactual experiment in a different context.

[21] This simulation (as well as the counterfactual in the Appendix) involves computing the sequence of shocks to the relevant variable that are necessary to produce the counterfactual path for that variable, with all other variables being allowed to follow whatever path is implied by the sequence of shocks. The experiments are designed to be "small" in the sense that the sequence of shocks is within the empirically plausible set.

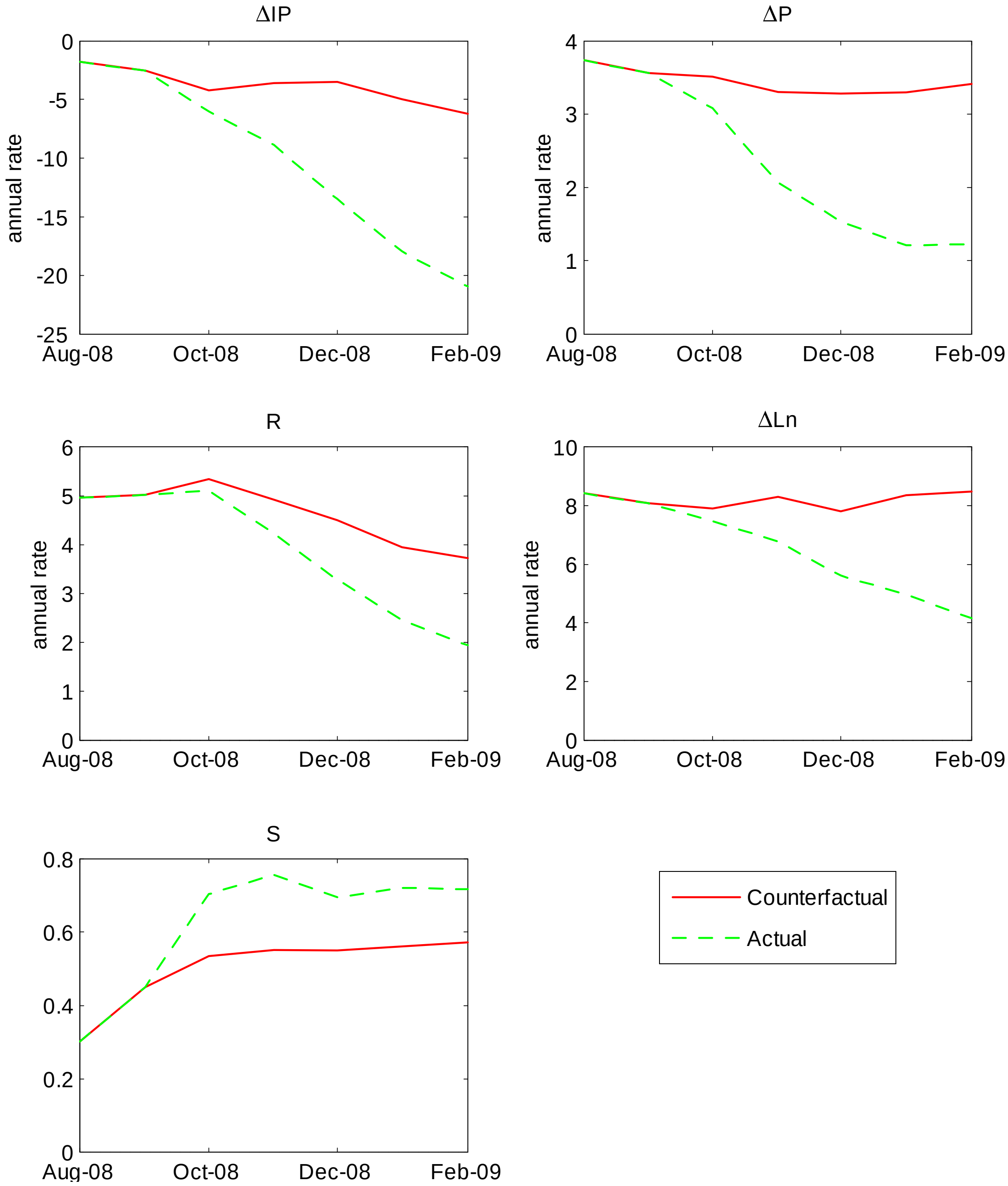

Figure 6: Counterfactual, tranquil times instead of systemic fragility, October 2008 to February 2009

