

Hartmann, Philipp; Hubrich, Kirstin; Kremer, Manfred; Tetlow, Robert J.

Conference Paper

Melting down: Systemic financial instability and the macroeconomy

Beiträge zur Jahrestagung des Vereins für Socialpolitik 2013: Wettbewerbspolitik und Regulierung in einer globalen Wirtschaftsordnung - Session: Financial Stability, No. G02-V3

Provided in Cooperation with:

Verein für Socialpolitik / German Economic Association

Suggested Citation: Hartmann, Philipp; Hubrich, Kirstin; Kremer, Manfred; Tetlow, Robert J. (2013) : Melting down: Systemic financial instability and the macroeconomy, Beiträge zur Jahrestagung des Vereins für Socialpolitik 2013: Wettbewerbspolitik und Regulierung in einer globalen Wirtschaftsordnung - Session: Financial Stability, No. G02-V3

This Version is available at:

<http://hdl.handle.net/10419/80487>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

Melting Down: Systemic Financial Instability and the Macroeconomy*

Philipp Hartmann[†] Kirstin Hubrich[‡] Manfred Kremer[§] Robert J. Tetlow[¶]

This version: August 30, 2013

PRELIMINARY AND INCOMPLETE - PLEASE DO NOT CITE WITHOUT
PERMISSION

Abstract

We integrate systemic financial instability in an empirical macroeconomic model for the euro area. We find that at times of widespread financial instability the macroeconomy functions fundamentally differently from tranquil times. We employ 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. Both the parameters that capture the transmission of shocks through the economy and the variances of the shocks change at times of high stress in the financial system. In particular, the negative output effects of sizeable increases in financial stress are much larger after such a regime

*We would like to thank participants at the Office of Financial Research/Financial Stability Oversight Council conference “The Macroprudential Toolkit”, the Deutsche Bundesbank/Institute for Monetary and Financial Stability/SUERF conference “The ESRB at 1”, a meeting of the ESCB Macroprudential Research (MaRs) network, the 2012 European Economic Association Meetings and a Bank of Canada seminar for comments. Vesela Ivanova and Cristina Manea provided excellent research assistance. The views expressed are only the authors’ and should not be associated with official views of the European Central Bank, the Eurosystem or the Federal Reserve Board.

[†]European Central Bank, Kaiserstr. 29, D-60311 Frankfurt am Main, Germany, e-mail philipp.hartmann@ecb.europa.eu, Erasmus University Rotterdam and Centre for Economic Policy Research (CEPR), London, United Kingdom

[‡]European Central Bank, Kaiserstr. 29, D-60311 Frankfurt am Main, Germany, tel. +49-69-1344-6358, e-mail kirstin.hubrich@ecb.europa.eu

[§]European Central Bank, Kaiserstr. 29, D-60311 Frankfurt am Main, Germany, tel. +49-69-1344-7065, e-mail manfred.kremer@ecb.europa.eu

[¶]Federal Reserve Board, Washington, D.C., USA, e-mail robert.j.tetlow@frb.gov.

change than during tranquil times. Macroprudential and monetary policy makers are well advised to take these non-linearities into account.

JEL Classification: E44, C11, C32

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

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 (see e.g. Kindleberger 1978, Davis 1995 or Reinhart and Rogoff, 2009). The world-wide financial crisis unfolding particularly as of 2008-9 is just the latest example. And yet, despite a long historical experience with the common features of these events and their often dramatic macro-economic consequences, financial instability was not a prominent feature of the macro-economic contributions to the literature—at least until recently before this crisis. Different characterisations of financial crises have been proposed, including nonlinearities stemming from amplification and feedback effects between financial markets and the real side of the economy. From this interaction episodes of systemic financial stress or crises with systemic features might emerge. Against this background it is an important area of research to incorporate realistic characterisations of widespread financial instability into empirical and theoretical macroeconomic models.

This paper contributes to the literature by developing an empirical macroeconomic model that embodies a number of key features of systemic financial crises and by analysing how shocks to systemic stability are transmitted through the economy.

In our view the most important elements such a model must possess include the following: first, a credible representation of the level of systemic instability in the financial system; second,

a macroeconomic model featuring standard variables and relationships and the possibility to link them to systemic instability; third, an approach that broadly considers insights from finance theory that associate the emergence of financial instability with discontinuous adjustments (non-linearities) or even switches between equilibria.

Proceeding along these lines, the starting point and a first key feature of our work is the comprehensive way in which we measure systemic financial instability. We employ a novel multi-dimensional index, the Composite Indicator of Systemic Stress (CISS), recently developed at the European Central Bank (Hollo, Kremer and Lo Duca 2012). This index is designed along standard definitions of systemic risk, covering the major components of financial systems. It is distinct from most previously used and often narrower measures of financial instability in at least two respects. First, by covering the main types of financial markets and intermediaries in a systematic fashion it is equally applicable to and comparable across more bank-based and more market-based financial systems. Second, by considering the time-varying dependence of stress levels between the main markets and intermediaries it particularly focuses on systemic instability.

Next, we embed the CISS – together with other major macroeconomic and financial variables – in a richly specified Markov-Switching Bayesian Vector Autoregression (MS-BVAR) model. Such a model is described in Sims, Waggoner and Zha (2008), has originally been used by Sims and Zha (2006) to assess structural change in US monetary policy rules and has recently also been applied to the US macroeconomy by Hubrich and Tetlow (2012). We allow both estimated parameters and error variances to change independently of each other, so that we can distinguish potential regime changes related to the structural functioning of the economy from regime changes related to the sizes of shocks reflecting, *inter alia*, shifts in economic uncertainty. So, another key feature of our analysis is that the model allows for non-linearities among and between financial and real variables.

A third key feature of our work is that we can embody the two-way relationship between the financial sector and the economy at large, taking account of feedback and amplification effects. Contrast this with standard stress-testing methodologies, as used by financial supervisors, which are usually limited to the first-round effects of a macroeconomic scenario on the banking system.

In this paper we are particularly focusing on how systemic financial stress affects economic performance in terms of the growth rate of output. The sharp decline in real economic activity in response to the enormous increase in systemic financial stress starting in September 2008 is a prominent example.¹ The data sample is monthly data of industrial production growth, inflation, 3-month money market rates, loan growth and the CISS for the euro area between January 1987 and December 2010.

Our results support the view that the macroeconomy functions fundamentally differently in times of widespread financial instability compared to tranquil times. Both the parameters that link key economic variables and the variances that reflect the size of shocks change materially.

We date the most fundamental regime change in 2008, somewhere in between the Bear Stearns takeover and the Lehman Brothers failure. The severity of the present crisis exceeds any precedents over the last quarter of a century. Interestingly, by dating this change in May 2008 the model somewhat anticipates the meltdown of the global financial system following the Lehman Brothers failure. A second drastic regime change of parameters and variances happens in September 2001, basically “now-casting” the financial turbulence around the terrorist attacks in the United States. But this change is rather short-lived.²

In general, the effects of systemic financial shocks in this regime of high systemic instability

¹Trichet (2011) illustrates the errors most forecasting institutions made in capturing these declines. They were in part due to standard macroeconomic forecasting models not considering financial sector developments very well, let alone widespread financial instability.

In our model financial instability is allowed to affect output growth both via reduced bank lending and via reduced aggregate demand. The first effect can be explained through weakened financial intermediaries not being able to extend credit to firms and households. The second effect can be explained through a surge in uncertainty that leads economic agents to assume a “wait-and-see stance” and postpone the purchase of consumer durables or investment goods (Bloom 2009).

²There are also other regime changes during our sample period, but they are much less drastic than these two.

are much larger than during tranquil times, as one would expect when material non-linearities are at work. For example, an increase of the CISS – which can range between 0 and 1 (maximum systemic instability) – by 0.1 leads to a sharp decline in output growth by 2 percentage points over the first five months. And changes to loan growth also seem to play an important role in the adjustment process. In contrast, the impulse response function of a similar shock on the CISS in the tranquil regime shows almost no growth losses. It should be noted that at critical times, such as August 2007 or September 2008, the CISS abruptly increased three to four times more than the shock assumed in the above exercise. This evidence from impulse response functions is corroborated by counterfactual exercises. For example, setting all shocks to the CISS to zero during a high-stress regime period leads to significantly higher loan and industrial production growth paths than observed in the real data. Doing the same exercise for a low-stress regime period leads to loan and industrial production growth paths basically indistinguishable from the eventually observed ones.

In order to preview the potential for using this model in practical macro-prudential surveillance, i.e. in the ongoing monitoring of systemic risks and instabilities, we also calculate the state probabilities for the regimes in real time for expanding samples and compare them to the probabilities for the full sample. It turns out that both indications of high-stress regimes when the situation stays quite tranquil in the end (type-1 errors or false positives) and indications of the situation calming down although the system ultimately stays in high stress (type-2 errors or missed positives) are quite rare. In other words, the model has some potential for at least now-casting episodes of systemic instability for a macro-prudential policy maker.³

Finally, with the objective of illustrating the importance of a credible representation of systemic instability, we replace the CISS with financial instability measures that were more standard

³The 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>).

in the macroeconomic literature before the crisis and lacked an explicit systemic dimension. For example, using a measure of realised stock market volatility we observe that the regimes found do not track known crisis situations very well any longer and that the impulse response functions show much less severe and less persistent real adjustments.

