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

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Key words: financial stability, systemic risk, macro-financial linkages, Markov switching VAR, non-linearities

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1 Introduction

Economic history has shown that financial crises are regular, if infrequent, occurrences, observed over extended periods of time, across a range of countries, encompassing a variety of economic systems (Kindleberger, 1978; Reinhart and Rogoff, 2009). Systemic financial crises—crises that impair the overall functioning of financial systems—can have particularly serious implications for economic growth and welfare; the recent financial crisis and the resulting great recession is just the latest example. In a systemic crisis, an initial adverse shock affects market functioning in broad classes of financial institutions and markets, so that it is propagated and amplified in a manner atypical of ordinary business cycles.[1] In particular, when financial instability becomes widespread—that is, when it affects many different financial institutions and capital markets—the financial and the real sector may enter into a pernicious feedback loop, aggravating systemic stress. The resulting nonlinearities and the profession's still limited understanding of the underlying forces pose significant challenges for macroeconomic modeling, and for crisis detection, at both the theoretical and empirical level. It is this notion of *systemic stress* that underlines our thinking in this paper.

The theoretical literature has made progress recently in incorporating within macromodels, financial instability and associated nonlinearities. One strand of the literature has investigated the origins and mechanisms that can lead to the extraordinary amplification and propagation of shocks through the economy; examples include He and Krishnamurthy (2014) and Archaya et al. (2010) who analyze systemic risk with a focus on financial intermediaries.[2]

Empirical contributions to modelling financial instability and associated nonlinearities in the interaction with the macroeconomy have been scarce to date. The aim of the present paper is to provide empirical evidence on the dynamic interaction of systemic financial instability and the macroeconomy in the euro area. To this end, we propose an empirical framework that is designed to capture state-dependent changes in the joint dynamics of a core set of macroeconomic variables and a broad-based measure of systemic financial instability.

A feature of what we do is make use of the Composite Indicator of Systemic Stress (CISS), recently developed at the European Central Bank by Hollo, Kremer and Lo Duca (2012) as a measure of the state of systemic financial instability in the euro area. The CISS is particularly well suited for our purposes. It captures the systemic dimension of financial instability, first, by

[1] Bekaert, Engstrom and Xing (2009) describe how reassessments of the vulnerability of market segments can be one source of financial fragility.

[2] See also, e.g., Bianchi (2011), Brunnermeier and Sannikov (2013), Martinez-Miera and Suarez (2012), Boissay, Smets and Collard (forthcoming), Adrian and Boyarchenko (2013), Goodhart et al. (2012) and He and Krishnamurthy (2011). The article by de Bandt and Hartmann (2002) reviews the topic of systemic risk, while de Bandt, Hartmann and Peydro (2010) updates the earlier article, but with a focus on banking.

encompassing the main classes of financial markets and intermediaries in a systematic fashion and, second, by capturing time-varying dependence of stress between these major segments of the financial system.[3] Of note is the inclusion within the CISS of financial intermediation, which is likely to be important because of the more bank-centered financial system in the euro area, as compared to the United States where capital markets have a more prominent role.

We embed the CISS—together with a selection of macroeconomic variables—in a richly specified Markov-switching Vector Autoregression (MS-VAR) model. Our specification allows for independent regime shifts in the coefficients of the model, and in the variances of the model shocks. With this framework we explore five central issues. First we uncover whether switching, as a driver of episodes of systemic stress, is confined to the variances of shocks, or whether something more fundamental takes place, namely switching in model coefficients and thus the transmission of shocks. The answer to this question is important for policy purposes, among other things, because it speaks to whether or not policy interventions should be directed toward apprehending the source of "exogenous" shocks, or whether inducing changes in the transmission mechanism need to be considered. Second, we analyze whether any statistically significant nonlinearities we find are also economically important. Third, we explore the origins of our results; in particular, we investigate whether certain features of our systemic stress indicator stand out as important for our results, which then casts light on whether particular channels in the financial system are critical for spread of systemic distress. Fourth, we delve into the critical role of bank lending as either the source of, or the propogation mechanism for, fluctuations in output. And fifth, we assess whether our model could prove to be useful for tracking systemic stress episodes in real time.[4]

We summarize our conclusions regarding these five central issues as follows. First, the macroeconomy functions fundamentally differently in what we refer to as periods of *high systemic stress*, as compared to more tranquil times. Both the coefficients and the variances of the identified shocks exhibit switching phenomena. It follows from this observation that the standard, constant-coefficient constant-variance model would likely yield misleading results in these situations. Second, this regime switching is economically important: the effects of financial stress shocks on output are much larger, more persistent, and more consequential for the real economy in regimes of high systemic stress than during tranquil times. Third, as part of an investigation of the contribution of the CISS, we find that alternative measures of finan-

[3] See Illing and Liu (2006) and Kliesen, Owyang and Vermann (2012) for overviews of the construction of financial stress indexes as applied, in these cases, to the United States.

[4] MS-VAR models have been used to assess structural changes in US monetary policy by Sims and Zha (2006), and to examine the effectiveness of monetary policy in periods of high financial stress by Hubrich and Tetlow (2015). See also Baele et al. (2012) and F. Bianchi (2014).

cial stress, in particular stock market volatility and corporate bond spreads, produce regimes that do not track known systemic stress episodes as well, and render dynamic properties that are less plausible than our baseline results. We also show that the inclusion of cross-market correlations and the financial intermediation sector in the CISS are important. We conclude that these findings show the value added of several of the features of our measure of systemic financial stress. Fourth, we show that bank lending has an independent role for real activity during episodes of high systemic stress. In particular, during such periods, exogenous identified shocks to loan growth have important consequences for the rest of the economy, whereas in tranquil times they do not. We argue that this result likely reflects binding credit constraints during high-stress periods. Fifth, as an initial test of the efficacy of the CISS as a possible aid to macroprudential policy, we also compute the state probabilities for the regimes in real time, and find few false positives. This suggests to us that the model has at least some potential for nowcasting systemic instability although further investigation using real-time data would be welcome.

This paper is related to the empirical literature on the real effects of financial distress and crises. Early contributions on the Great Depression and the 1990s US credit crunch include Bernanke (1983) and Bernanke and Lown (1991), respectively. More recently, Barkbu, Eichengreen and Mody (2012), and Schularick and Taylor (2014) measure, among other things, the output cost of crises for a set of countries, taking a longer-term historical perspective. These previous contributions employ linear models, in contrast to the nonlinear model framework that we use here. Studies that investigate the predictive power of systemic stress measures for economic activity, also using linear models, include Allen, Bali and Tang (2012), and Giglio et al. (2012). Dovern and van Roye (2014) use a financial stress index to examine some of the same issues as we do here, but confine themselves to linear vector autogressive models. Apart from the nonlinear framework that we employ here, we also investigate the role of bank lending in the connection between financial shocks and real activity.

The rest of the paper is structured as follows. Section 2 describes the econometric methodology behind our model and details the main features of the systemic stress indicator as well as the macroeconomic variables used. Section 3 presents the empirical results, including the smoothed probabilities of states in shock variances and coefficients, impulse responses to a financial stress shock, counterfactual analyses, explorations of the role of bank lending in the episodes of systemic stress, and the estimated real-time state probabilities. Section 4 compares our main results with those obtained with alternative measures of financial stress such as aggregate stock market volatility and corporate spreads, as well as results using different variants of the CISS. Section 5 offers some summary remarks as well as our conclusions.

2 The model and data

Several choices have to be taken at the initial stage of model specification. First, we need a flexible econometric model framework that can accommodate systemic stress episodes and allow for discrete shifts in economic dynamics. Second, we need a measure of systemic financial instability that ably captures the spreading of financial stress across markets and institutions. Third, the variables that fill out the rest of the model have to be representative of macroeconomic dynamics in general and interactions between the macro economy and financial stability in particular. And fourth, the model needs to be identified. 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 empirically identified. For this purpose we apply a richly specified Markov-switching VAR model that can estimate discrete changes in the economic dynamics. Our specific MS-VAR framework distinguishes between two independent sources of regime switching, namely, shifts in the variances of shocks and shifts in the economic structure that transmits those shocks.

There are alternatives to using an MS-VAR model; the two that come immediately to mind are time-varying parameter (TVP) models and threshold models. TVP models, like MS-VAR models, allow for time variation in parameters or shocks, or both, but typically model that variation as drifting coefficients. Our use of the MS-VAR modeling framework reflects our understanding of the nature of systemic financial stress and its effects on macroeconomic dynamics; systemic financial stress, almost by definition, tends to involve discretely nonlinear or non-Gaussian effects, either in the financial sector itself, or in their macroeconomic consequences, or both.[5] As such, the MS-VAR framework seems like a natural choice. Threshold models, like

[5] Sims, Waggoner and Zha (2008) note that by expanding the number of Markov states in coefficients the MS-VAR model can approximate, at least in principle, a TVP model.

MS-VAR models, can allow for discrete shifts in parameters (or in the distributions of shocks), but the researcher is obliged to prespecify a threshold variable. Given the wide range of stories that have been advanced concerning the origins and propagation of financial events, it seems reasonable to us to avoid such prespecification. Our modeling choices notwithstanding, we would not argue that there are no insights to be gleaned from TVP or threshold models in this context, although the particular questions under study might differ in some ways.

Estimation of and statistical inference from the MS-VAR model rests on recently developed Bayesian methods that have made feasible the estimation and inference for richly parameterized models; see Sims and Zha (2006) and Sims, Waggoner and Zha (2008). Some details on the relevant techniques are provided in the Appendix B.

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

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

where y_t is an $n \times 1$ vector of endogenous variables; s_t^m, $m = v, c$ are unobservable (latent) state variables, associated with 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[6] 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. $\varepsilon_t^{\prime}\Xi^{-1}(s_t^v)$ 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:

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

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

[6] Note that we impose identifying restrictions such that A_0 is triangular.

be recovered as follows:[7]

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

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 independently of each other.