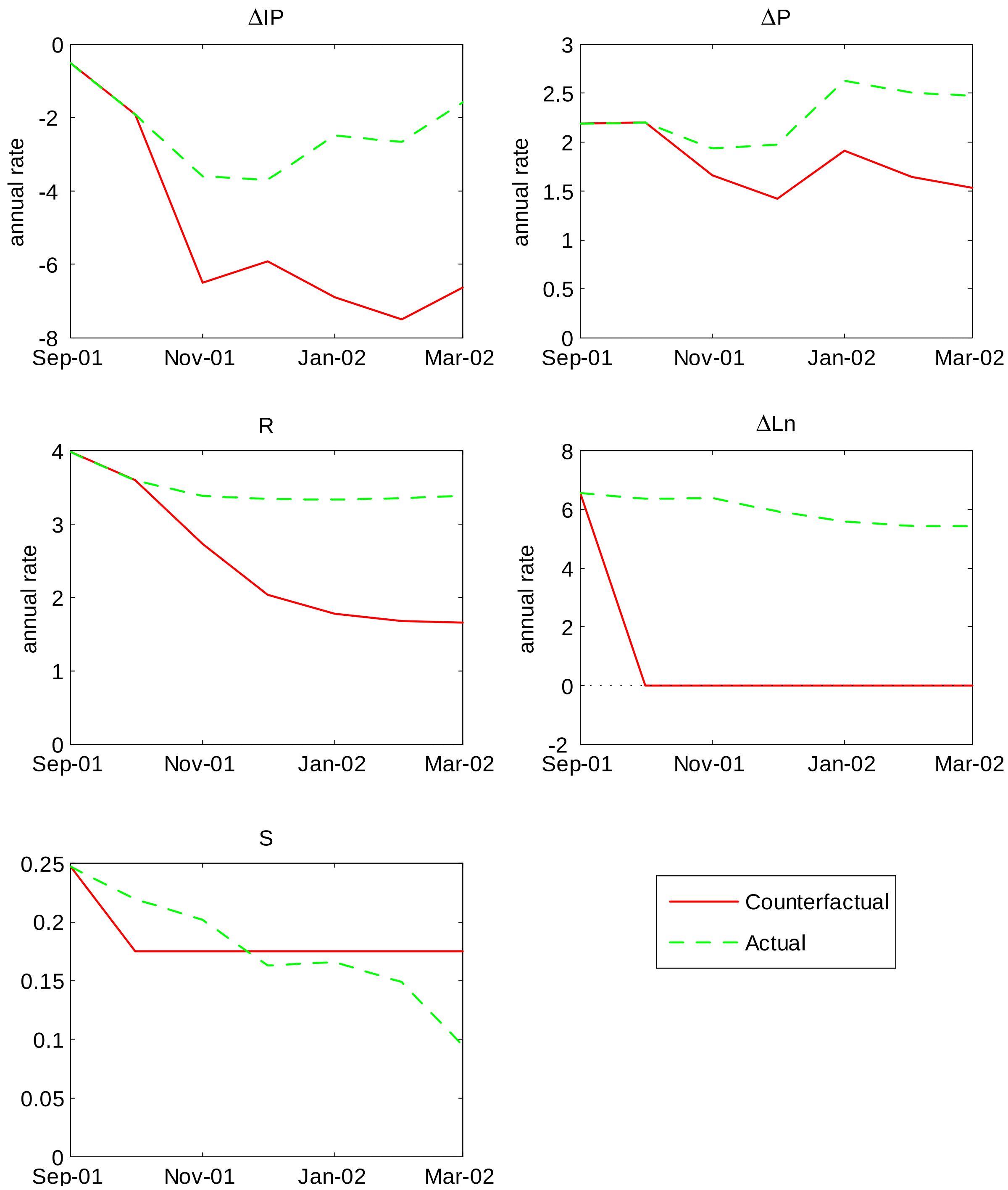

Figure 7: Counterfactual, path in loan growth to zero, path in financial stress to no change of average actual path over counterfactual period, October 2001 to March 2002

of financial stress and therefore add to those.[22]

3.4 Macro-prudential Surveillance and Real-time Probabilities

A necessary condition for this model to be useful as a macroprudential surveillance tool would be to demonstrate the reliability of the model for real-time nowcasting of switches in regime. As a step in this direction, we estimate the state probabilities in pseudo real-time based on a recursively expanding window. The results are shown in Figure 8. While the blue and red colored lines represent the full sample estimates of the smoothed state probabilities of regimes 4 and 6, the gray lines are the estimates based on the recursively expanding samples. If the model is successful in this way, it should lead to relatively few false signals of change in regime, meaning that the gray lines should be small and not terribly frequent. As can be seen, the estimation of the regime probabilities is rather robust. The model only rarely indicates a regime switch (indicated by a real-time regime probability of larger than 0.5, for instance) that would not be confirmed by the full-sample estimate *ex post*. As might be expected at the beginning of the sample period, when information from the data is scarce, real-time probabilities of being in a systemic fragility regime sometimes rise, but they never reach a value close to 0.5. At the same time, when the full-sample estimates signal the presence of a systemic fragility regime, the real-time probabilities tend to do so as well. In other words, falsely predicting high stress and falsely predicting a return to tranquil times, i.e. making type one and type two errors, is limited based on the pseudo real-time probabilities from this model.

This demonstration, while compelling in its own right, is not sufficient to establish the model's ability to serve as an effective real-time macroprudential tool. A more comprehensive assessment, building on real-time data among other things, would be useful—but is a topic we leave for future research.

4 Alternative Measures of Financial Stress

We have, in this paper, tried to establish the usefulness of the CISS as an efficacious tool for measuring systemic financial distress. The CISS is not, however, the only measure that has been proposed for purposes of this nature. In this section, we take two steps towards investigating

[22] If we set loan growth to 0 between October 2001 to March 2002, but let financial stress react freely instead of fixing it to the average actual path over the counterfactual period, we get a reduction in output growth by 2ppt which is the lower bound of the output loss, since financial stress is declining in response to the loan growth reduction and thereby might counteract the negative growth effect coming from the loan growth reduction.