The paper is structured as follows. Section 2 briefly surveys the related literature. Section 3 describes the main features of the systemic stress indicator and discusses the econometric approach pursued to address our main research questions. Section 4 presents and discusses the empirical results obtained from specifying, estimating and analysing the Markov-switching VAR model. We characterise the macroeconomic regimes that emerge and how they relate to financial stress, examine their occurrence over time and relate them to crises and other financial stress events during the sample period, analyse the dynamic responses of key variables to different shocks and run a series of counterfactual exercises. Section 5 contains the estimations of state probabilities for expanding samples as a reality check for practical macro-prudential surveillance. Section 6 compares our models results with those obtained when replacing the CISS by aggregate stock market volatility. Section 7 draws some conclusions, also on the potential relevance from a monetary and macro-prudential policy perspective. Appendices A and B provide technical details about the systemic stress measure and the econometric approach, respectively.

2 Related Literature

Our work is related to a number of different strands in the literature. First, it builds on the econometric literature introducing regime changes in economics, notably the Markov-switching models pioneered by Lindgren (1978) and Hamilton (1989). It applies the methods for calculating the marginal likelihoods and for inference in Bayesian Markov-Switching Vector Autoregressions by Sims, Waggoner and Zha (2008) to the problem of how financial instability can affect the macroeconomy in a non-linear fashion.

Markov-switching representing regime changes has already been used in macroeconomics for different questions. Sims and Zha (2006), Bianchi (forthcoming) and Evans and Wachtel (1993) use it to capture different monetary policy or inflation regimes. More on the finance side, Ang, Bekaert and Wei (2008) employ it to explain yield curve movements and Bekaert, Hodrick and Zhang (forthcoming) to explain stock market volatility. While we also allow for regime changes in the VAR error variances and include inflation and interest rates, our focus is on widespread financial instability (way beyond stock market volatility) and not on monetary policy or the term structure.

The crisis has triggered an evolving theoretical and empirical literature how to better integrate financial factors in macroeconomic models. Some of the earlier theoretical contributions include Bernanke and Gertler (1989) and Kiyotaki and Moore (1997) introducing financial accelerators in business cycle models, Mendoza (2002) incorporating occasionally binding collateral constraints on borrowers, Dubey, Geanakoplos and Shubik (2005) developing a general equilibrium model with imperfect credit markets and default and Lorenzoni (2008) discussing how limited commitment in financial contracts can lead to over-borrowing ex ante and excessive volatility ex post. More recently, He and Krishnamurthy (forthcoming a), Bianchi (2011), Korinek (2012) and Brunnermeier and Sannikov (2013) make important steps in the direction of financial instability amplifying aggregate fluctuations considering occasionally binding constraints and endogenous financial risks, fire sales and pecuniary externalities, non-linearities and the dynamics far away from the steady-state equilibrium. Most recently, work by He and Krishnamurthy (forthcoming b), Aoki and Nikolov (2012), Boissay (2011), Goodhart, Kashyap, Tsomocos and Vardoulakis (2012), Martinez-Miera and Suarez (2012) and Boissay, Smets and Collard (2013) puts the emphasis on the role of banks/financial intermediaries and their incentives in systemic financial instability. Our contribution also captures stress in the banking system, aggregate amplification effects and non-linear adjustments, but it is empirical and does

not rule out specific channels through which instability may be transmitted.

In line with the financial accelerator view there is also a literature on financial indicators predicting economic activity. For example, Harvey (1988) and Estrella and Hardouvelis (1991) use the yield curve, Gertler and Lown (1999) and Gilchrist and Zakrajsek (2012) credit spreads, Estrella and Mishkin (1998) stock market performance, Bloom (2009) and Bekaert and Hoerova (2013) (components of) the Chicago Board Options Exchange VIX index of implied stock market volatility as a measure of uncertainty. Others combine a range of these and other financial variables in so-called financial conditions indexes, often to support monetary policy considerations (see e.g. Mayes and Viren (2001), Gauthier, Graham and Liu (2004), Swiston (2008), Hatzius, Hooper, Mishkin, Schoenholtz and Watson (2010) or Matheson (2012)). We also use a composite indicator of a range of financial variables, the ECB's CISS developed by Hollo, Kremer and Lo Duca (2012), but rather than focusing on general financing conditions this indicator is firmly oriented towards measuring systemic financial instability. Not only does it systematically cover the most important parts of the financial system but it also focuses all its components on the prevailing level of instability. Recently also other composite financial stability indexes have been developed, notably by or in cooperation with different central banks or international organisations (see e.g. Illing and Liu (2006), Nelson and Perli (2007), Cardarelli, Elekdag and Lall (2011) or Kliesen, Owyang and Vermann (2012)). The main distinctive features of the CISS include its conceptual foundation in a standard economic definition of systemic risk and the application of portfolio-theoretic principles when aggregating its different components (notably taking their dependence into account).

Our work is perhaps most 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. Bordo, Eichengreen, Klingebiel and Soledad-Martinez (2001), Hoggarth, Reis and Saporta (2002), Barkbu, Eichen-

green and Mody (2012) and Schularick and Taylor (forthcoming) measure, *inter alia*, the output costs of many crises across many countries taking a historical perspective. We also look at the effects of financial distress on output, but we do not date crises and then calculate output losses observed during those times. We rather include a characterisation of systemic financial stress in our empirical approach and let the Markov-switching model find the times of regime changes from the data. Moreover, we are also interested in the macroeconomic dynamics, estimating impulse response functions of output growth (and other variables in our VAR) to shocks in the level of systemic financial stress.

Last, but not least, our decision to use a regime-switching approach is inspired by finance theory that associates financial crises with discontinuous, rather abrupt changes. For example, the seminal work by Diamond and Dybvig (1983) describes bank runs as sudden shifts between two entirely different equilibria. Morris and Shin (2003) show how self-fulfilling currency attacks can emerge as a unique equilibrium. Morris and Shin (2012) characterise asset market breakdowns as an adverse selection phenomenon. Allen and Gale (2000) discuss how certain shocks can turn liquidity risk sharing through interbank markets into contagious bank failures. Diamond and Rajan (2005) illustrate how the information sensitivity of bank assets can undermine the liquidity of the banking system. Brunnermeier and Pedersen (2008) model how self-feeding downward liquidity spirals in financial markets can emerge from collateralisation and margin requirements. Gorton and Metrick (forthcoming) argue that sudden runs can also happen in important wholesale funding markets of financial intermediaries. We allow for discontinuous changes in both systemic financial stress and its transmission to the rest of the economy. But we do not pre-determine specific sources where they emerge from. We rather let the data speak when they occur and in what form. We hope that this also makes some contribution to the efforts in building bridges between macroeconomics and finance.

3 Measuring Systemic Financial Instability and General Model

Setup

In this paper we develop a small-scale but richly parameterised non-linear macro-financial VAR model that shall help us gaining empirical insights about how the macroeconomy works in different states of systemic financial instability. We do not attempt to build a structural model that highlights specific channels through which financial instability may spread to the real economy, because the theoretical literature in this area is at an early stage. Hence, having primarily an empirical interest, we do not want to impose too many economic restrictions *ex ante*, because this would risk leading to model misspecification, and rather let the data speak on how the macroeconomy behaves when financial instability strikes.

There are several choices to be taken at the initial stage of model specification. First, we need to operationalise the concept of systemic financial instability in a way that is credible and can be meaningfully integrated in a multivariate time series model. Second, the model needs to allow for sizable discontinuous (non-linear) change, a property which economic history and finance theory have shown to be essential for transition from normal times to financial crises. The Markov-Switching VAR (MS-VAR) framework that we employ in this paper seems to be well suited to capture such drastic changes and the different macroeconomic dynamics that can unfold in tranquil and crisis regimes. Third, the selection of all the endogenous model variables has to ensure a sufficient representation of macroeconomic dynamics in general and interactions among the key variables, including particularly between the financial stability measure employed and other, more standard macroeconomic variables.

As to the first choice, we use a composite indicator that summarises the general instability in the financial system and is presented in the following sub-section.⁴ Whilst this approach is

⁴The idea of using composite indicators as a reduced-form approximation of certain more complex phenomena is a recently expanding area of research in empirical finance and macroeconomics (see the overview in section 2 on the related literature). Hubrich and Tetlow (2012) use a financial stress index that has been constructed by

data-driven, it is founded in standard economic definitions of systemic risk, as they have been derived from finance theory and practical experience. Moreover, - to our knowledge - there is hardly any work deriving empirical measures of general systemic instability from rigorous economic theory, let alone agreement about them.⁵ A quite standard definition of systemic risk, for example, describes it as “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). And our indicator is precisely describing how widespread and severe instability in the financial system is at a given point in time. Absent safe grounds for structural modelling of root causes and transmission channels of crises an advantage of our approach is that we can start the analysis from what potentially recurring, truly systemic crises have in common, namely widespread financial instability. The key is therefore to employ an indicator of financial instability that particularly focuses on the systemic dimension.

3.1 Systemic stress indicator

The Composite Indicator of Systemic Stress (CISS), which has been recently developed by Hollo, Kremer and Lo Duca (2012), is particularly suited for the present purpose since its statistical design is shaped along the notion of *systemic risk* as just defined, where *systemic stress* is interpreted as a materialisation of systemic risk. In what follows we briefly describe the main features of the indicator design and refer to Appendix A for further details.