2.2 Systemic stress indicator

To be suitable, a systemic stress indicator must have several attributes. First, as the word *stress* suggests, it needs to capture not just activity or even disruption in the financial sector, but stresses that might be of concern to market participants and policy makers. Second, as the word *systemic* indicates, it should ideally distinguish between stress that is 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 spread through the entire system. It is presumably when stress is widespread that it has 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, 2010). Third, as the word *indicator* suggests, the candidate measure of systemic stress needs 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 Lo Duca (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 directly through capital markets or indirectly through financial intermediaries. 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

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

market return correlations (see Table 4 in Appendix A for a precise description of the data). Aggregation of each set of three constituent stress measures—after appropriate transformation to harmonize their scale and variances—results in five segment-specific subindexes of financial stress.

The way 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. This time variation in the correlations means that relatively more weight is applied to components during periods in which stress prevails in several market segments at the same time. Thus, the CISS is designed to capture what might be called the epidemiology of risk, meaning the way in which instability in one market infects other markets, leading to widespread and possibly severe financial instability with systemic implications.

The aggregate 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.[8] 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.

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 stylized 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

[8] See Hollo, Kremer and Lo Duca (2012) for a more extensive coverage of historical stress events which coincide with peaks in the CISS. The review article by de Bandt and Hartmann (2002) describes methods for measuring systemic risk.

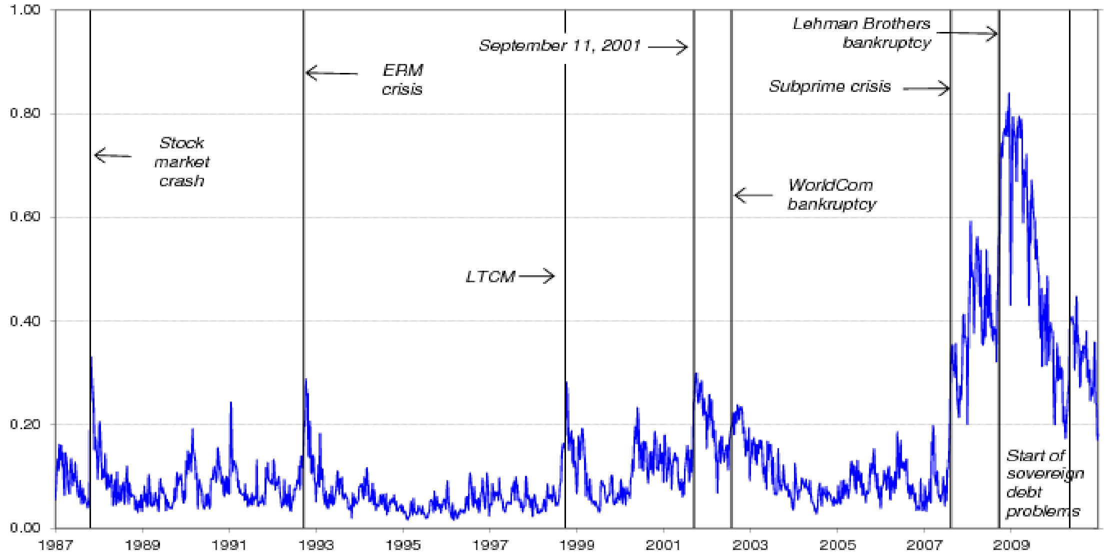

Figure 1: Composite Indicator of Systemic Stress ("CISS") for the euro area and specific financial stress episodes, January 1987 to December 2010

strong role that bank lending played in the most severe financial crises in history; e.g. Schularick and Taylor (2012). It can also be 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 (ΔIP), consumer price inflation (based on the Harmonised Index of Consumer Prices, HICP; ΔP) and nominal bank loans to the private sector (ΔLn) 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 (R) 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 (S) are monthly averages of weekly data and are 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.[9]

The conventional ordering in the macro VAR literature places the short-term interest rate last, implicitly assuming that monetary policy may react simultaneously to shocks in the other

[9] 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.

variables while no other variable is allowed to respond contemporaneously to monetary policy shocks.[10] 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 affect the rest of the economy only with a lag. This ordering reflects the conventional practice in the recent VAR literature of allowing 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.[11] 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.[12]

3 Systemic stress, regimes and financial crises

3.1 Model estimation and evaluation

The five-variable structural MS-VAR model in equation (1) is estimated using three lags with Bayesian methods.[13] We employ a blockwise optimization algorithm to estimate 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

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

[11] 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).

[12] 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.

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

is indeed the most likely estimate.[14]

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 determine our preferred specification, we employ a mixture of criteria, two statistical and one economic. Our first and most important statistical criteria is goodness of fit as determined by comparison of the logarithm of marginal data densities (MDDs) of candidate specifications. This is the method usually employed for ranking models in Bayesian econometrics.[15] In addition, however, we use another recently developed statistical criteria, the regime classification measure (RCM) pioneered by Ang and Bekaert (2002) and subsequently extended by Baele (2005). This metric evaluates the relative performance of the models according to their ability to sharply distinguish one regime from another. We particularly focus on the RCM for the coefficient regimes since those are most central to our investigation; in effect, the RCM penalizes the addition of variance regimes that do not lead to a sharper regime distinction for the coefficient regimes than the more parsimonious specifications. Finally, we also assess our candidate models on economic criteria: models should make sense in terms of the dates of regime switches, the duration of regimes, and their model properties. As we show below, the ranking of the models based on these three criteria are mostly pointing in the same direction.

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 (Waggoner and Zha 2012, Appendix C3).[16]

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.[17]

[14] To ensure that solutions are robust, and likely to be global, candidate solutions are perturbed using 5 large random perturbations and 5 random perturbations in the neighbourhood of each of the resulting peaks.

[15] The Bayesian counterpart to frequentist hypothesis testing is to compare MDDs, or equivalently, to assess Bayes factors, across models.

[16] In the Markov Chain Monte Carlo (MCMC) algorithm we use 100000 proposal draws and 5 million posterior draws with a thinning factor of 10, so retaining 500000 posterior draws. The burn-in period is 10%.

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

Table 1: Goodness-of-fit statistics, selected model regime specifications

Regime combination	[1] $1v1c$	[2] $2v1c$	[3] $3v1c$	[4] $2v2c$	[5] $3v2c$	[6] $4v2c$
log(MDD)	-6.05	92.4	131.9	126.1	147.4	170.7
- *difference. from* $1v1c$	0	98.4	138.0	132.1	153.4	177.2
RCM	n.a.	20.9	12.4	14.8	6.0	7.5

Notes: Log MDDs are calculated as in Sims, Waggoner and Zha (2008); $\{i\}v\{j\}c$ where i = no. of variance and j = no. of coefficient regimes; RCM is the Regime Classification Measure (Ang and Bekaert, 2002, Baele 2005).

3.2 Determining and interpreting regimes

3.2.1 Model selection

Before turning to the results, a few words on notation are useful in order to interpret the table to follow. In table headings and elsewhere, a v indicates the Markov chain associated with switching in shock $v$ariances, while a c refers to the 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.

According to Jeffreys (1961), differences in log MDDs of 10 or more can be taken as strong evidence that one model is more likely than the other. 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 the other, simpler models.[18] Indeed, on the basis of log MDD comparison, a model allowing even more states in shock variances, the $4v2c$ model in column [6], is favored.[19] However, these more elaborate models might not be very different from each other. The RCM evaluates the abililty of the different models to sharply distinguish one regime from another. Lower readings of the RCM indicate sharper regime classification. Regarding the distinction between the $2v2c$, the $3v2c$ and the $4v2c$,the RCM effectively penalizes the addition of variance regimes that do not lead to a sharper regime distinction for the coefficient regimes than the more parsimonious specifications. According to the RCM the $3v2c$ specification is preferred. Finally, our review of the economic properties of the $3v2c$ specification of the model suggests to us that this specification is at least as good as the alternative candidates, based on the criterion of economic plausibility.[20] On this basis, we select the $3v2c$ specification as our preferred model. In the next subsection, we turn to the economic characterization of the different regimes of our preferred model in the following.

3.2.2 Economic characterization of regimes

Table 2 shows the estimated standard deviations of the structural shocks across the three identified variance regimes, normalized such that the volatilities of the first regime are unity. For reasons that will only become clear a bit later on, we will call our three variance regimes "low" (vL), "medium" (vM), and "high" (vH) regimes; similarly, we will refer to the two regimes for VAR-equation coefficients as cL and cH. Several noteworthy conclusions arise from the table. First, switching in shock variances is consequential, at least statistically, as can be seen by the substantial differences in (normalized) 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 or fall uniformly from regime to regime. Third, for the shock of principal interest for this paper, namely the CISS (S) shock, the variance of the shock in vH state clearly stands out. Finally, while the S shock and also the inflation shock, (ΔP), rises substantially, in vH relative to vL, the pattern is the opposite for shocks to loans, (ΔLn), and the interest rate (R),while there is little difference across states in the variances of shocks to industrial production, (ΔIP). Precisely what to make of the lack of uniformity in shock variances across regimes is not entirely clear from these particular statistics, but it does suggest that shocks to financial stress play a more important role in driving dynamics in vH

[18] Marginal data density computations do penalize non-parsimony of models. Kass and Raftery (1995) show that the Schwarz criterion (or BIC) gives a rough approximation to the logarithm of the Bayes factor.

[19] Models with additional coefficient regimes could not be estimated given the high number of parameters.

[20] Our results, in particular the smoothed probabilities and impulse responses for the different models, show that the extra variance regime of the $4v2c$ specification captures only a few outliers at the beginning of the sample. Details are available from the authors, on request.