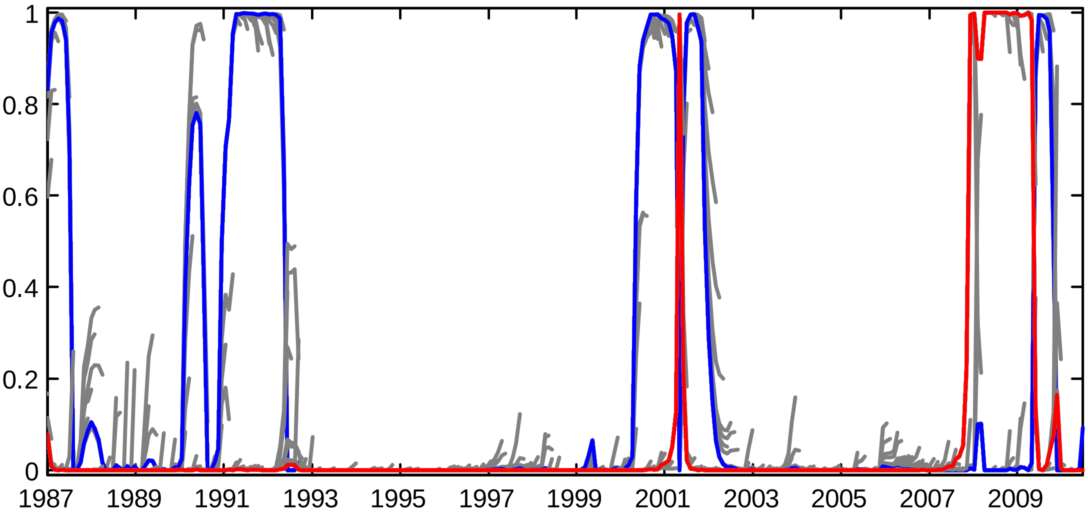

Figure 8: Real-time probabilities; Recursively expanding estimation window; Red: High stress variances and strong financial-real linkages (systemic fragility regime 6); Blue: Medium stress variance and strong financial-real linkages (regime 4)

the role of the particular construction of the CISS for our results. In particular, in one subsection, we explore the replacement of the CISS by two plausible alternative measures that have been suggested and used in the literature; in another subsection, we isolate two features of the construction of the CISS.

4.1 Stock market volatility and corporate bond spreads

It has often been argued that the VIX or realized stock price volatility are useful indicators of risk aversion and financial stress in general (see e.g. Coudert and Gex 2008, Bekaert, Hodrick and Zhang 2012, Bekaert and Hoerova 2014). In order to assess the value added of the CISS, in this section, we re-estimate our preferred model replacing the CISS with a measure of realized stock market volatility, measured as the square root of average daily squared log price returns on the broad EMU equity price index maintained by Thomson Financial Datastream. We compute the IRFs and the smoothed regime probabilities for the full sample and the real-time recursive sample for the model including realized stock price volatility as a variable measuring financial stress. Figure 9 presents the impulse responses to a one standard deviation shock in stock market volatility. Comparing the responses in output growth to financial stress shocks from that model with the IRFs of the model with the CISS (see Figure 4) we find that in the former case the output responses are much smaller and much less persistent than for the model using the CISS.

This result suggests that, if one is interested in capturing the effects of systemic instability on the real economy, relying exclusively on stock market volatility as a measure of systemic stress is not sufficient but tends to underestimate such effects. This is plausible because stock market volatility does not capture other often more persistent symptoms of financial stress such as higher risk premia. This might explain the low persistence of the real effects that we observe in response to a financial stress shock measured by stock price volatility.

A different strand of the literature argues that corporate bond spreads possess substantial predictive content for the business cycle and macroeconomic developments since they proxi default risk and the quality of borrowers' balance sheets, in particular the financial health of the non-financial corporate sector (see e.g. Gertler and Lown, 1999, Gilchrist and Zakrajcek, 2012). Corporate bond spreads might also more generally capture disruptions in the financial system We therefore estimate another model substituting the CISS in our MS-VAR model with a yield spread between German non-financial corporate bonds and the average yield of all German government bonds as published by the Bundesbank. Comparable data for other euro area countries or even the euro area as a whole do not exist for the entire sample of our study. The estimated regime probabilities indicate that the recent global financial crisis started in September 2008 but displayed very little persistence since it terminated already at the beginning of 2009. The continuation of the global financial crisis is identified as a medium-variance, high-coefficient stress regime. Overall, the regime identification is rather plausible. The impulse responses to the financial shock identified in this model are economically implausible, however.

Overall, our results suggest that for the euro area a broadly based systemic financial stress indicator to capture financial instabilities in many different sector is key to uncover the nature of the interaction between financial instabilities and the macroeconomy, in particular in episodes of high systemic stress and fragility. The results also suggest that both realised volatilities of the stock market as well as corporate bond spreads provide indeed useful information for financial-real interaction and should be incorporated in some ways in a broadly based measure of systemic financial stress for the euro area.