Ideally, the indicator should capture strains in each part of the financial system, weighted by its systemic importance. However, a real-world financial system constitutes a highly complex and complicated network of a multitude of financial markets, financial intermediaries and financial infrastructures, and it is practically impossible to measure the level of stress in each and every of its elements. In order to reduce the level of complexity, it seems to make sense to limit

the staff of the Federal Reserve Board to analyse the economy in real time during the crisis.

⁵A valuable attempt to provide a theory-based systemic risk measure has been presented by, e.g., Goodhart and Tsomocos (2007).

attention to those parts of the financial system which can be regarded as both systemically most important and sufficiently representative for the system as a whole.

Accordingly, the CISS identifies five highly aggregated market segments of a financial system capturing, in a stylised fashion, the main flows of funds from ultimate lenders/savers to borrowers/spenders, where funds are channeled either indirectly through financial intermediaries or directly via short-term and long-term asset markets: 1. The financial intermediaries sector (notably banks, but also insurance companies, pension funds and other financial services providers); 2. The money market (broadly defined as including in principle all forms of short-term wholesale debt financing in the economy, e.g., interbank and commercial paper markets); 3. The bond market (only longer term sovereign and non-financial corporate issuers); 4. The equity market (only non-financial corporations); and 5. The foreign exchange market (capturing cross-border financing activities). The selection of these five market segments can be justified on grounds of their systemic importance.

Each of these five market segments is itself composed of three individual stress indicators, where each indicator captures typical symptoms of financial stress in its respective market segment. In order to ensure representativeness, the indicators should ideally cover market-wide developments. In most cases, the indicators therefore draw on broad market indices or certain assets with benchmark status for the pricing of a wider range of close substitutes (e.g., government bonds). The set of 15 individual stress indicators includes realised asset return volatilities (included in all five subindices), risk spreads, a time-varying stock-bond return correlation coefficient, banks' recourse to marginal central bank lending ("discount window") and measures of cumulated equity valuation losses. All the underlying raw data are available via standard data providers (most are from Thomson Financial Datastream). Furthermore, all data are reported at a daily or weekly frequency and with a publication lag of one day at most, which underscores the "real-time" nature of the CISS. Five separate subindexes of stress result from taking sim-

ple averages of the three constituent stress indicators of each market segment after appropriate transformation based on order statistics (probability integral transformation) to harmonise their scale and distributional properties.

The main innovative feature of the CISS is the application of basic portfolio-theoretical principles to the aggregation of the subindexes into the final composite indicator. Along the lines of how portfolio risk is computed from the risks of individual assets, the subindexes are aggregated by way of their time-varying cross-correlations calculated as exponentially weighted moving averages. As a result, the CISS puts relatively more weight on situations in which stress prevails in several market segments at the same time which, in turn, captures the idea that systemic stress is high if financial instability *spreads widely* across the whole financial system. At the same time, the time-variation in the cross-correlations captures changes in the degree of interconnectedness between the market segments, which are likely to be relatively strongly interconnected in general but in particular so during times of stress.

The calibration of segment-specific index weights according to their relative systemic importance offers another route to bring in features of systemic risk within the portfolio-theoretic framework. For instance, in Hollo, Kremer and Lo Duca (2012) the subindex weights mirror the relative strength of the cumulated impact each stress subindex has on economic activity estimated within different regression frameworks. For the present purpose, however, we dispense with such a “relevance” weighting scheme in order to avoid potential artificial correlations when adding the CISS to industrial production growth and other macro variables in our VAR framework. Instead, each stress-subindex receives an equal weight of 20% in the computation of the CISS which still preserves the essential properties of the indicator.⁶ In either case, given that financial institutions, and notably banks, clearly dominate money market activities in the euro area, the financial intermediary sector covers de facto a large part (40% with equal weighting)

⁶See Hollo, Kremer and Lo Duca (2012) for a comparison between the CISS with real-impact weights and equal weights, respectively.

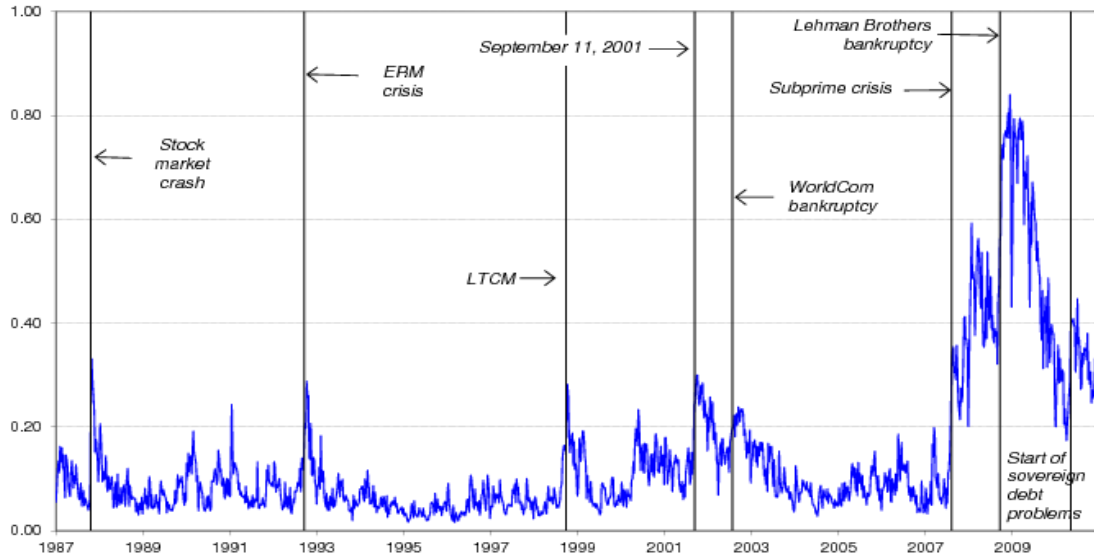


Figure 1: Composite Indicator of Systemic Stress (“CISS”) for the euro area and specific financial stress episodes, January 1987 to December 2010

of the CISS.

The final indicator is plotted for the euro area and the whole sample period (January 1987 to December 2010) at weekly frequency in figure 1. By construction, the CISS is unit-free and bounded within the continuous interval $(0,1]$. The figure shows that the largest spikes in the CISS capture well-known financial stress episodes, such as the 1987 stock market crash, the 1992 crisis of the European exchange rate mechanism, the 1998 Long Term Capital Management crisis as well as the financial stress around the terrorist attacks on 11 September 2001.⁷ Moreover, the CISS clearly shows that the recent financial crisis stands out over the last quarter of a century in terms of its systemic dimension, in particular following the Lehman Brothers bankruptcy in September 2008 but also following its outbreak in August 2007 and the worsening European sovereign debt crisis in the second half of 2011.

⁷See Hollo, Kremer and Lo Duca (2012) for a more extensive coverage of historical stress events which coincide with peaks in the CISS.

3.2 Non-linear multivariate model framework

A second 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 a systemic financial crisis emerges or disappears. In particular, we want to ask whether specific non-linearities in the form of regime switches in the relationships between key macroeconomic variables can be identified empirically, notably in terms of the role of systemic financial stress and potentially also capturing amplification effects and feedback mechanisms. For this purpose we embed the CISS in a richly specified Markov-switching VAR model with which one can estimate abrupt, discrete changes in economic dynamics. Our MS-VAR framework also allows us to investigate the nature of the regime changes or non-linearities. We aim to distinguish whether it is just the volatility of the shocks that changes during a financial crisis or also the structure of the economy and therefore the transmission of shocks, i.e. whether there is also evidence of an amplification of shocks through the economy.

This methodology builds on the work by Sims and Zha (2006) and Sims, Waggoner and Zha (2008) to estimate the MS-VAR model using recently developed Bayesian methods (see Appendix B for more details on the techniques).⁸

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

$$y_t' A_0(s_t^c) = \sum_{l=1}^p y_{t-l}' A_l(s_t^c) + z_t' C(s_t^c) + \varepsilon_t' \Xi^{-1}(s_t^v), \quad (1)$$

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 variances, v , and for intercepts and slope coefficients, c . p 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 is an $n \times n$ matrix

⁸These recent developments in Bayesian econometrics have facilitated the estimation of and inference for such richly parameterised models like ours.

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 $A_t(s_t^c)$ is a $n \times n$ matrix of parameters of the endogenous variables. 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 $\{1, 2, \dots, h^m\}$ and evolve according to a first-order Markov process with the following state probabilities:

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

Let

$$A_+' = [A_1(k)', A_2(k)', \dots, A_p(k)', C(k)'] \quad \text{and} \quad x_t' = [y_{t-1}', \dots, y_{t-p}', z_t'],$$

then the model can be written as

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

T is the sample size. Let us designate $Y^t = \{y_0, y_1, \dots, y_t\}$ as the vector y stacked in the time dimension. We assume that ε_t is conditionally standard normal:

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

The variance-covariance matrix $\Sigma(s_t^m)$ of the reduced-form shocks can be computed as⁹

$$\Sigma(s_t^m) = (A_0(s_t^c) \Xi^2(s_t^v) A_0'(s_t^c))^{-1}. \quad (4)$$

Since the matrix A_0 varies across coefficient regimes s_t^c , the number of regimes of the reduced-form shocks obtains as a multiple of the number of variance regimes of the structural shocks s_t^v

⁹See Sims, Waggoner and Zha (2008), p. 265.

since coefficients and variances are assumed to switch independently of each other.