Table 2: Relative standard deviations of structural shocks by regime

	ΔIP	ΔP	R	ΔLn	S
Low-variance regime (vL)	1.00	1.00	1.00	1.00	1.00
Medium-variance regime (vM)	0.91	1.53	0.29	0.74	0.62
High-variance regime (vH)	0.85	1.99	0.65	0.56	2.98

Notes: Entries are normalized for each variable to unity for the first regime.

than do shocks to loan growth and real activity, operating independently of financial stress. In short, the suggestion is that in the vH regime, it is stress shocks that dominate.

Table 3, which shows descriptive statistics for endogenous variables conditional on each of the six possible combinations of our independent variance and coefficient regimes, sheds some light on the economic characterization of regimes from the viewpoint of financial stability.[21] For ease of comparison, the regimes are ordered such that regimes with $v = vL$ and c varying from cL to cH are presented in the first two rows of the table, while regimes with $v = vM$ and $v = vH$ are displayed in the subsequent four rows with the respective coefficient regimes. Several interesting observations arise with regard to the interpretation of these data. First, and most obviously, as one moves down the rows of 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.[22] 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], the $vHcL$ regime and the $vHcH$ regime are periods of extremely high levels of financial stress—at least twice as high as in other states—but are relatively rare, as judged by their sample shares of 5 and 7 percent, respectively. Third, while growth in loans, ΔLn, and growth in real activity, ΔIP, rise as one goes from vL to vH when $c = cL$, they both fall sharply and montonically with v when $c = cH$. Evidently, periods of financial stress also feature reduced lending activity and deterioration in real economic performance. And clearly, shifts from regime cL to cH 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 3.2.3.

For ease of presentation, it is useful to give names to our identified regimes, as well as to certain combinations of those regimes. These names are summarized in the third column from

[21] These summary statistics compute the moments, conditional on regime, for 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 in the analysis of the smoothed probabilities in Section 3.2.3, regime dominance is rarely ambigious in our model.

[22] There is an element of arbitariness in designating a variance regime as "high" or something else. In the present case, our assignment of labels reflects how the regimes coincide with the level, on average, of financial stress as measured by the CISS, shown in the table. So, for example, the vL regimes shown in rows [1] and [2] of the table have the lowest levels of S, as noted in the column second from the right, and the vM states in rows [3] and [4] have larger average levels of S than their counterparts in vL states, and so on.
Similar logic follows for cL and cH where for any state for v it can be seen that the average level of S is higher in what we call cH than it is in cL.

Table 3: Descriptive statistics, by regime

Line	regime specification		conditional means					shares
#	label	characterization	ΔIP	ΔP	R	ΔLn	S	(%)
[1]	$vLcL$	tranquil	0.54	2.26	5.85	5.97	0.071	16.1
[2]	$vLcH$	tranquil	3.39	3.01	6.13	8.43	0.092	17.8
[3]	$vMcL$	tranquil	2.78	1.96	3.22	6.33	0.081	35.3
[4]	$vMcH$	elevated stress	1.16	2.83	5.85	6.11	0.110	18.9
[5]	$vHcL$	systemic fragility	3.96	2.43	4.18	9.66	0.260	5.2
[6]	$vHcH$	systemic crisis	-11.3	1.57	2.88	4.66	0.520	6.6

Notes: $v\{i\}$ var. regime, $i = L, M, H$. $c\{j\}$ coeff. regime, $j = L, H$; the union of [4] $(vMcH)$ and [6] $(vHcH)$ is referred to as regimes of "high systemic stress"

the left in Table 3, as well as in one of the notes to the table. The $vLcL$, $vLcH$ and $vMcL$ regimes are associated with periods of relatively low levels of financial stress. Inasmuch as these three regimes collectively prevail in about 70 percent of the sample period and they are periods where the economy behaved in a manner that could be regarded as "normal," we will refer to as *tranquil times*. Even so, these normal periods do include episodes of occasional, short-lived spikes in financial stress. One way to think about this collection of regimes is that they feature either shocks of modest magnitude (the $vLcL$ and $vLcH$ regimes) or weak propagation of shocks as will be demonstrated below is the case when $c = cL$ $(vMcL)$, or both $(vLcL)$. The $vMcH$ regime, shown on line [4] of the table, might be labelled *elevated stress* in part because, as we show below, it occurs during the first two years of the bursting of the dot-com bubble—during which, according to the CISS, financial stress persisted at an elevated, though not extremely high level—and it occurs over the roughly half a year immediately after the failure of Lehman Brothers in August 2008 (see Figure 1).

Tables 2 and 3 showed that, in general, no uniform ranking exists in terms of regime-dependent shock volatilities or conditional means; nevertheless, all of the series exhibit their "worst" readings in terms of conditional means in the $vHcH$ regime, shown in row [6] of Table 3. That is, these were the periods where stress levels were at their highest, and were also associated with negative growth in industrial production and the lowest levels in each of loan growth, inflation and interest rates. Consequently, we label this regime the *systemic crisis* regime. Lastly, as shown in row [5], the $vHcL$ regime, which involves a substantial degree of shock-driven volatility, but as we demonstrate below, little propagation of those shocks, is labelled the *systemic fragility* regime.

Regime probabilities Time series of the (smoothed) probabilities are presented in Figure 2. In general, the regime probabilities are either very close to one or very close to zero, indicating that the model classifies regimes rather sharply. The five panels in the figure show the periods that contribute to estimates of the parameters of the variance and coefficient regimes. As can be seen, the estimation of the two coefficient regimes is supported by data spanning several elongated periods. It follows that these periods are comfortably sufficient for estimating the parameters of the coefficient regimes.[23]

In the next subsection we demonstrate that the coefficient regime cH features much stronger transmission of financial stress to the broader economy than does coefficient regime cL. Building on this assertion, Figure 3 shows the probability of *high systemic stress*, which we will define as regimes where there are relatively large shocks and where the propagation of those shocks is substantial—that is, the elevated stress ($vMcH$) and the systemic crisis ($vHcH$) regimes. These are, as we already noted, periods in which absolute the level of the CISS, (S), is high. These two regimes are also periods in economic history that are associated with demonstrable financial turmoil, as can be seen by comparing panels of Figure 2 with the events shown in Figure 1. Episodes captured by these regimes include the aftermath of the 1987 stock market crash; the Gulf war in 1990; the run-up to the crisis in the European Exchange Rate Mechanism (ERM) in the early 1990s; the bursting of the dot-com bubble in the early 2000s; the US terrorist attacks in September 2001; the global financial crisis of 2008 and the associated meltdown of the euro area economy; and finally a time period in 2009 when the financial crisis was moderating until the euro area sovereign debt crisis emerged in early 2010.[24] As line [6] of Table 3 notes, there were only two periods that are associated with vH regimes: a short episode immediately following the US terrorist attacks in September 2001, and the culmination of the global financial crisis, including the large decline in output growth, the "meltdown" as it were, of the euro area economy. Interestingly, the initial stages of the recent global financial crisis are associated with a *systemic fragility* regime, $vHcL$. While not itself a state of high systemic stress, this regime might be considered a precursor to such states; it shares the large shocks of the systemic crisis regime but lacks the strong propagation of those shocks. Thus, according to the model, the initial stages of the subprime crisis had not yet reached the point of being *systemic stress* and thus did not immediately bring about large-scale output losses. The full, systemic crisis developed - according to our model - in early in the summer of 2008—that is, a few months prior to the bankruptcy of Lehman Brothers.

[23] The small number of parameters associated with each variance regime—five in our base-case specification—is simpler to estimate.

[24] We note that the level of the CISS index itself was not elevated in 1991-92, a period when the Eurosystem came under stress following German reunification. And yet Figure 3 indicates that this was a period of systemic stress. This observation demonstrates the fact that the (unobservable) regimes representing systemic stress are functions of all the variables in the system, and cannot be inferred solely by the values of the systemic stress index.