4.2 The systemic dimension of the CISS and the role of financial intermediation

Two important elements characterize the construction of the CISS as a measure of systemic stress: first, that the dependence between financial market segments are taken into account in its construction; and second, that the CISS encompasses five different, broadly based financial

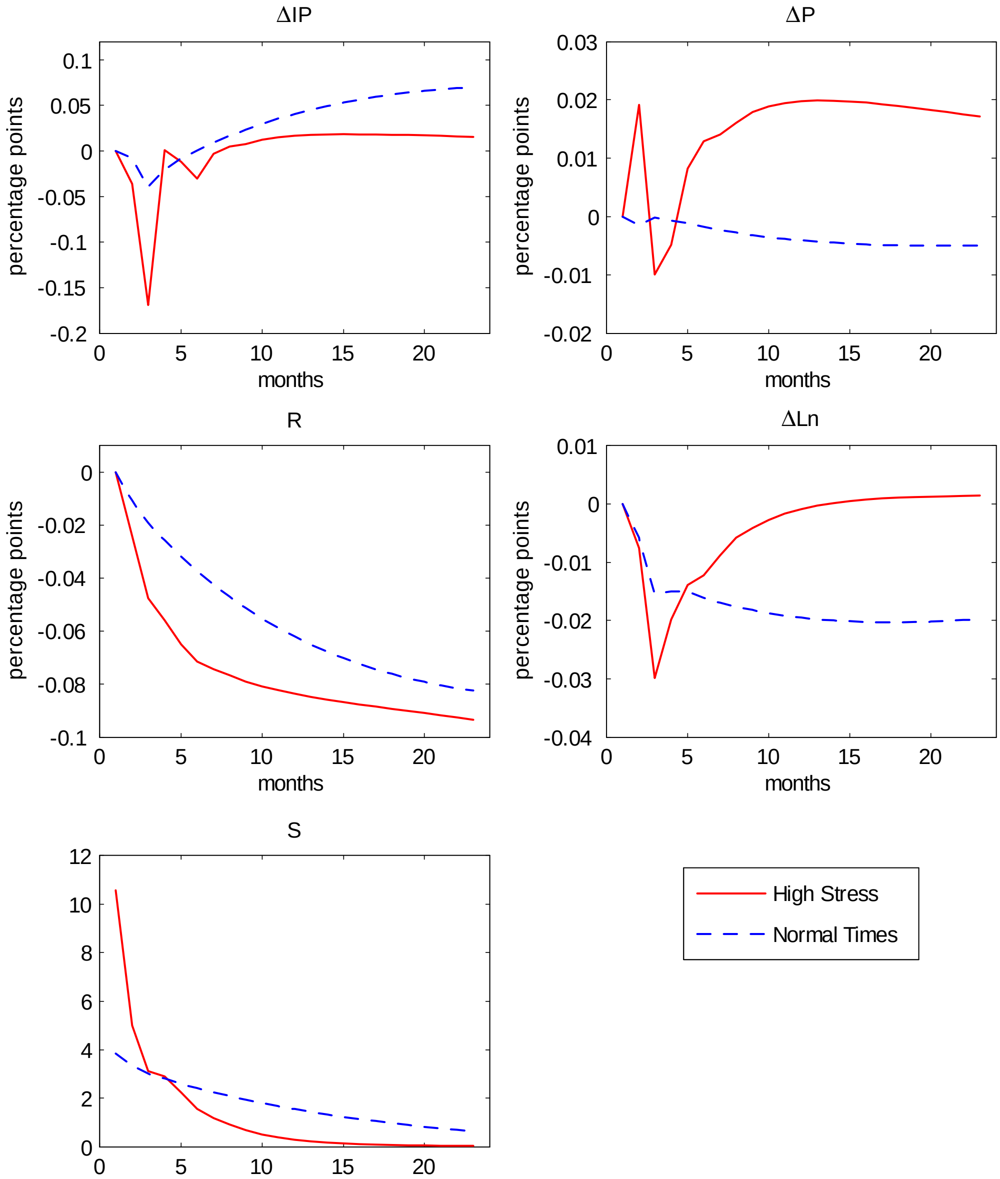

Figure 9: Impulse responses of a financial stress shock in a model with realised stock price volatility as measure of financial stress

market segments. With respect to the latter feature, the role of financial intermediaries is of special importance for a bank-centered financial system like the euro area. To investigate the importance of these features, we carry out two different experiments.

First, we set aside the time-varying correlations between the different subindexes of the CISS, replacing them with a simple (time-invariant) equally-weighted average. We then re-estimate our preferred $3v2c$ model. The estimated regime probabilities show that not all regimes are identified in this instance and the impulse response functions exhibit economically rather implausible results. We take these results as illustrative of the importance of taking the systemic aspect of financial stress into account. The relevance of the systemic dimension of financial stress has been emphasized in the literature on systemic risk. The tighter interdependence in the global financial system has also increased the risk of cross-market and cross-country disruptions. A number of proposals in the literature focus on microlevel systemic risk measures.[23] The comovement of the financial firm's assets with the aggregate financial sector in a crisis has been argued to be an important component of systemic risk (see e.g. Acharya et al 2012). The CISS captures the related notion of cross-market correlations of systemic stress on an aggregate level by incorporating cross-market risk that is particularly useful for incorporating financial instability into an empirical macroeconomic model like ours and our results in this section provide evidence for that.

Second, we investigate how the exclusion of the banking sector—by excluding the financial intermediaries segment —affect our results. We find that excluding financial intermediaries suggests less persistent state probabilities and therefore makes the identification of systemic stress regimes less straightforward. We find impulse responses of output growth to a financial stress shock in the regime with high stress in coefficients and in shock variances that are much smaller than if we include the CISS with all its components in our analysis (up to -0.5 percentage points instead of -1.8 percentage points) and much less persistent (10 months or less instead of 2 years). Responses of this magnitude seem small and of low persistence given the severity of the historical phenomenon that this high stress episode represents.