3.3 Other variables and data sources

Since MS-VARs with even a moderate number of different regimes require estimation of a large number of parameters, we opt for a low-dimensional model with five endogeneous variables and three lags. 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 forthcoming). It is also justified by the relatively large share of bank loans in the overall financing of the euro area economy. The setup is similar to the one in Hubrich and Tetlow (2012) but differs in some important respects, namely that our model uses data for the euro area instead of the US, that we introduce a financial stress index that explicitly embeds the idea of widespread (systemic) financial instability, and that we include loans in the model instead of a monetary aggregate.

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 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 (computed with equal-weights instead of real impact-weights) is taken from Hollo, Kremer and Lo Duca (2012) and is transformed into monthly data by averaging weekly observations.

4 Systemic Financial Instability and the Macroeconomy

4.1 Model specification

4.1.1 Structural identification

The model employed in our analysis is a five-variable MS-BVAR as summarised in equation 1, with three lags ($p=3$). The contemporaneous relationships between all 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 decides about the contemporaneous causality structure, where the (shocks in the) variable ordered first is assumed to be contemporaneously uncorrelated to the shocks in all other variables, while the variable being last in the order depends on the contemporaneous shocks in all other equations.

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 contemporaneous shocks in the other 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

¹⁰See e.g. Cristiano, Eichenbaum and Evans (1999).

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. 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 (or money market rates more generally) can react simultaneously to surging financial stress (as it may happen indeed particularly during crisis periods), 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). So, in what follows we only show results for the above ordering with the CISS being last, which should also constitute the most conservative estimates for the key link between systemic financial instability and the real economy we are most interested in.

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.¹¹

¹¹Results not displayed in the paper are available from the authors upon request.

4.1.2 Regime changes in the macroeconomy: Shifts in volatility, in transmission, or both?

The most important step in the model specification consists of identifying possible regime changes at the macroeconomic level in the euro area between 1987 and 2010. What types of regimes do we a priori have in mind in the context of the present paper? We may expect regimes which single out episodes of heightened financial stress characterised by the presence of large financial shocks to be captured by the CISS. In addition, we may anticipate regimes in which severe financial stress becomes widespread and thus systemic with adverse implications for the functioning of the financial and the real sectors due to, for example, an amplified transmission of financial shocks to the real economy. In order to capture and disentangle such different states of the world statistically, our empirical framework distinguishes between two types of regime changes, one in the size of the structural shocks (i.e., in the structural error variances) and another in the basic structure of the economy as reflected in the model coefficients. We allow a priori for independent switches in one or the other.

To identify the type and number of regimes in the data, we use log marginal data densities (log mdds), as it is common practice for model selection in the Bayesian econometrics literature. The mdds, or posterior model probabilities, are a measure of model fit, whereby larger numbers imply a better fit. Since the log mdds are on a log-likelihood scale, very small “differences of one or two in absolute value mean little, while differences of ten or more imply extreme odds ratios in favour of the higher-marginal-data-density model” (Sims and Zha, 2006, p. 61).¹² Table 1 presents the log mdds for several combinations of the two types of regime changes, combining different numbers of regimes in variances and coefficients, respectively. The log mdds are presented both in absolute terms and relative to a conventional constant parameter VAR model as a benchmark.

¹²Log(mdd) differences can be considered as posterior odds ratios assuming equal weights for the models as priors. We use a method to calculate the marginal data densities proposed by Sims, Waggoner and Zha (2008).

Table 1: Marginal data densities for different model specifications (types and number of regimes)

Types of regime changes	no changes	variances change		variances and coeff. change	
Number of regimes	1v1c	2v1c	3v1c	2v2c	3v2c
log(mdd)	-6.05	92.36	131.95	126.08	147.36
Diff. to constant parameter model	0	98.41	138.00	132.13	153.41

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

The results suggest strong evidence against a constant-parameter specification. The difference between the constant-parameter model (1v1c) and all models with regime-switching is at least 98 in terms of log mdds, and in most cases much above 100. In other words, there is clear statistical evidence that during the period considered, the dynamics of the euro area macroeconomy can be well described by a non-linear behaviour in the form of Markov-switching regimes. Allowing for two and three regimes, respectively, in the structural shock variances while keeping all coefficients constant does already clearly improve the model fit in terms of log mdd over the 1v1c model. If we additionally allow for two coefficient regimes the fit is again substantially improved. The specification with three variance regimes and two independent coefficient regimes (3v2c) outperforms all the other models considered and will thus be selected as our preferred model variant for the empirical exercises in this rest of this paper. This means that we are going to deal with six different regimes, reflecting non-linear changes in error variances and model coefficients and thus in the structural functioning of the euro area economy during the sample period considered.

4.2 Model analysis and interpretation

While the previous section dealt with the statistical identification of the different Markov-switching regimes, we are now facing the challenging task of interpreting the identified regimes in economic terms and then analyse the implications of regime changes for macroeconomic dynamics. The next two sub-sections deal with the former issue, looking first at the volatility of our endogenous variables for the different regimes and then at the times at which the switches

Table 2: Relative structural shock standard deviations across three variance regimes

	production	inflation	interest rate	loans	CISS
First regime (v1)	1.000	1.000	1.000	1.000	1.000
Second regime (v2)	0.905	1.525	0.285	0.738	0.617
Third regime (v3)	0.853	1.994	0.645	0.563	2.980

Notes: Entries for each variable are normalised on the unit standard deviation of the first variance regime (v1).

occur. Once we have established solid economic interpretations for the regimes, we then conduct the central analysis of our paper in the following two sub-sections. Sub-section 3 presents estimates of impulse-response functions (IFRs) and sub-section 4 further quantifies the results based on counterfactual simulations, set in historical context.

4.2.1 Economic regimes: A first characterisation

The labelling of empirically identified regimes is often not straightforward in such richly specified MS-VAR models. We use several inputs for deriving economic characterisations of the six regimes, namely the estimated standard deviations of the structural shocks across the three variance regimes, the estimated standard deviations of the reduced-form shocks across all six regimes, and some regime-specific descriptive statistics of the endogenous variables.

Let us first take a look at Table 2 which shows the estimated relative standard deviations of the structural shocks in our five endogenous variables across the three identified variance regimes (v1 to v3), where the standard deviations in the first regime are normalised to one. While the differences across regimes are generally rather pronounced, there exists no common pattern in the ranking order of relative volatilities across all five variables. While the order across the three variance-regimes is high-medium-low for industrial production growth and loan growth, it is low-medium-high for inflation, high-low-medium for the interest rate and medium-low-high for the CISS. This picture remains basically unchanged for the regime-specific volatilities of the (potentially) correlated prediction errors (“reduced-form shocks”), which combines each variance regime with two coefficient regimes (see Table 3) and thus allows to further discriminate between

Table 3: Standard deviations of reduced-form shocks across six regimes

	production	inflation	interest rate	loans	CISS
First regime (v1,c1)	1.165	0.110	0.271	0.341	0.028
Second regime (v1,c2)	1.722	0.173	0.294	0.329	0.034
Third regime (v2,c1)	1.054	0.167	0.077	0.252	0.017
Fourth regime (v2,c2)	1.558	0.263	0.084	0.243	0.021
Fifth regime (v3,c1)	0.994	0.219	0.175	0.192	0.082
Sixth regime (v3,c2)	1.469	0.344	0.190	0.185	0.102

Notes: v_i =variance regime ($i=1$ to 3); c_j =coefficient regime ($j=1, 2$).

the three identified variance regimes. The non-uniformity of relative shock sizes notwithstanding, what stands out is the vastly increasing volatility of structural shocks in the CISS in variance regime v3, where the standard deviation triples and quintuples vis-à-vis regimes v1 and v2, respectively. The implied changes in the size of reduced-form shocks demonstrates this point as well, with CISS-shock volatility in regimes 5 and 6 amounting to 0.08 and 0.10 in the original units of the CISS (defined over the unit interval), whereas average CISS shocks in regimes 1 to 4 only range between 0.02 and 0.03). Hence, regimes 5 and 6 are unambiguously associated with extreme changes in systemic financial stress.