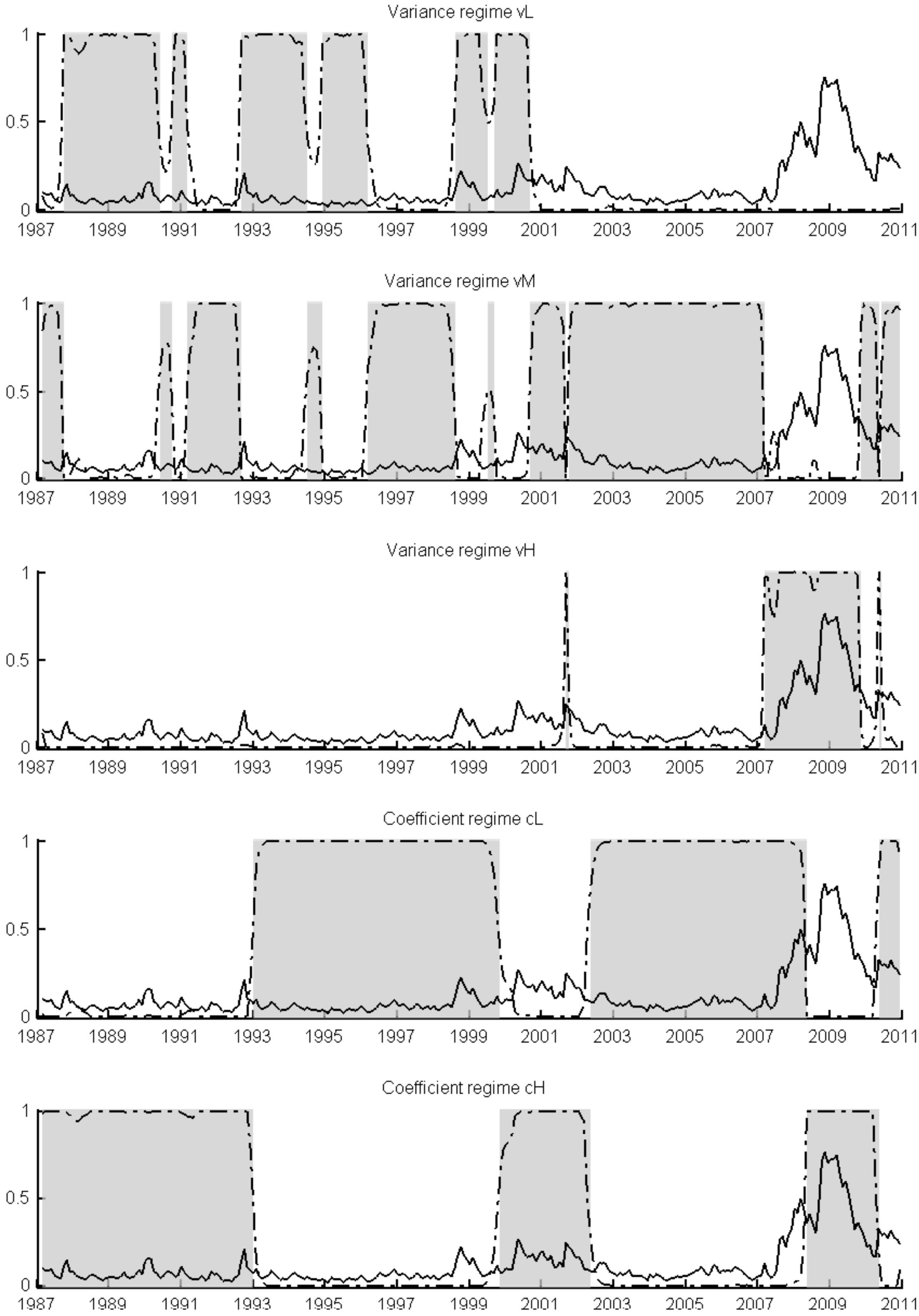

Figure 2: CISS and regime probabilities (dominant regime shaded)

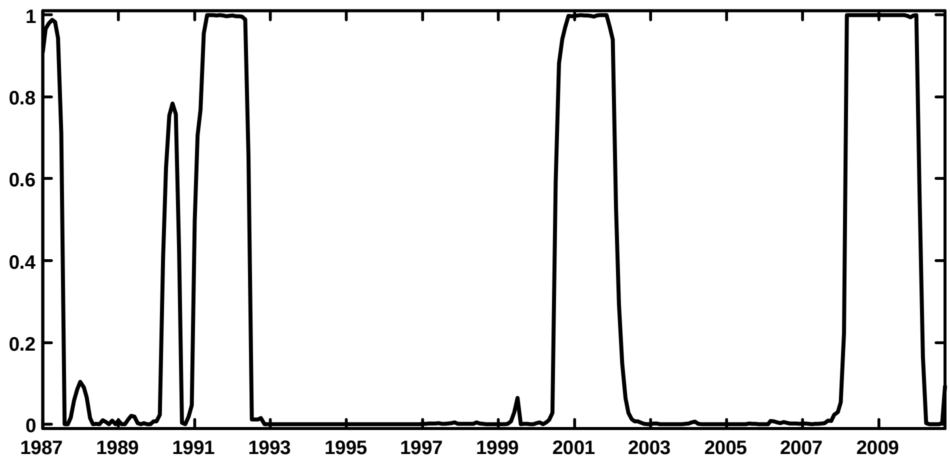

Figure 3: Smoothed state probabilities; systemic stress regime (vMcH and vHcH)

3.2.3 Transmission of financial shocks

We now explore the properties of the various regimes through comparisons of their regime-specific impulse response functions (IRFs).[25] While the three shock-variance regimes differ in the magnitude of one-standard-deviation shocks, but their propagation will differ only to the extent that the coefficient regime differs. Because the main purpose of our paper is to study state dependencies in the transmission of systemic financial instability to the real sector, we focus on the IRFs describing the dynamic effects of structural shocks to the CISS. Figure 4 plots the impulse responses to shocks in the CISS (S) for two starkly different regimes, the $vHcH$ regime (solid red lines) and the $vLcL$ regime (blue dashed lines). To aid in the interpretation, the figure also includes the IRFs for a constant-coefficient Gaussian VAR model (the $1v1c$ specification).[26]

The differences in IRFs between systemic crisis and tranquil times are striking. In the $vLcL$ regime, industrial production growth (as well as all other variables) displays hardly any response at all to a CISS shock. It thus appears that financial stress shocks are effectively irrelevant in tranquil periods, an observation that accords well with the fact that the CISS aims to measure systemic stress and not general financing conditions. By contrast, in the $vHcH$ regime, a positive shock in financial stress leads to a quick, severe and protracted contraction in economic activity. On this evidence, we conclude that the cL coefficient regime implies weak financial-real linkages—which is to say, weak propagation of financial stress shocks—while the cH coefficient regime implies very strong ones. These findings ratify our designation of the $vHcH$ regime, featuring the largest CISS shocks and the strongest financial-real linkages, as a

[25] Note that the impulse responses presented here are computed at the posterior mode.

[26] The IRFs are calculated for a positive one-standard-deviation shock to the CISS for the two most different regimes, the systemic crisis regime ($vHcH$) and in the tranquil regime ($vLcL$). Up to a scaling factor, similar conclusions arise for comparisons of the systemic crisis regime ($vHcH$) to the systemic fragility regime ($vHcL$).

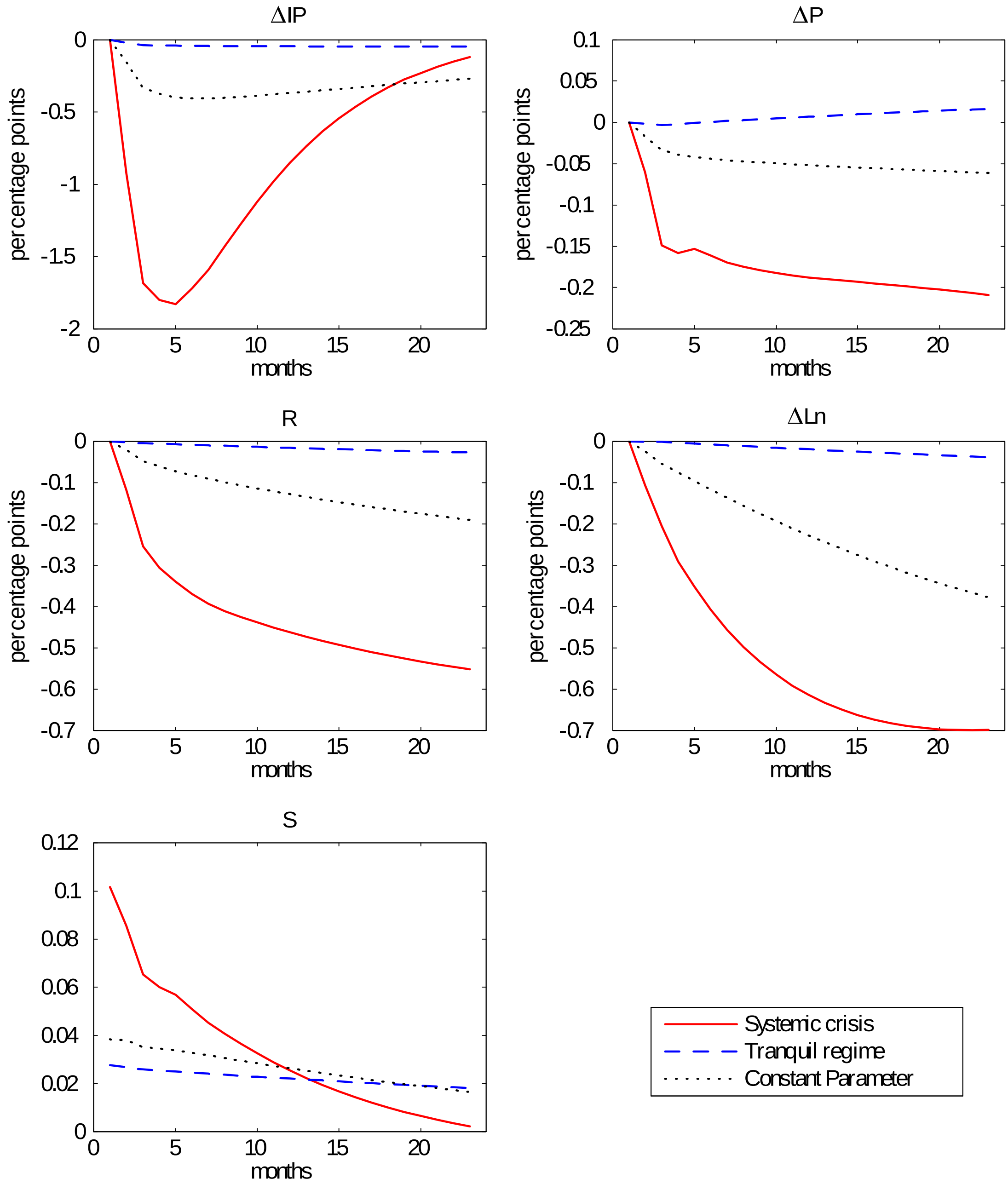

Figure 4: Impulse responses to financial stress shock, one standard deviation shock; responses in output growth (ΔIP) inflation (ΔP), interest rate (R), loan growth (ΔLn) and systemic financial stress (S); comparison constant parameter model with systemic crisis (vHcH) and tranquil regime (vLcH) of our two coefficient and three variance regime model (3v2c)

regime of systemic crisis.[27]

The lower-right panel of Figure 4 shows a relatively strong, gradual and persistent effect of a CISS shock on loan growth in the systemic crisis regime. This suggests that bank lending may also play a role in amplifying the transmission of financial stress to the real economy in times of financial turbulence. The 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.[28] At the same time, this fact is also in line with a lagged reaction of lending following the strong and immediate decline in output growth.