We conclude that for an economy like the euro area, where the banking sector plays a more important role than is the case in the United States, for example, a systemic financial stress index like the CISS that is broadly based on all financial market segments is well suited to

[23] Acharya et al. (2012) and Brownlees and Engle (2012) have proposed an economic and statistical approach to measure the systemic risk of financial firms, respectively. Correlation-based measures of connectedness, including systemic risk, are discussed, for instance, in Diebold and Yilmaz (2013) who propose another way of measuring the connectedness of financial firms.

investigate the interaction between systemic financial instability and the macroeconomy.

5 Concluding remarks

In this paper we introduced a representation of systemic financial instability in an empirical macroeconomic model for the euro area that can exhibit structural instability. The emphasis is on the non-linear effects of systemic financial instability on economic activity. Our approach was to embed a novel Composite Indicator of Systemic Stress (CISS) within a richly parameterized multivariate Markov switching VAR model with standard macroeconomic and financial variables, and estimate that model with recently developed Bayesian methods.

We find that in episodes of high systemic stress and systemic fragility the interaction between the financial sector and the macroeconomy changes fundamentally. Both the parameters characterising the relationships within the economy as well as the shock variances characterising the size of shocks change regime. Impulse response analyses as well as counterfactual exercises indicate that as a consequence of such fundamental non-linearities the adverse real effects of systemic financial shocks become much more pronounced during such a regime of systemic fragility than during tranquil times. Our analysis suggests that the careful representation of widespread financial instability and the possibility to allow for regime changes and amplification effects between the variables incorporated in the VAR model are crucial for this result. Our results suggest that loan growth does play a material role for macroeconomic dynamics during high systemic stress episodes in addition to systemic financial stress.

We find that the CISS has two particularly useful features to uncover the nature of the interaction between financial instabilities and the macroeconomy in the euro area, namely taking into account the systemic dimension of financial stress as well as integrating measures of instabilities in financial intermediation. Including alternative indicators of financial stress promoted in the literature provides less convincing estimates of regime changes than when using our systemic stress indicator, the CISS, and/or does not capture well the underlying relations between financial instability and the macroeconomy, in particular the real effects of systemic stress.

Our findings suggest that assessing the out-of-sample forecast performance of our model is a promising avenue for further research. The presence of nonlinearities documented in this paper helps to understand why most forecasts missed the severe real effects of the financial crises that started in September 2008. Whilst we leave the assessment of forecast performance for further research, the pseudo real-time state probabilities of different regimes based on our model suggest that this model may be usable as a tool for macro-prudential surveillance.

Overall, both monetary and macro-prudential policies can benefit from the availability of an empirical tool like this one, that can capture systemic financial instability and the non-linearities associated with its interaction with the macroeconomy.

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A Appendix: The Composite Indicator of Systemic Stress

This appendix provides a few more technical details about the CISS. For full details the reader is referred to Hollo, Kremer and Lo Duca (2012). As mentioned in Section 2.2, the CISS comprises 15 mostly market-based individual financial stress indicators grouped into five broad market segments supposedly covering the main sources of financing in the economy, namely the financial intermediaries sector (notably banks, but also insurance companies, pension funds and other financial services providers); money markets (broadly defined as including in principle all forms of short-term wholesale debt financing in the economy, e.g., interbank and commercial paper markets); bond markets (only longer term sovereign and non-financial corporate issuers); equity markets (only non-financial corporations); and foreign exchange markets (capturing cross-border financing activities). Each of the five market segments is populated with three individual stress measures capturing certain symptoms of financial stress in the relevant market. Table 4 contains a brief description of all 15 individual stress measures comprised in the CISS.

Prior to aggregation, in order to harmonize their scale and distributional properties, all individual stress indicators are transformed by means of their empirical cumulative distribution function involving the computation of order statistics (probability integral transform). Accordingly, each observation of a particular raw stress indicator at time t is first replaced by its ranking number $r(t)$ in the ascendingly ordered sample of size $\tau(t)$ which includes, apart from the observation in time t, only past observations back to the sample origin $t = 1$. The ranking number is then scaled by the total number of observations $\tau(t)$ in the respective sample such that the transformation yields the value $r(t)/\tau(t)$ which corresponds to the (r/τ)-th quantile of the cumulative distribution function. The fact that both the ranking number and the sample size are indexed by time reflects the recursive nature of the transformation in order to preserve the "real-time" nature of the CISS. The transformation projects raw stress indicators into variables which are unit-free and measured on an ordinal scale with range $(0, 1]$. The transformation yields a set of 15 homogenised, standard uniform distributed indicators.

For each market category a separate financial stress subindex is computed by taking the arithmetic average of its three constituent stress factors.

The subindexes are now aggregated on the basis of portfolio-theoretical principles, i.e. by taking into account a measure of time-varying correlations $\rho_{ij,t}$ between them (collected in the cross-correlation matrix Ω_t). The cross-correlations are calculated as exponentially weighted moving averages with a decay factor of 0.93. Since we apply the probability integral transform to the raw stress indicators prior to aggregation, the cross-correlations represent a time-varying variant of Spearman's rank correlation. The CISS is then computed as:

$$CISS_t = (w \circ s_t)' \Omega_t (w \circ s_t),$$

with $w = (w_1, w_2, w_3, w_4, w_5)'$ being the vector of subindex weights, which are assumed to be constant and equal at 20%; $s_t = (s_{1,t}, s_{2,t}, s_{3,t}, s_{4,t}, s_{5,t})'$ represents the vector of subindexes. The CISS is hence continuous, unit-free and bounded between zero and one.