Since systemic financial instability and its real implications is at the centre of this paper, we continue in this vein and focus particularly on regime-specific patterns in the CISS for the labelling of regimes. For this purpose, we now also consider regime-specific descriptive statistics mainly for the CISS. As a first step we determine for each month the dominant regime - i.e., the regime with the highest smoothed probability estimated from the MS-BVAR model - and then compute the conditional moments of each variable over all months in which a certain regime dominates. Comparing average CISS levels across regimes allows us to further discriminate between regimes (see Table 4). While regimes 5 and 6 are clearly confirmed as periods of extreme financial stress (with means of 0.26 and 0.52, respectively), a much weaker though broadly consistent order emerges across the remaining regimes. For instance, the average CISS level in regimes 1 and 2 (0.07 and 0.09, respectively) is somewhat below that of regimes 3 and

Table 4: Regime-specific descriptive statistics

	conditional means					sample
	production	inflation	interest rate	loans	CISS	shares
First regime (v1,c1)	0.535	2.264	5.850	5.973	0.071	16.1%
Second regime (v1,c2)	3.391	3.007	6.130	8.426	0.092	17.8%
Third regime (v2,c1)	2.783	1.959	3.219	6.325	0.081	35.3%
Fourth regime (v2,c2)	1.163	2.834	5.850	6.108	0.110	18.9%
Fifth regime (v3,c1)	3.958	2.430	4.178	9.658	0.260	5.2%
Sixth regime (v3,c2)	-11.293	1.571	2.878	4.655	0.520	6.6%

Notes: vi=variance regime (i=1 to 3); cj=coefficient regime (j=1, 2).

4 (0.08 and 0.11, respectively). Furthermore, a strictly decreasing order across the six regimes also results when comparing the conditional standard deviations, the respective maxima and the conditional range (maximum less minimum) of the CISS (data not shown).

It also strikes that within each of the three variance regimes, it is always the second coefficient regime (c2) which has larger conditional means and larger reduced-form shock volatilities of the CISS than regime c1. This already points towards the possibility that the second coefficient regime may be associated with higher financial stress than the first coefficient regime. This claim, which will also be confirmed in later sections, receives further support by the fact that regime 5 comes along with a healthy rate of growth in industrial production (about 4% p.a.), while economic activity sharply contracts (-11% p.a.) during regime 6 which combines high stress variance with the second coefficient regime. In fact, all three more material recessions in the euro area since 1987 at least started in coefficient regime c2.

With respect to the regime-specific behaviour of the other endogenous variables, it stands out that the volatility of reduced-form shocks in inflation also broadly increases with the numbered regimes, where inflation shocks tend to be particularly sizeable in regime 6 (0.34 percentage points). This regime also displays the lowest average inflation level with 1.6%, while the differences in average inflation across the other regimes are rather modest. In a similar vein, the short-term interest rate and loan growth are both particularly low in regime 6, reflecting the

mitigating response of monetary policy and a very cautious financing behaviour of lenders and borrowers during times of severe systemic stress. Interestingly, average loan growth during the high-stress regime 5 is the highest across all regimes, probably reflecting the still extremely buoyant lending conditions when the euro area financial system entered into the subprime mortgage crisis in 2007.

The overall picture of this first step in our analysis seems to suggest associating the first three regimes with periods of relatively low financial stress in general, a situation which can probably also be regarded as “normal” given that these three regimes together prevail in about 70% of the sample period (see the last column in Table 4). Such normal periods can include occasional and very short-lived spikes in financial stress as experienced in 1987, 1992, 1998 and 2000, for instance. Regime 4 might be labelled as one with intermediate levels of stress, as it occurred 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 about one year after the Lehman debacle, equally displaying rather high stress levels (see Figure 2). Regimes 5 and 6, in contrast, obviously manifest persistent financial turmoil and systemic financial stress, respectively. Such severe levels of financial stress did occur exclusively in the context of the recent financial crisis (see Figure 2) and represent “rare events” as judged by the mere 5% and 7% sample shares of both regimes. In addition, it appears to be justified to label coefficient regime c2 as the “high-stress coefficient regime” and coefficient regime c1 as the “low-stress coefficient regime”. All in all, this analysis can thus be taken as a first sign that the structural instability of the euro area macroeconomy as captured by regime-switching may be related to systemic financial instability, in particular if it exceeds a certain level.

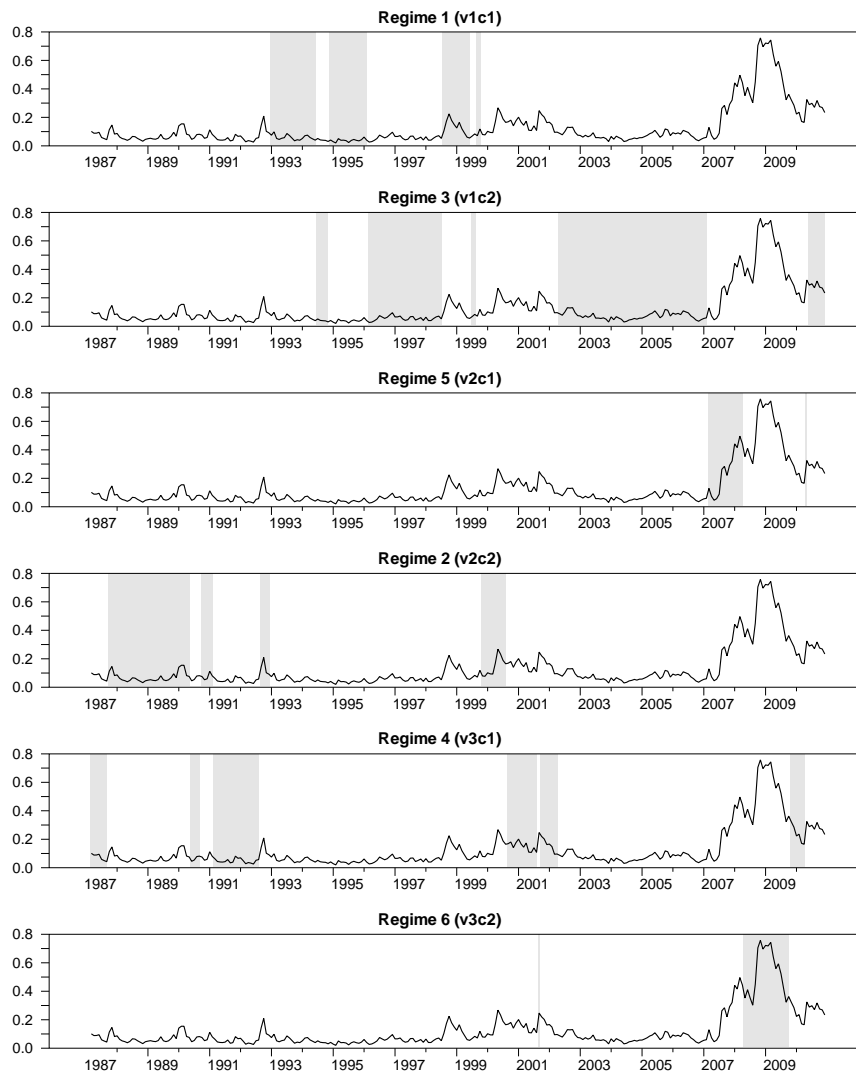


Figure 2: CISS and model regimes (shaded)

4.2.2 Timing of regimes and financial crises

The link between systemic financial instability and the macroeconomic regime changes identified can be further ascertained by looking at the times when the model changes regime. In particular, do high-stress variance ($v3$) and/or high-stress coefficient ($c2$) regimes emerge around the times when financial crises or financial stress break out? To answer this question we compute the regime probabilities for each possible state with our preferred $3v2c$ specification. In general, these probabilities line up nicely with well-known financial stress events.

Let us consider first the most extreme regimes 6 and 5 in Figure 3. The red line shows two episodes of regime 6, with both variances and coefficients being in the "high-stress" category. The first one in time is dated September 2001 and therefore matches up well with the financial stress around the September 11 US terrorist attacks. The second episode starts in May 2008 and lasts until October 2009 and therefore corresponds to a core period of the recent financial crisis. The green line in the same figure represents the probability of being in the "high-stress" variance and "low-stress" coefficient state. The first episode of this regime starts in March 2007, when early signs of the imminent subprime mortgage crisis emerged. In line with the usual narrative that the early phase of the crisis resembled more a "market turmoil" rather than a full-blown systemic crisis, however, the change to the "worst" regime happened not before May 2008. The second episode of regime 5 is associated with the start of the Greek sovereign debt crisis in May 2010.

In addition to the close association between severe financial stress episodes and the emergence of the most extreme macroeconomic regimes, it is also noteworthy that according to Figure 3 our model discovers the 2007 "market turmoil" and the 2008 systemic meltdown relatively early, compared to the usual narratives. The former is dated to start in March rather than August 2007 and the latter in May 2008, i.e. clearly before the Lehman Brothers failure of September 2008. This raises the issue as to whether the model has potential to being further developed

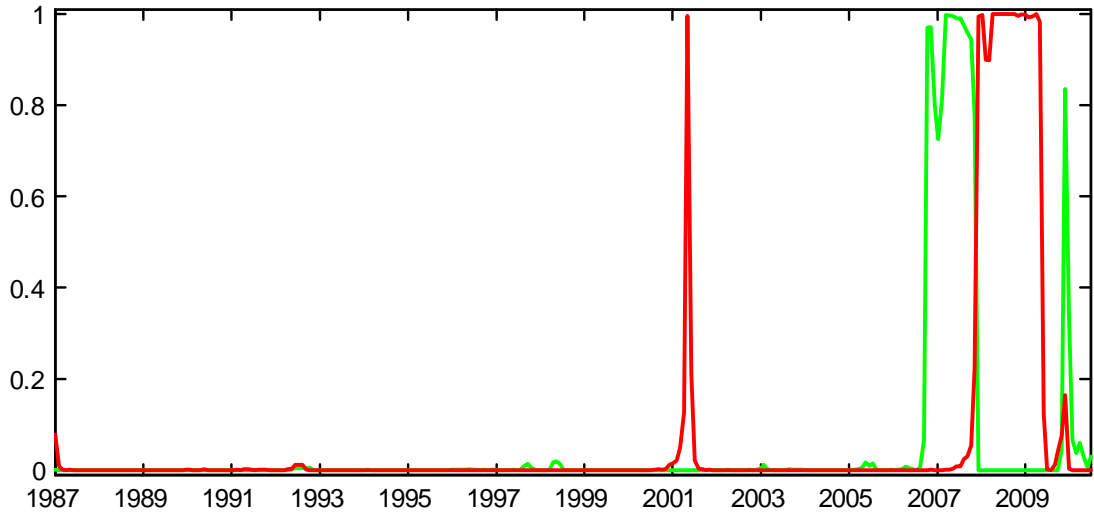


Figure 3: Probability of high stress variance high stress coefficient stress regime (red line), high stress variance low stress coefficient (green line)

towards a practical now-casting or early-warning tool (an issue that we briefly touch upon in Section 5).