Figure 4 also illustrates that the IRFs estimated for a constant-parameter Gaussian VAR model (the black dotted lines) would clearly underestimate the effects of financial stress shocks on economic activity in certain states of the world, as well as on the other macro aggregates. We conclude that inference with, and policy guidance from, such a model, in circumstances of financial stress, is likely to be misleading.

3.3 Counterfactual analyses

In this section we carry out counterfactual simulations ir order to illustrate the differential effects of financial shocks during systemic crises and in tranquil times. Counterfactual analysis provides much the same information as impulse response functions do, but also provide some historical context. We also investigate the importance of bank lending for the real activity in our framework.

3.3.1 The role of systemic stress

To explore the fundamental change in economic dynamics 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 incurring the switch to systemic crisis that our baseline specification says took place.[29] Figure 5 demonstrates that in this scenario the level of systemic stress would have been substantially lower, by almost 0.2, and that impact of this switch on output growth was substantial. The figure shows that growth in industrial production would have declined

[27] Note that if we normalise the shock in tranquil times to be the same as in the systemic crisis regime, the impulse response in the tranquil regime is only slightly larger and has the same shape as for the shock size based on the tranquil episode as displayed in the figure.

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

[29] 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.

at only 6 percent annual rate, instead of "melting down" at a 21 percent pace; 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 crisis versus tranquil times are presented in Appendix C. They show that an increase in systemic financial stress has little effect in tranquil times, but substantial effects in episodes of systemic crisis.

3.3.2 The role of lending

In this Section we investigate the role of bank lending for the macroeconomy. In particular, we are interested whether lending has an impact for the real economy beyond that which originates from financial stress. To this end, we conduct a counterfactual experiment that assesses the real effects of a reduction in the growth in bank lending to zero percent—as opposed to growth of about 6 percent in the baseline—between October 2001 and March 2002. Our model characterizes the counterfactual period as one of elevated stress, $vMcH$.[30] In order to isolate the effects of loan growth independent of the effect operating through fluctuations in financial stress we hold the path for financial stress constant at its average level over this period. The situation is one such that credit growth during the burst of the dot-com bubble would have declined as much as it actually did during the 2008-09 financial crisis.[31] We find that if loan growth had been flat during the counterfactual period, output growth would have been about 5 percentage points lower, as displayed in Figure 6. Inflation and the interest rate would have also been substantially lower, specifically by about 2 percentage points, compared to history. The lower interest rate would have probably reflected a monetary policy reaction to the output losses and the contraction in loan growth. These results suggest that bank loans may play a material role for the macroeconomic dynamics during regimes of systemic stress that imply a strong shock propagation, bearing in mind that the estimated effects of lower loan growth are derived under

[30] Note that we also carried out the opposite experiment for the systemic crisis episode starting in October 2008, namely we kept lending constant over the counterfactual period instead of the actual decline. The results point in the same direction, that lending plays a relevant role.

[31] This simulation (as well as another counterfactual shown in an appendix) involves computing the sequence of shocks to the relevant variable that is 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, except where otherwise indicated. For a discussion of how counterfactual experiments work in a linear framework, see Waggoner and Zha (1999). The experiments are designed to be “small” in the sense that the sequence of shocks is within an empirically plausible set.

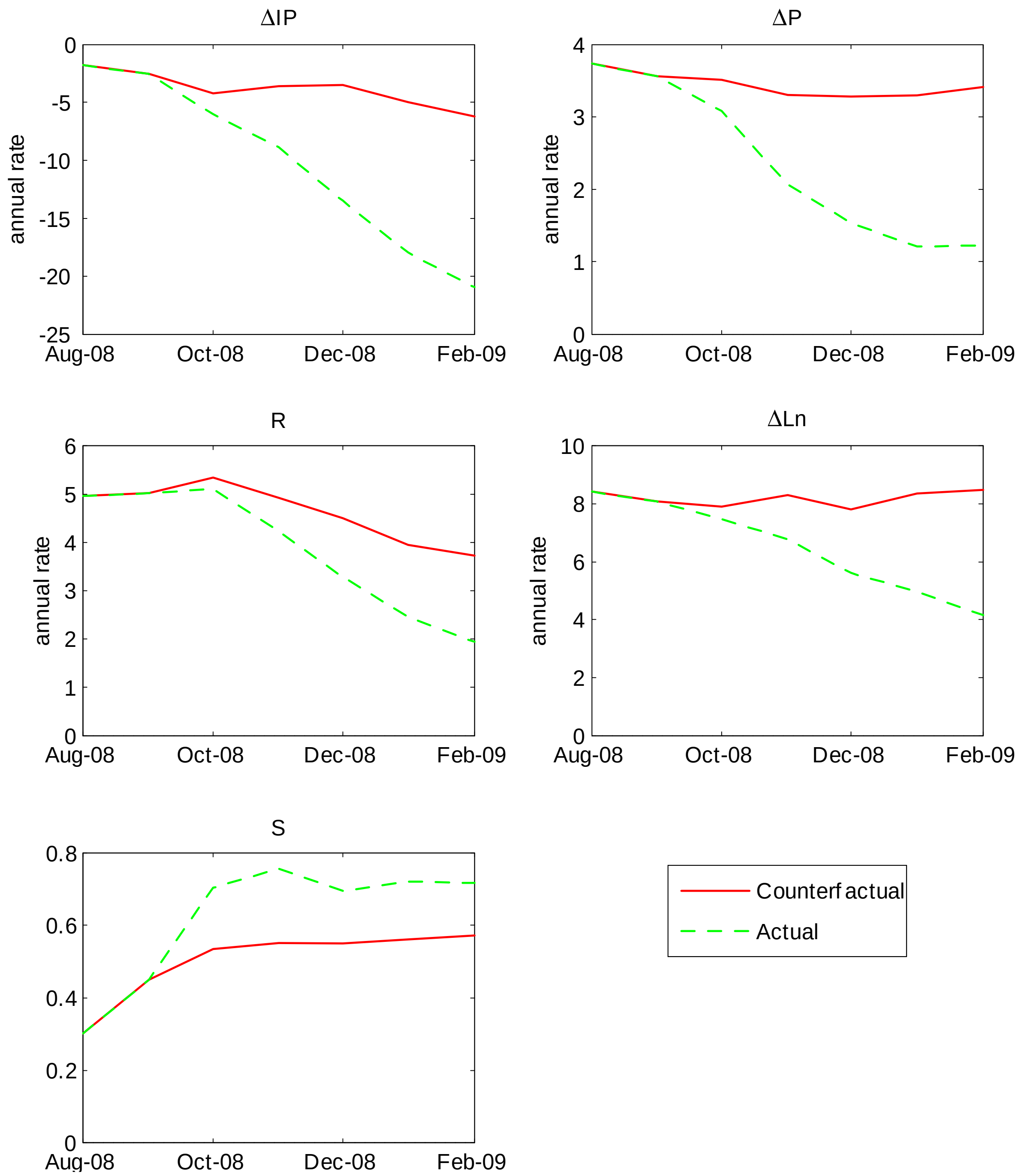

Figure 5: Counterfactual, tranquil times (vLcL) instead of systemic crisis regime (cHcH), October 2008 to February 2009