Table 4: Individual financial stress indicators included in the CISS

Money market

1. Realised volatility of 3-month Euribor rate; weekly average of absolute daily rate changes; data start 8 Jan. 1999; source: Datastream.
2. Interest rate spread between 3-month Euribor and 3-month French T-bills; weekly average of daily data; data start 8 Jan. 1999; source: Datastream.
3. Monetary Financial Institution's (MFI) recourse to the marginal lending facility at Eurosystem central banks, divided by their total reserve requirements; MFIs can use the marginal lending facility to obtain overnight liquidity from the national central banks against eligible assets and, typically, at an interest rate which is higher than the prevailing overnight market interest rate; weekly average of daily data; data start 1 Jan. 1999; source: ECB.

Bond market

4. Realised volatility of German 10-year benchmark government bond index; weekly average of absolute daily yield changes; data start 5 Jan. 1990; source: Datastream.
5. Yield spread between A-rated non-financial corporations and government bonds (7-year maturity); weekly average of daily data; data start 3 Apr. 1998; source: Bloomberg.
6. 10-year interest rate swap spread; weekly average of daily data; data start 4 Mar. 1987; source: Datastream.

Equity market

7. Realised volatility of Datastream non-financial sector stock price index; weekly average of absolute daily log returns; data start 4 Jan. 1980; source: Datastream.
8. Maximum cumulated loss (CMAX) of Datastream non-financial sector stock price index (x_t) over a moving 2-year window: $CMAX_t = 1 - x_t/\max[x \in (x_{t-j}|j = 0, 1, ..., T)]$ with $T = 104$ for weekly data; data start 1 Jan. 1982; source: Datastream.
9. Stock-bond correlation; weekly average of the difference between the 4-year (1040 business days) and the 4-week (20 business days) correlation coefficients between daily log returns of Datastream total stock price index and the 10-year German government benchmark bond price index; final indicator is assigned a value of zero for negative differences; data start 8 Jan. 1982; source: Datastream.

Financial intermediaries

10. Realised volatility of idiosyncratic equity return of Datastream bank sector stock price index over the total market index; weekly average of absolute daily idiosyncratic returns; idiosyncratic return calculated as residual from OLS regression of daily log bank return on log market return over a moving 2-year window (522 business days); data start 1 Jan. 1982; source: Datastream.
11. Yield spread between A-rated financial and non-financial corporations (7-year maturity); weekly average of daily data; data start 3 Apr. 1998; source: Bloomberg.
12. CMAX of Datastream financial sector stock price index interacted with the sector's book-price ratio; both indicators transformed by their recursive sample CDF prior to multiplication; final indicator obtained by taking the square root of this product; data start 1 Jan. 1982; source: Datastream.

Foreign exchange market

13. Realised volatility of euro exchange rate vis-à-vis US dollar; weekly average of absolute daily log foreign exchange returns; data start 6 July 1990; source: Datastream.
14. Realised volatility of euro exchange rate vis-à-vis Japanese Yen; weekly average of absolute daily log foreign exchange returns; data start 6 July 1990; source: Datastream.
15. Realised volatility of euro exchange rate vis-à-vis British Pound; weekly average of absolute daily log foreign exchange returns; data start 6 July 1990; source: Datastream.

B Appendix: Priors for the estimation of the Markov-switching VAR model

Two sets of priors are relevant for our model, one on the reduced-form parameters of the VAR conditional on a state, s, and the other on the transition matrix. The priors on the reduced-form VAR are the standard Minnesota prior of Litterman (1986) on the lag decay dampening the influence of long lags. In other words, this prior shrinks the model towards a random walk. $\mu_1$controls the overall tightness and the prior of A_0. μ_2 controls the tightness of the random walk prior on the lagged coefficients. The prior for constant terms is zero and the prior standard deviation is μ_3.The priors that further play a role are μ_4 that controls the tightness of the prior that dampens the erratic sampling effects on lag coefficients (lag decay). μ_5 and μ_6 are the priors that express beliefs about unit roots and cointegration.

Let

$$A'_+ = [A_1(k)', A_2(k)^{'}, ...A_p(k)^{'}, C(k)^{'}] \text{ and } x_t^{'} = [y_{t-1}^{'}, ...y_{t-p}^{'}, z_t^{'}],$$

then the model in equation (1) can be written as

$$y'_t A_0(s_t^c) = x'_t A_+(s_t^c) + \varepsilon'_t \Xi^{-1}(s_t^v), \qquad t = 1, 2...T. \tag{3}$$

$A_0(s_t)$ and $A_+(s_t)$ could, in principle, be estimated straightforwardly, using the method of Chib (1996) for example, but as n or h grows, the curse of dimensionality quickly sets in. The matrix A_+can be rewritten as

$$A_+(s_t) = D(s_t) + \hat{S}\ A_0(s_t) \ \ where \quad \hat{S} = \left[\begin{array}{cc} I_n & 0_{(m-n)\times n} \end{array} \right] \tag{4}$$

which means that a mean-zero prior can be placed on D which centers the prior on the usual reduced-form random-walk model that forms the baseline prior for most Bayesian VAR models; see Sims and Zha (1998) for details on this particular prior set-up. The relationship contained in (4) means that a prior on D tightens or loosens the prior on a random walk for the reduced-form parameter matrix B.