Figure 4 shows the probability of regime 6 along with that of regime 4. The state probability of this medium-stress variance, high-stress coefficient regime (v_2, c_2) is represented by the blue line. This intermediate regime emerges more frequently than the more severe regimes 5 and 6. Episodes correspond to the aftermath of the 1987 stock market crash; the Gulf war in 1990; the build-up of the crisis in the European Exchange Rate Mechanism (ERM) in the early 1990s; a protracted period right after the turn of the millennium related to the breakdown of the so-called "dot-com bubble"; and finally, to the time in 2009 when the financial crisis was moderating until the euro area sovereign debt crisis took off in early 2010.

In sum, the evidence from state probabilities corroborates the insight from the previous sub-section that the most severe macroeconomic regime changes in the euro area over the last quarter of a century were associated with the "worst" systemic financial events. Moreover, whilst systemic financial crises have occurred with some regularity over economic history, they are still so rare that since 1987 there was only one such episode leading to a protracted change to the

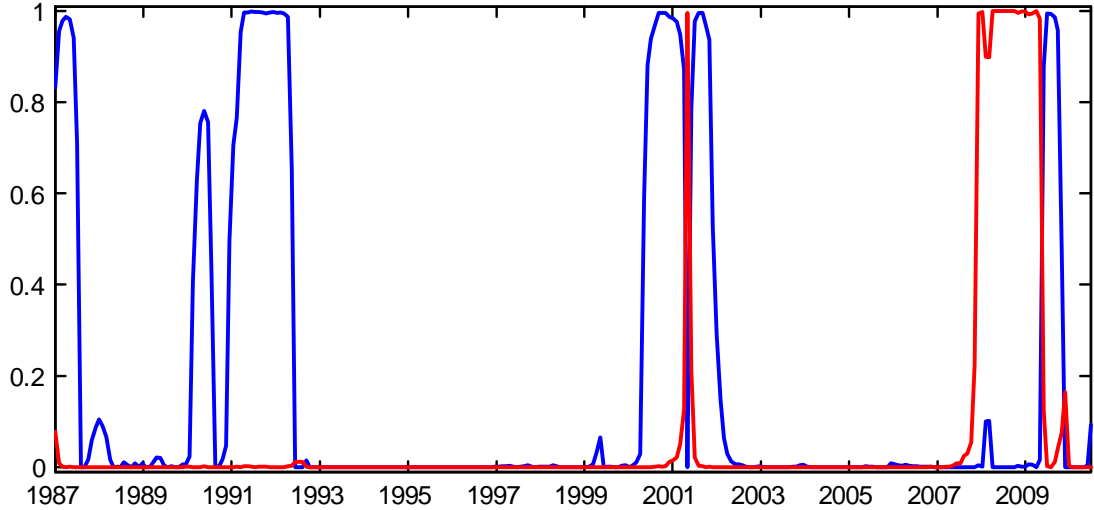


Figure 4: State probabilities, Red: High stress variance high stress coefficients, Blue: Medium stress variance high stress coefficients

"worst" macroeconomic regime.

4.2.3 Impulse response functions to systemic stress shocks

We now assess potential non-linearities in the transmission of financial stress to the real economy on the basis of regime-dependent impulse-response functions (IRFs) for structural shocks in the CISS. 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 focus at this point on the IRFs resulting from shocks in the financial stress index (S).¹³ Figure 5 plots IRFs for two different coefficient regimes, namely high-stress ($c2$, solid red lines) and normal times ($c1$, blue dashed lines). The dynamic multipliers are calculated for a positive shock in the CISS by one standard-deviation from the high-stress variance regime ($v3$) in the first case and from the low-stress variance regime ($v1$) in the second case, respectively. For comparative purposes the graphs also include the IRFs from a standard constant-parameter VAR (the 1v1c model specification).

The lower left panel in Figure 5 displays the impulse-response function of the CISS (S) to a

¹³Note that the impulse responses presented here are based on the posterior mode.

regime-specific positive own shock by one standard deviation. It reveals that the financial stress shock is much smaller in normal times than during times of financial turmoil (see also Table 2). At the same time, the CISS shock is less persistent in the high-stress coefficient regime than during normal times.

We can now directly address the issue of potential amplification effects during periods of severe systemic stress on the basis of the state-dependent dynamic responses of output growth to a given shock in the CISS (see the upper left panel in Figure 5). The differences in the IRFs from the two different coefficient regimes are striking. In the regime labelled “normal times” industrial production (as well as all other variables) display hardly any reaction to a shock in the CISS. It thus appears as if the CISS becomes a *quantité négligeable* under conditions of normally functioning financial markets which, in turn, accords well with the fact that the CISS aims to measure systemic stress and not general financing conditions. By contrast, in the high-stress coefficient regime a positive shock in financial stress leads to a quick, severe and protracted contraction in economic activity. These different patterns of reactions to shocks in financial stress is one of the core results of the present study. It first evidences the presence of actually very strong amplification effects in situations of elevated systemic stress: a positive shock in the CISS of a uniform size exerts dynamic effects on industrial production in the high-stress regime which are a manifold of the impacts in the low-stress regimes. Second, the indicated abrupt regime switches from economically negligible effects of financial stress on economic activity to very strong ones is also consistent with the idea that such discontinuous effects may originate from sudden investor panics and/or financial constraints which only bind during occasional crisis times as mentioned in Section 2. Third, when comparing the IRFs from the MS-VAR with those from a constant-parameter VAR against the background of the first model’s statistical superiority and economic plausibility, one may conclude that predictions derived from a single-regime model may at times provide very misleading guidance for policy makers, for instance.

The lower right panel in Figure 5 shows that in the high-stress regime 6, the financial stress shock has a relatively strong, gradual and persistent effect on loan growth. For instance, an increase in the CISS by 0.1 in a high-stress environment triggers a decline in nominal loan growth by -0.7 percentage points after 24 months. This may suggest that bank lending does also play a role in amplifying the adverse transmission of financial stress to the real economy in times of financial turbulence. The rather gradual decline in bank loans to an adverse shock in the CISS could reflect firms' ability to draw down existing credit lines at the early stages of a financial crisis, thus perhaps mitigating the overall constraints on bank loan supply in the short term (for US evidence, see Ivashina and Scharfstein, 2010). 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. In general, the direct adverse impacts of increased financial stress on bank lending might reinforce other more direct effects, e.g. those operating via increased risk aversion and uncertainty.

To conclude, the evidence presented so far suggests that the much more pronounced and durable output losses during times of heightened financial stress compared to more normal times are not only brought about by larger adverse shocks but also by a stronger transmission of financial shocks to the real economy. A similar analysis to uncover non-linearities in macro-financial linkages for the US by Hubrich and Tetlow (2012) draws similar conclusions.

4.3 Counterfactual analyses

To investigate the differential effects of changes in systemic stress in high-stress episodes and normal times in a historical context, we carry out a counterfactual analysis where a path of systemic stress different from the actual one is achieved by an appropriate sequence of shocks. Figure 7 presents a path change in financial stress increasing by 0.25 in an episode starting in March 1995 (regime 1) that according to our model is representing tranquil times in terms