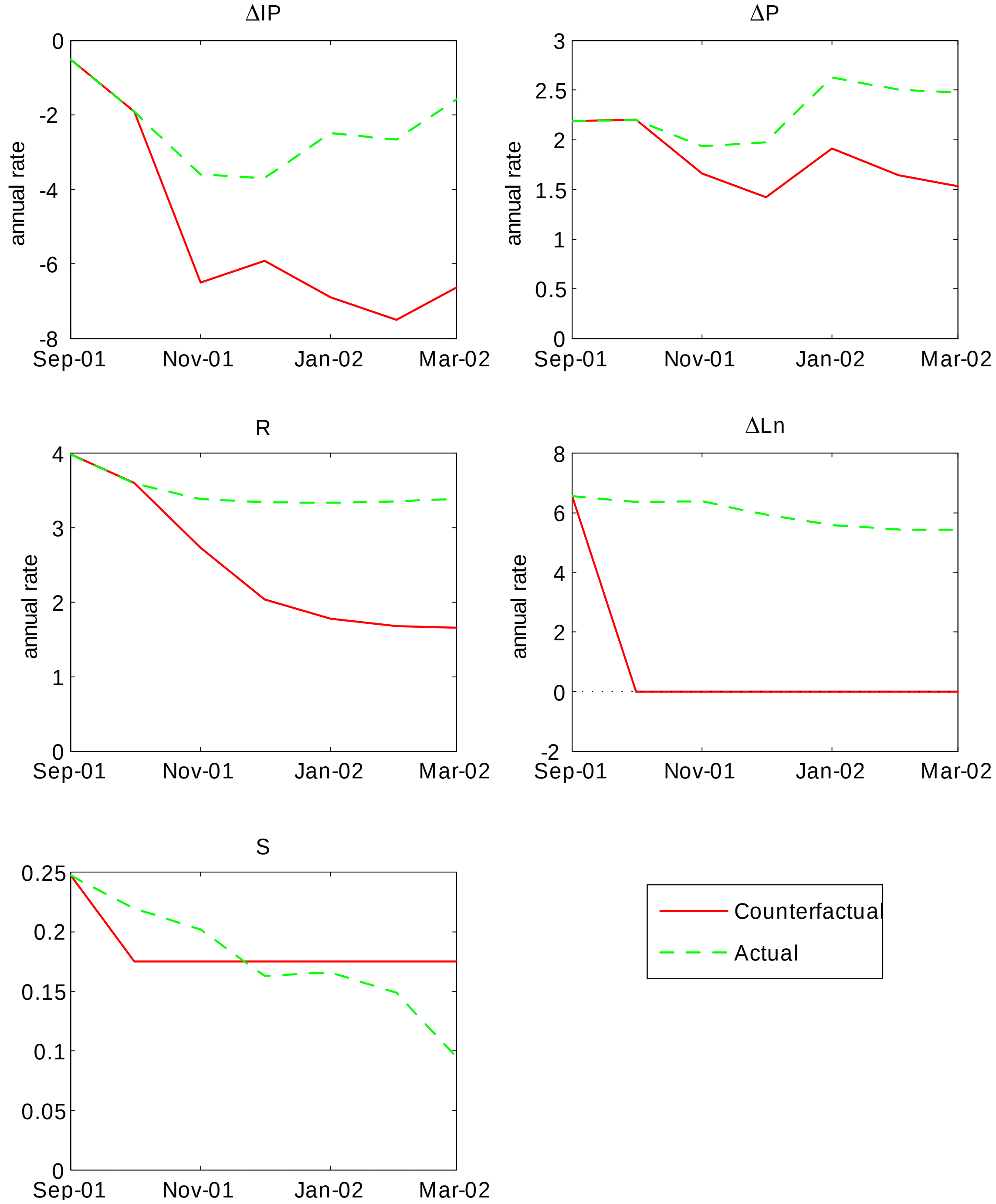

Figure 6: Counterfactual, path in loan growth to zero, path in financial stress to no change of average actual path over counterfactual period, October 2001 to March 2002

the assumption that financial stress remains unchanged over the counterfactual period.[32] To further illustrate the implications of disturbances to bank lending, we also present the impulse responses to lending shocks for two regimes with different coefficient regimes but the same variance regime, where the size of the lending shock is comparable across regimes.

These impulse responses, shown in Figure 7, demonstrate that in response to an exogenous shock to bank lending, output growth is not declining in time of systemic fragility (vHcL), where large shocks affect the economy, but there is no strong shock propagation. However, in systemic crisis episodes (vHcH) output growth is declining since in those periods credit supply is binding. Since this is an identified shock and output growth is initially being held constant, this shock is properly interpreted as a loan supply shock. Moreover, the negative, though small, reaction in financial stress can be explained by a loosening of montary policy in response to the loan reduction, which more than offsets the increase in financial stress.[33]

3.4 Macroprudential 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 modest step in this direction, we estimate the state probabilities in pseudo real time based on a recursively expanding window, holding VAR model coefficients at their full-sample estimates. These probabilities provide an indication of what the real-time state of the economy is, and it is important for early warning signal for crises.

The results are shown in Figure 8. While the blue colored lines represent the full sample estimates of the smoothed state probabilities of the $vMcH$ and $vHcH$ regimes, the gray lines are the estimates based on the recursively expanding samples. If the model is successful, 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 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, pseudo-real-time probabilities of being in a high systemic stress 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 high systemic stress regime, the real-time probabilities tend to do so as

[32] Note that if unrestricted, financial stress would go down. This might be explained by a looser montary policy stance in response to the loan reduction, which alleviates the increase in financial stress that might have otherwise been generated.

[33] This interpretation is in line with the evidence of a credit supply reduction during the global financial crisis based on credit register data for Portugal, e.g. Iyer, Lopes, Peydro and Schoar (2014).

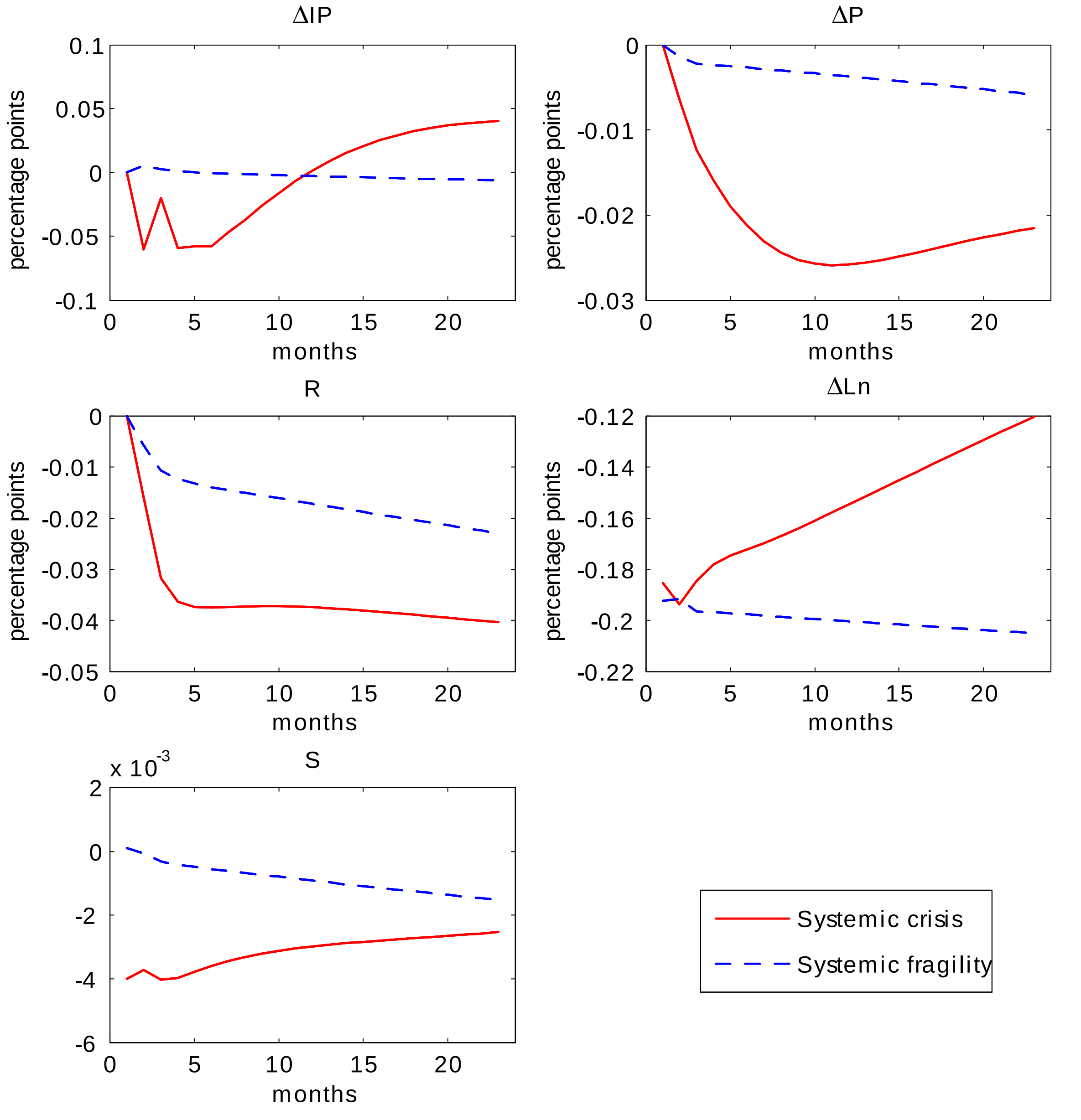

Figure 7: Impulse responses to a one-standard-deviation identified shock to bank lending; systemic crisis ($vHcH$) and systemic fragility regime ($vHcL$), both regimes with high stress variance regime but different coefficient regimes; $3v2c$ model

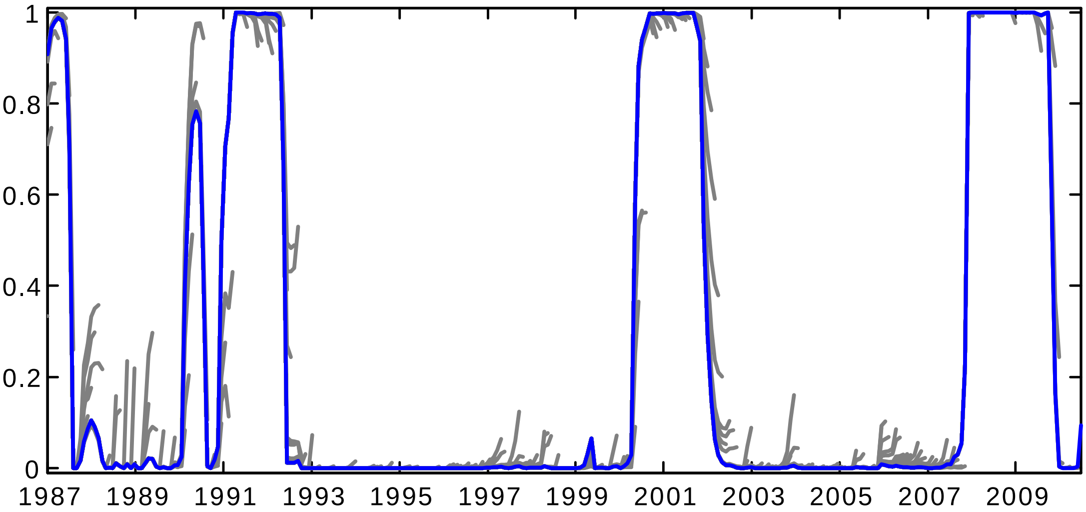

Figure 8: Real-time smoothed probabilities; systemic stress regime (vMcH and vHcH)

well. In other words, falsely predicting high stress and falsely predicting a return to tranquil times 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, employing real-time estimates of model coefficients and using vintage data, for instance, would be useful.