The fact that the latent state, s,is discrete and that the transition probabilities of states must sum to unity lends itself toward the priors of the Dirichlet form. Dirichlet priors also have the advantageous property of being conjugate. Letting α_{ij} be a hyperparameter indexing the expected duration of regime i before switching to regime $k \neq i$, the prior on P can be written:

$$p(P) = \prod_{k\in H} \left[\frac{\Gamma(\sum_{i\in H} \alpha_{ik})}{\Pi_{i\in H}\ \Gamma(\alpha_{ik})} \right] \times \prod_{i\in H} p_{ik})^{\alpha_{ik}-1} \tag{5}$$

where $\Gamma(.)$ is the gamma distribution. The Dirichlet prior enables a flexible framework for a variety of time variation including, for example, once-and-for-all shifts and, by letting h become arbitrarily large, diffusion processes. In the application presented in this paper we allow for switching in shock variances determined by a separate process from the one controlling shifts in coefficients.

For our baseline specification, we use priors that are well-suited for a monthly model. In particular, we specify μ_k $k = \{1, 2, ...6\} = \{0.57, 0.13, 0.1, 1.2, 10, 10\}$. With the values of μ_k we employ what Sims and Zha (1998) and SWZ (2008) suggest for monthly data. The Dirichlet priors we use are looser than what would be usually used for monthly data. They imply an 87 and 83 percent prior probability for the variances and coefficients, respectively, that the economy will, in the next period, continue in the same state as it is in the current period. These probabilities imply a shorter duration of regimes than the priors used in SWZ (2008) use for the macroeconomic application based on quarterly data, consistent with the notion that in our study jumps in financial markets play an important role in driving the regime shifts. We found that the data move the posterior away from the prior in the sense that coefficient regimes turn out to be more persistent than the variance regimes. Interestingly, our results are relatively robust to some variation in the Dirichlet prior. For instance, if we impose a 74 and 85 percent probability, implying a more persistent coefficient regime than variance regime, we get similar impulse responses and regime durations of variance and coefficient regimes from the resulting model than from our model.

C Appendix: Counterfactuals on role of systemic financial stress in tranquil versus high stress episodes

Figure 10 and 11 present some further counterfactual experiments. The first simulation sets the CISS 0.25 above the level that was historically the case, starting in March 1995, as shown in the bottom-left pane of Figure 10. According to the model, these were tranquil times (regime 1, $v1, c1$). The effect on output growth, the upper-left panel, would have been trivially small given the magnitude of the change in the level of systemic stress; it drops by at most 0.5 percentage points below its historical path. In contrast, a similar increase in the level of the CISS carried out in October 2008—during the systemic fragility regime—would have lead to a massive decline in output growth by about 7 percentage points, relative to the historical path, as displayed in Figure 11. Moreover, inflation and loan growth decline by 0.5 percentage points, or 1 percentage point more than was the case historically, respectively, and the short-term interest rate falls more strongly by about 1 percentage point, probably reflecting a systematic easing of conventional monetary policy in response to the deteriorating financial and macroeconomic environment.