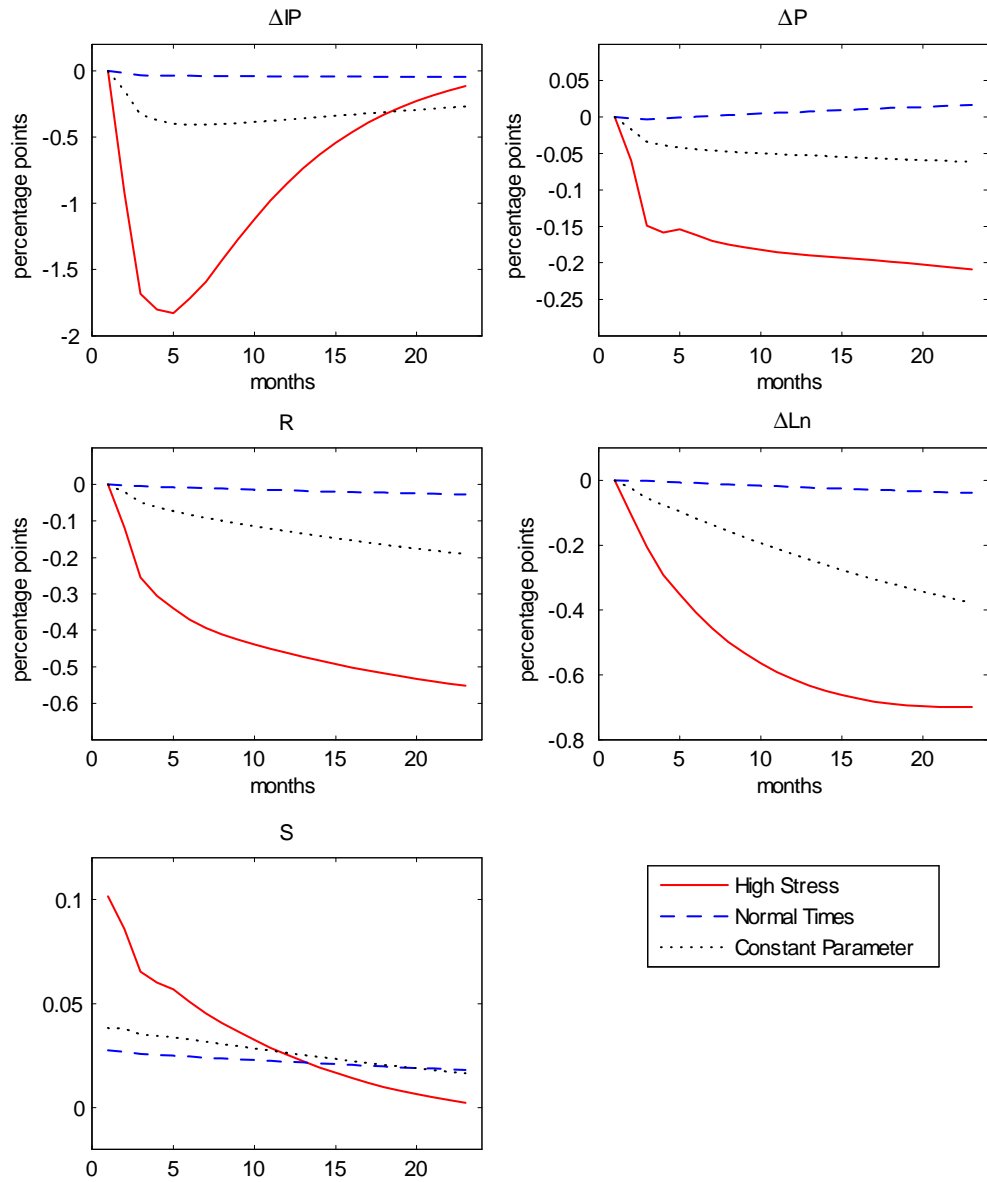


Figure 5: Impulse responses to financial stress shock, one standard deviation shock, comparison constant parameter model and 2 coefficient regimes

of the structure of the economy and thereby the transmission of shocks. The effect on output growth is small given that this is a large change in the level of systemic stress, it just drops by less than 0.5 percentage points. In contrast, the same increase in the level of systemic stress in a high-stress episode starting in October 2008 (regime 6) leads to a huge reduction in output growth, namely by about 7 percentage points, as displayed in Figure 7. Inflation declines by 0.5 percentage points following the output growth decline, while standard monetary policy addresses the inflation decline by lowering the interest rate substantially to about 1%. These developments are also associated with a decline in loan growth by 1 percentage point. To shed more light on the difference in the response of the macroeconomy to a financial stress shock between high stress times and more tranquil times, we also investigate the effects of setting a financial stress shock to zero in a historical context. The results are presented and discussed in Appendix B.

To illustrate further the fundamental change in the dynamics of the economy in high stress and crisis episodes, we carry out a counterfactual that investigates what would have happened if tranquil times instead of high stress in both coefficients and shock variances would have persisted from October 2008 to February 2009. The results in Figure 8 show that in that case systemic stress would have been substantially lower in tranquil times by almost 0.2 (on a scale between 0 and 1 of the CISS), while the decline in production growth would have been much more moderate (a 6 percentage points decline instead of a decline of 21 percentage points until February 2009). Loan growth would have remained more or less the same over this period instead of declining by 2.5 percentage points, while inflation would have only slightly declined to about 4.4% instead of going down to 1.2%. Monetary policy is shown to be less accommodative given the relatively small declines in output growth and inflation. Additional experiments (not shown to save space), where only the coefficients are assumed to change regime for the counterfactual path or only the shock variances are assumed to change, reveal that the change in the coefficients has a larger impact on the counterfactual outcome than the variance change.

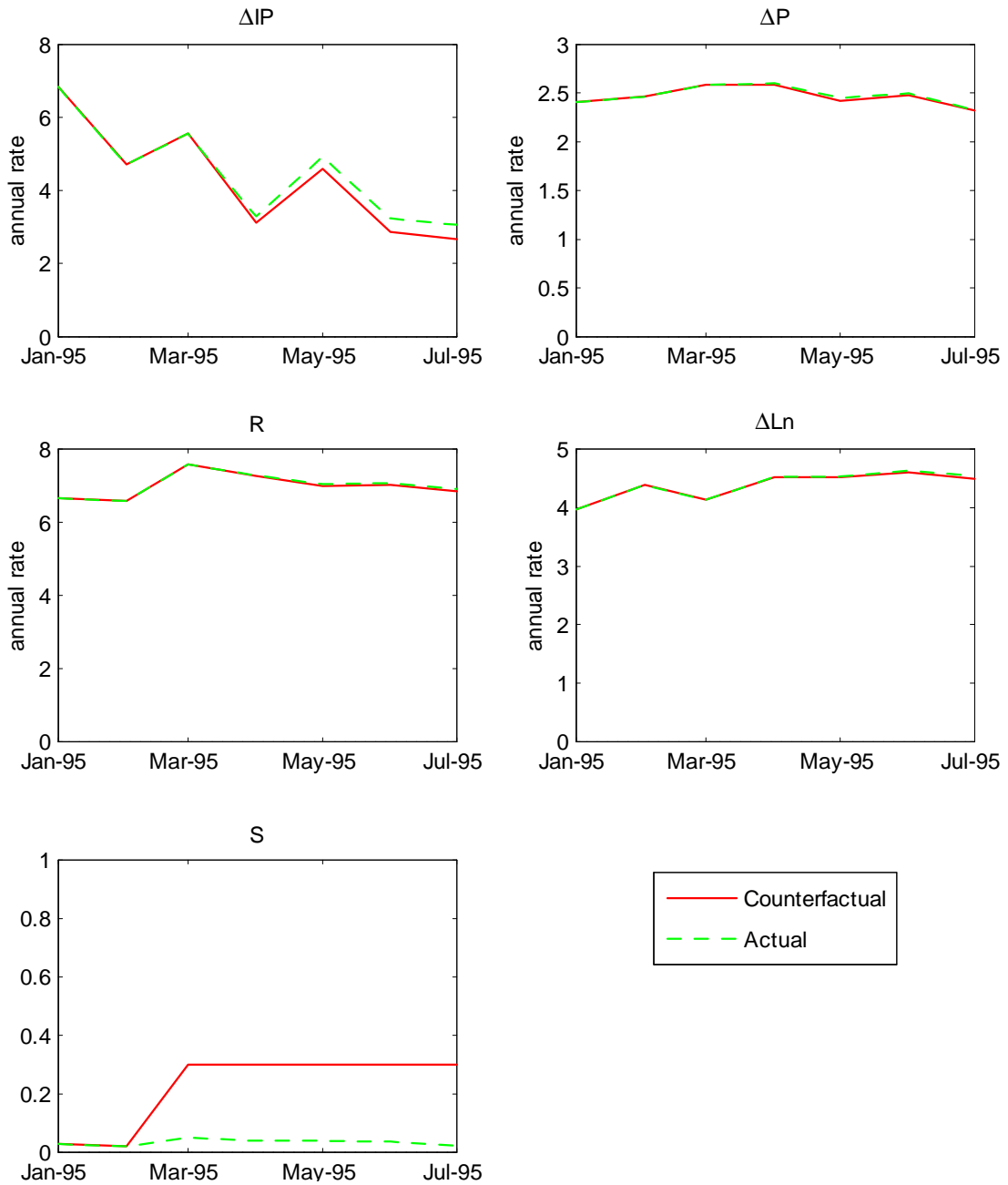


Figure 6: Counterfactual, path change in systemic stress, increase by 0.25 starting in March 1995, tranquil times