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 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 is often argued that the VIX or realized stock price volatility are useful indicators of risk aversion and financial stress more generally; see e.g. Coudert and Gex (2008) and Bekaert and Hoerova (2014). As one assessment of 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. In this instance, we measure realized volatility as the square root of average daily squared log price returns on the broad EMU equity price index, as maintained by Thomson Financial Datastream.

Figure 9 displays the impulse responses to a one-standard-deviation shock in realized stock market volatility. Comparing the responses of output growth to this shock with their counterparts from the model using the standard CISS (see Figure 4), we find that with the model that uses stock market volatility, the output responses are much smaller and much less persistent. Thus if one were to adopt the prior belief financial stress is an important driver of output fluctuations in times of systemic stress, relying exclusively on stock market volatility as a measure of systemic stress might be regarded as unsatisfactory. This interpretation may be regarded as plausible because stock market volatility does not capture other, less transitory markers of financial stress, such as increased risk premiums. In point of fact, the level of stock market volatility displays notably less persistence that does the CISS, especially during the recent crisis; this observation might explain, at least in part, the lower estimated persistence of the real effects of a shock to stock price volatility as compared with a financial stress shock measured by the CISS.

A different strand of the literature argues that corporate bond spreads, in particular for bonds of non-financial corporations, contain predictive content for the business cycle and other macroeconomic aggregates. Corporate bond spreads arguably capture changes in market perceptions of the quality of borrowers' balance sheets and thus their default risk; these measures tend to lead the business cycle, as documented by Gertler and Lown (1999) and Gilchrist and Zakrajšek (2012). Corporate bond spreads also move when the price of risk changes, and spreads can capture general disruptions in the financial system either through declines in the value of such bonds as collateral or via decreases in second market trading and thus in liquidity premiums. To explore the adequacy of the corporate bond spreads as a measure of systemic financial stress—or almost equivalently, to explore how much the documented success of the CISS is because it contains corporate bond spreads—we re-estimate our base case model, substituting in place of the CISS the spread between German non-financial corporate bonds and the average yield of all German government bonds, as published by the Bundesbank.

The regime identification based on this model variant appears plausible in general. While the estimated regime probabilities suggest that the global financial crisis started in September 2008, they also indicate a relatively quick termination of the worst state of systemic stress, in the beginning of 2009. This is in contrast with our base case model with the CISS which dates

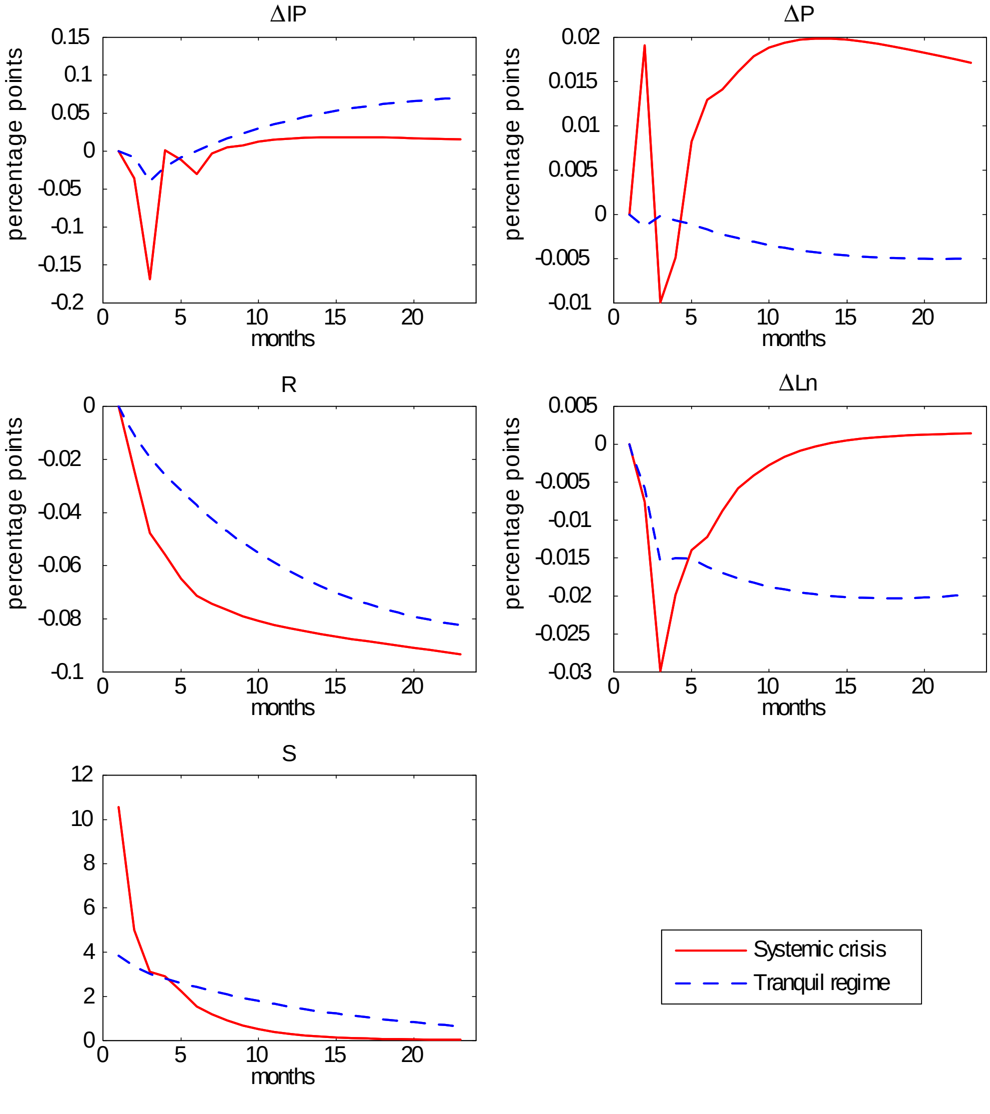

Figure 9: Impulse responses to a one-standard-deviation financial stress shock in a model with realised stock price volatility as measure of financial stress; systemic crisis (vHcH) and tranquil regime (vLcL)

the end of the global financial crisis in October 2009, after the release of the U.S. bank stress test results in May of that year. In broad terms, the two models identify approximately the same date ranges as being periods of systemic stress. However, the impulse responses to the financial shock identified in this model are economically implausible. We conclude that the corporate bond spread is a useful indicator of systemic stress and that it probably is a major contributor to the applicacy of the CISS.

Overall, our assessment is that a broad-based systemic financial stress indicator is arguably better able to uncover the nature of the interactions between financial instabilities and the macroeconomy than is a single-market single-indicator measure of financial stress. Even so, our analysis with corporate bond spreads suggests that more work in this area is called for.

4.2 Exploring the composition and construction of the CISS

Two important elements characterize the construction of the CISS as a measure of systemic stress: first, that the CISS encompasses five different, broad-based financial market segments; and second, that the time-variation in the dependence between these financial market segments is taken into account in its construction. With respect to the former feature, the role of financial intermediaries is of special importance for a bank-centered financial system as in the euro area. To investigate the importance of these features, we carry out two different experiments. Our first experiment explores the importance of the banking sector within the construction of the CISS, by rerunning our preferred $3v2c$ model, along with some of the associated model assessment exercises, using a version of the CISS that excludes the banking sector.[34] Some of the recent theoretical literature has emphasized the role of disruption in financial intermediation as an important mechanism driving large output fluctuations; see, for example, He and Krishnamurthy (2014) and Boissay, Collard and Smets (2013). To succinctly summarize our results, we find that excluding financial intermediaries from the CISS leads to estimated durations of states that are too short lived to be regarded as plausible, and to model properties that are difficult to explain. In particular, we find implausibly small and not very persistent responses in output growth to financial stress shocks in periods of systemic crises.

Our second experiment examines the systemic dimension of the CISS. The base case construction of the CISS encompasses the notion of cross-market correlations of systemic stress on an aggregate level by allowing time variation in the weights of the index's five components.[35]

[34] Arguably, this part of the analysis complements the counterfactual experiments demonstrating the role of lending to the private sector, which also highlight the importance of financial intermediation for the transmission of financial shocks to the macroeconomy, conditional on the Markov state.

[35] Allen, Bali and Tang (2012) similarly argue that their macromeasure of systemic risk complements microlevel systemic risk measures.

We explore the importance of this feature of the CISS by replacing the time-varying correlations between the different subindexes with a simple (time-invariant) equally-weighted average. Then we once again re-estimate our preferred model and analyze its properties.[36] Our results show that not all regimes are identified with this modified CISS. And this version of the model exhibits impulse response functions with economically implausible features. We take these results as demonstrative of the importance of taking the systemic aspect of financial stress into account by incorporating time-varying cross-correlation between different financial markets.

We conclude that for an economy like the euro area, where the banking sector plays a more important role than is for instance the case in the United States, a systemic financial stress index like the CISS that covers all major segments of a financial system and emphasizes the contagion of financial instability from market to market, is well suited for capturing the interaction between systemic financial instability and the macroeconomy.

5 Concluding remarks

In this paper, we introduced a representation of systemic financial instability in a Markov-switching vector-autogressive model for the euro area. Our principal goal was to examine the initiation and nonlinear propagation and amplification of financial shocks through the macroeconomy and to uncover whether such shocks are state contingent. Toward this end, we employed a new Composite Indicator of Systemic Stress (CISS), recently developed at the European Central Bank, together with conventional macroeconomic and monetary variables, and estimated the model with recently developed Bayesian methods.