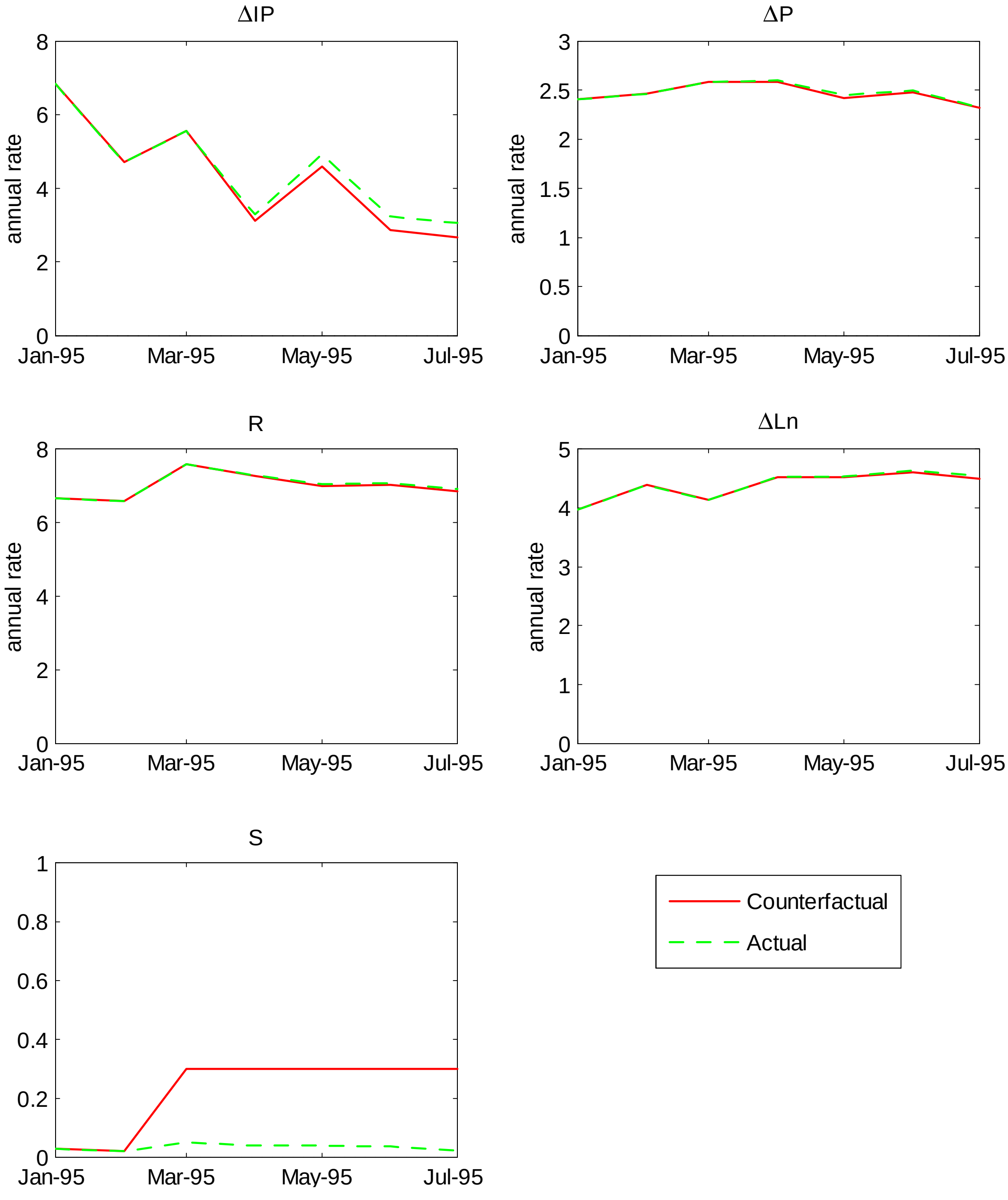

Figure 10: Counterfactual in tranquil times (regime 1), CISS path increased by 0.25 starting in March 1995

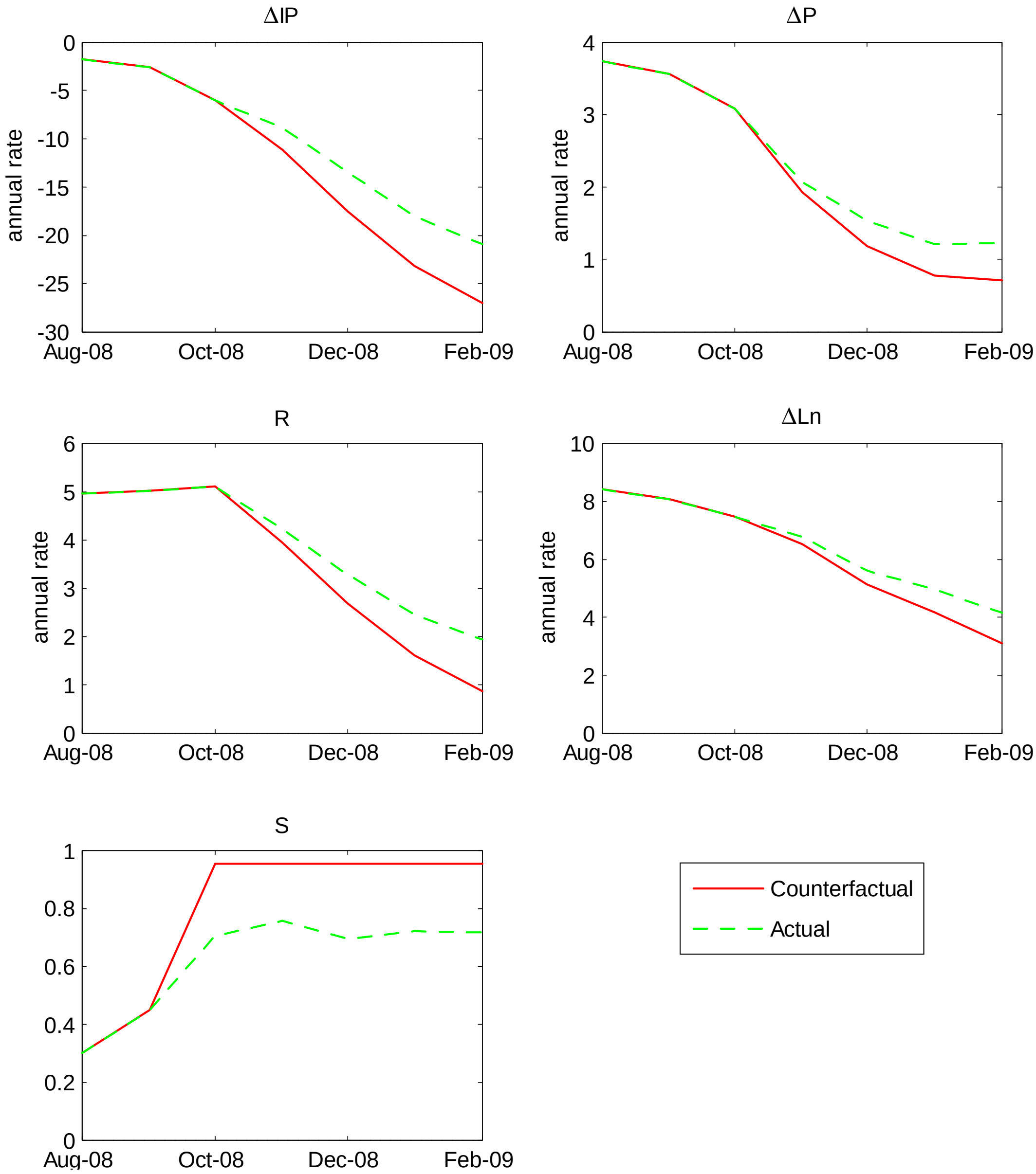

Figure 11: Counterfactual in systemic fragility period (regime 6), CISS path increase by 0.25 starting in October 2008