We found evidence that the Euro area economy is subject to occasional switches into what we called periods of high systemic stress. We further found that switching behavior manifested itself in both the variances of model shocks and in the structural characteristics of the model; that is, in the parameters that propagate those shocks throughout the economy. Our results show that this switching behavior is economically important. In particular, the effects of financial stress stress shocks on output are much larger, more persistent, and more consequential for the real economy in regimes of high systemic stress than during tranquil times, and bank lending plays an independent role for the determination of real activity during episodes of high systemic stress,

[36] The relevance of the systemic dimension of financial stress has been emphasized in the literature on systemic risk. 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 stress. Acharya et al. (2012) have proposed an economic and statistical approach to measure the systemic risk of financial firms. Correlation-based measures of connectedness, including systemic risk, are discussed, for instance, in Diebold and Yilmaz (2014) who propose another way of measuring the connectedness of financial firms.

with exogenous identified shocks to loan growth having important consequences for the rest of the economy, whereas in tranquil times they do not. It follows from this that a single-regime, constant-variance characterization of the economy will miss these features and is therefore likely to provide misleading answers to questions of this nature.

We found that the CISS has two particularly useful features for capturing the nature of the interaction between financial instabilities and the macroeconomy. The first of these is the inclusion of measures of instability in financial intermediation, a feature that is particularly relevant for economies that have bank-centered financial systems as does the Euro area. The second is the taking into account of the systemic dimension of financial stress through the use of time-varying, cross-market correlations of the components of the CISS, which appears to us to capture credit constraints that are binding during high-stress periods. Finally, the quasi-real-time state probabilities of the estimated regimes from our base-case model suggest at least some prospects for the model's use as a tool for macroprudential surveillance, although more research, preferably using vintage data would be in order before drawing definitive conclusions on this score.

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Appendix A : 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

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.

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.

Appendix B : Priors

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 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

$$y_t' A_0(s_t^c) = x_t' A_+(s_t^c) + \varepsilon_t' \Xi^{-1}(s_t^v), \quad t = 1, 2...T. \tag{3}$$

$A_0(s_t)$ 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

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

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:

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

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 Sims, Waggoner and Zha (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 Sims, Waggoner and Zha (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.

Appendix C : Counterfactuals on role of systemic financial stress

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 ($vLcL$). 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.

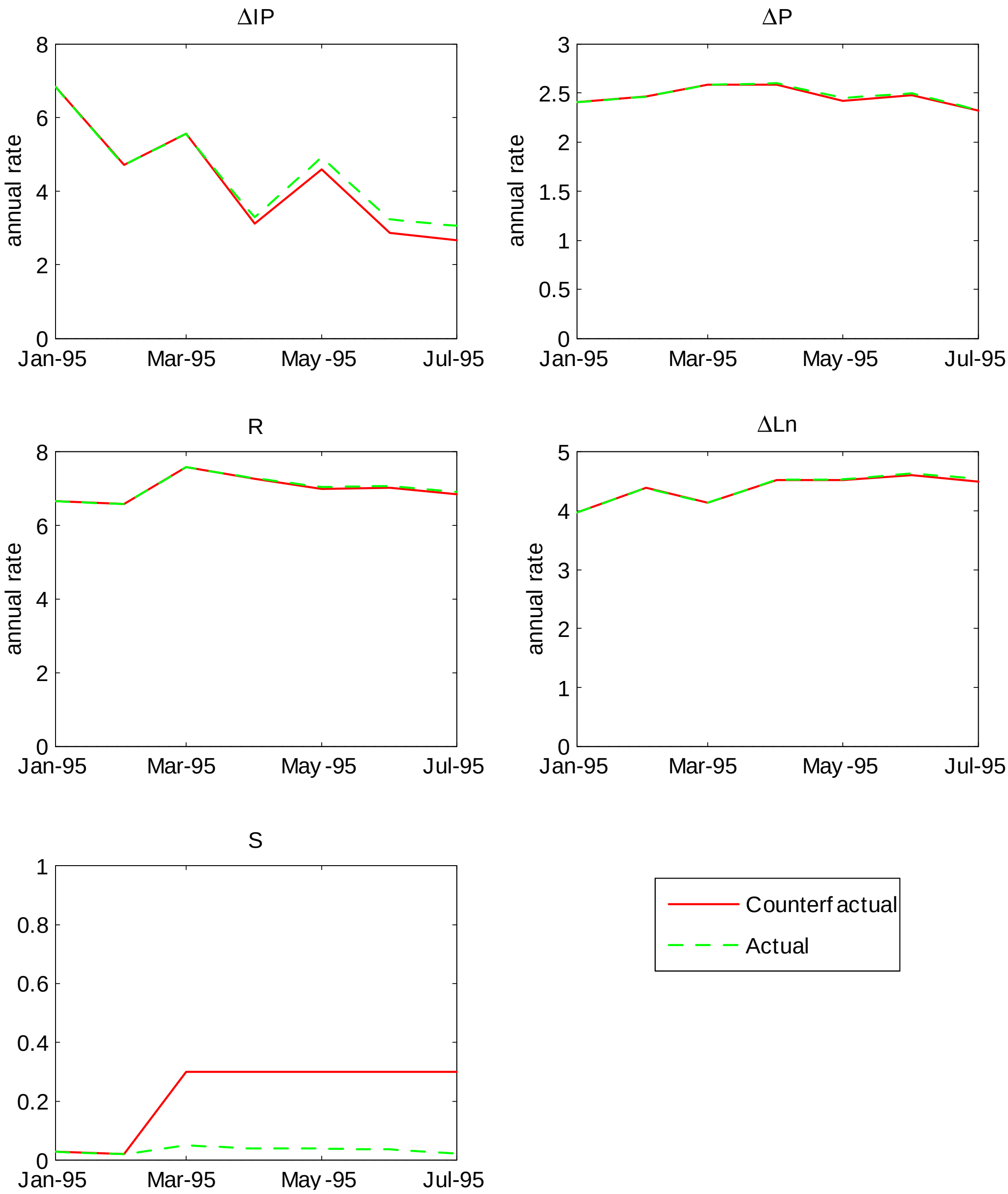

Figure 10: Counterfactual in tranquil times (vLcL), CISS path increased by 0.25 starting in March 1995

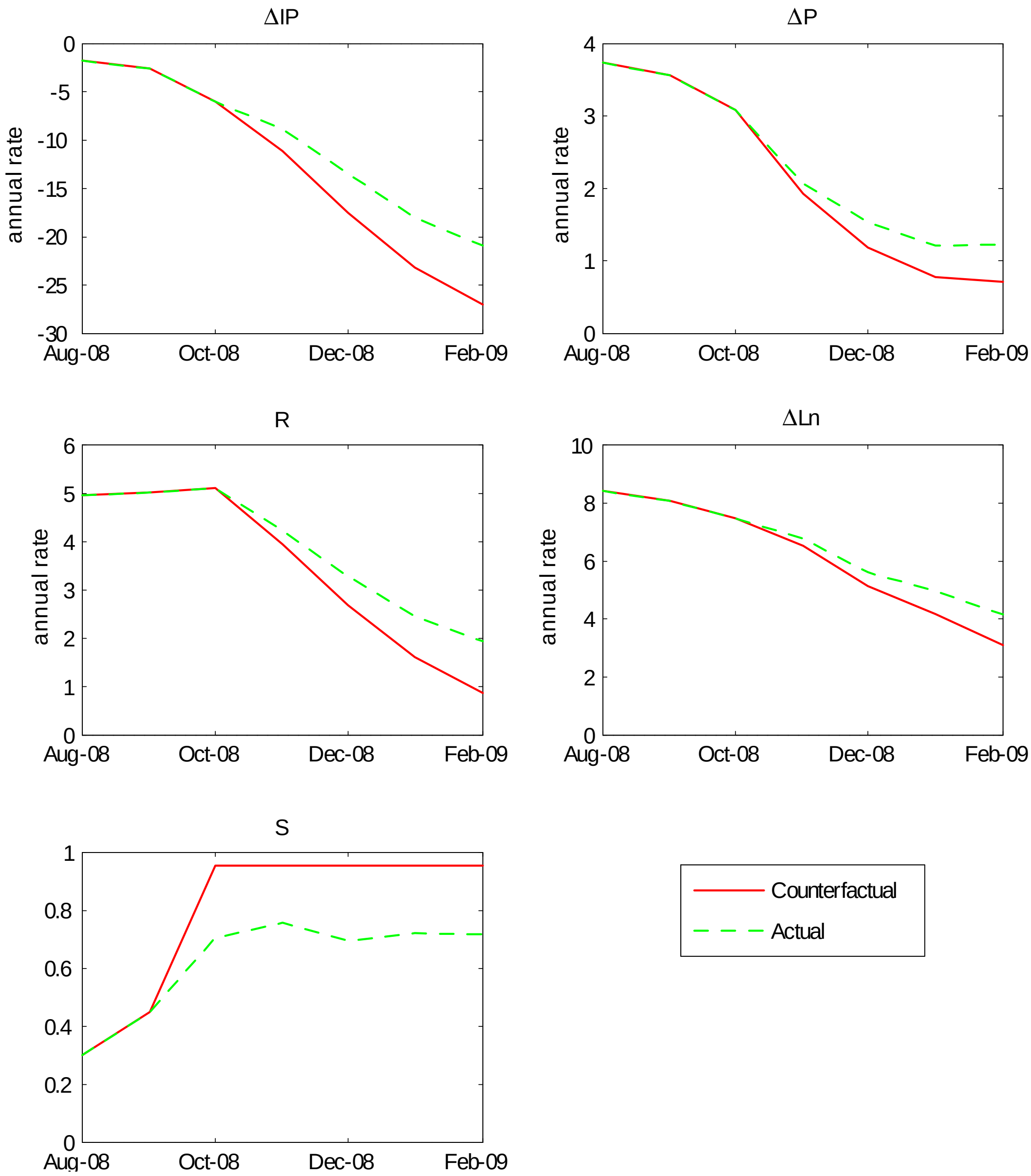

Figure 11: Counterfactual in systemic crisis period (vHcH), CISS path increase by 0.25 starting in October 2008