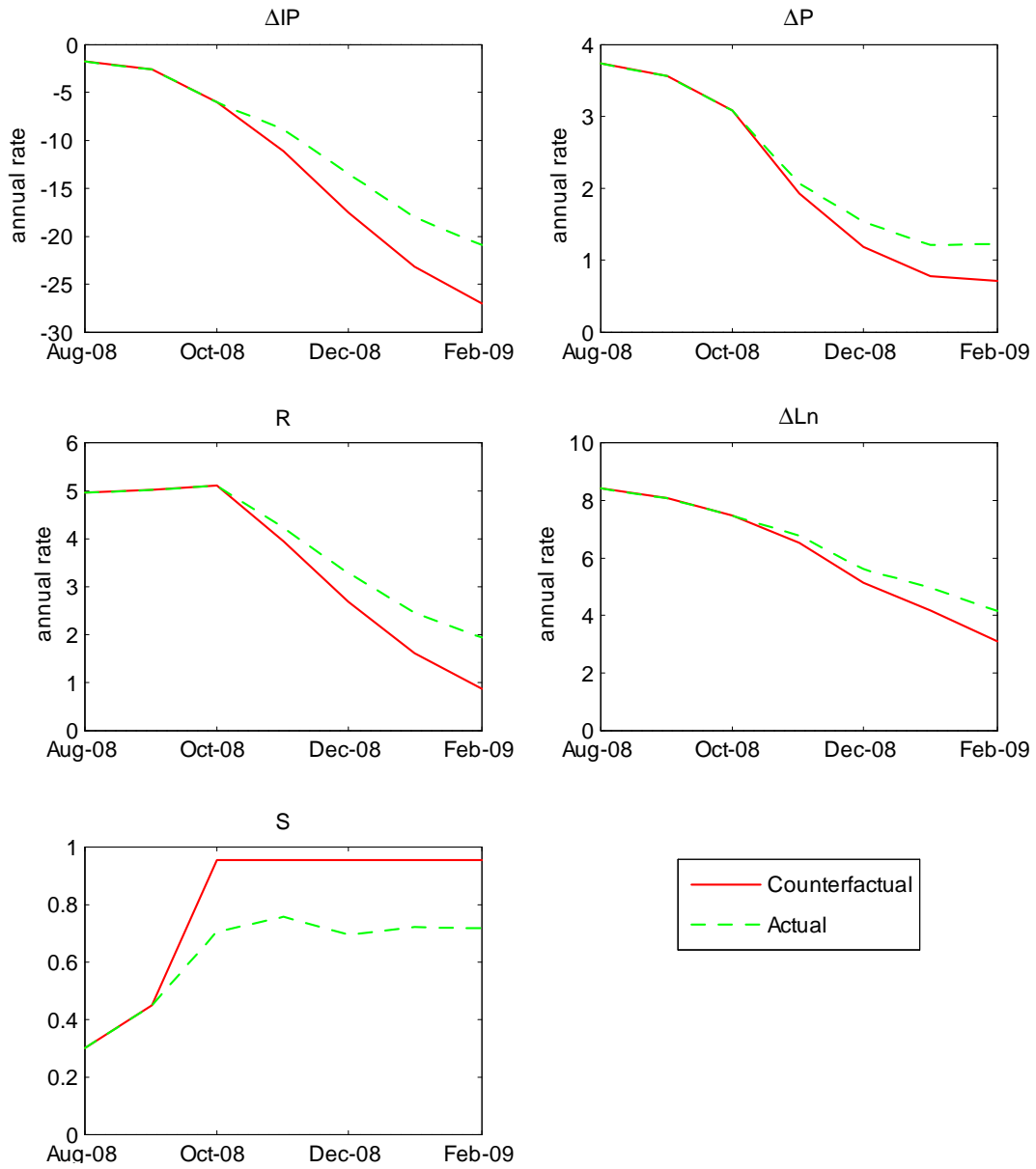


Figure 7: Counterfactual, path change in systemic stress, increase by 0.25 starting in October 2008, high stress

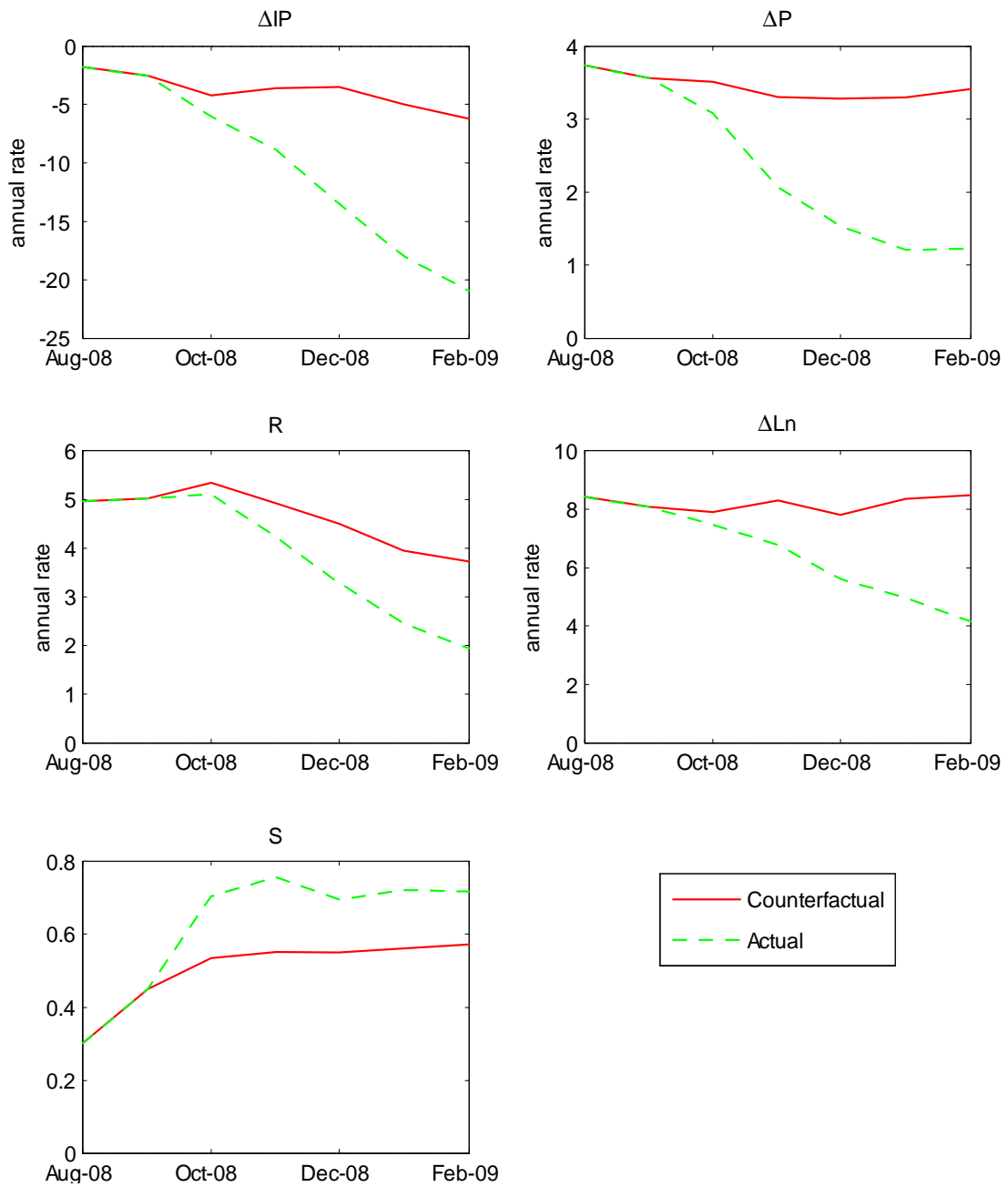


Figure 8: Counterfactual, tranquil times instead of high stress, October 2008 to February 2009

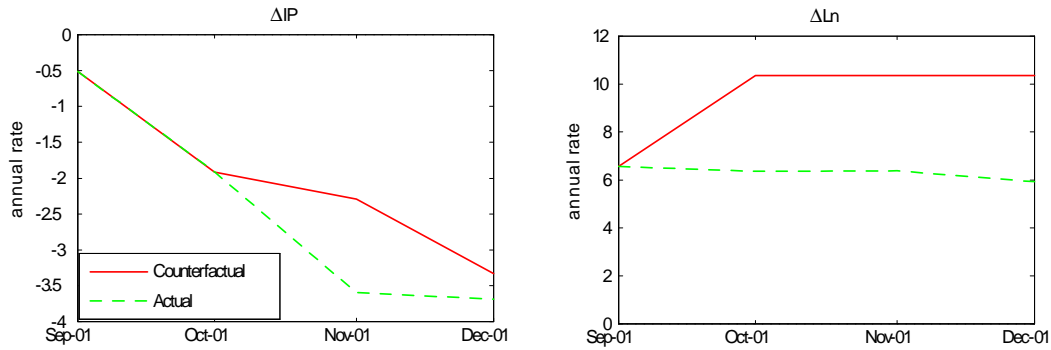


Figure 9: Counterfactual, path change in loan growth, increase in loan growth by 4 ppts starting in October 2001, high stress episode

Finally, Figure 9 presents a counterfactual on the real effects of an increase in loan growth by 4 percentage points. A counterfactual on real effects of additional loan growth during an episode of high stress according to our model, namely during the dot-com bubble, is presented. This episode is associated with high stress coefficients according to our model, but medium stress variances. A similar counterfactual experiment on an episode during the recent crisis is carried out as well (not presented, but available upon request) that is associated with high stress coefficients and high stress shock variances. During the dot-com bubble period there is an increase in output growth of about 1.5 percentage points that, although transitory, leads to a permanent level effect. This finding in the 2001 episode and during the recent crisis reflects some common pattern across high coefficient stress episodes according to our model, namely that in those episodes credit constraints have sizable real effects.

5 Macro-prudential Surveillance and Real-time Probabilities

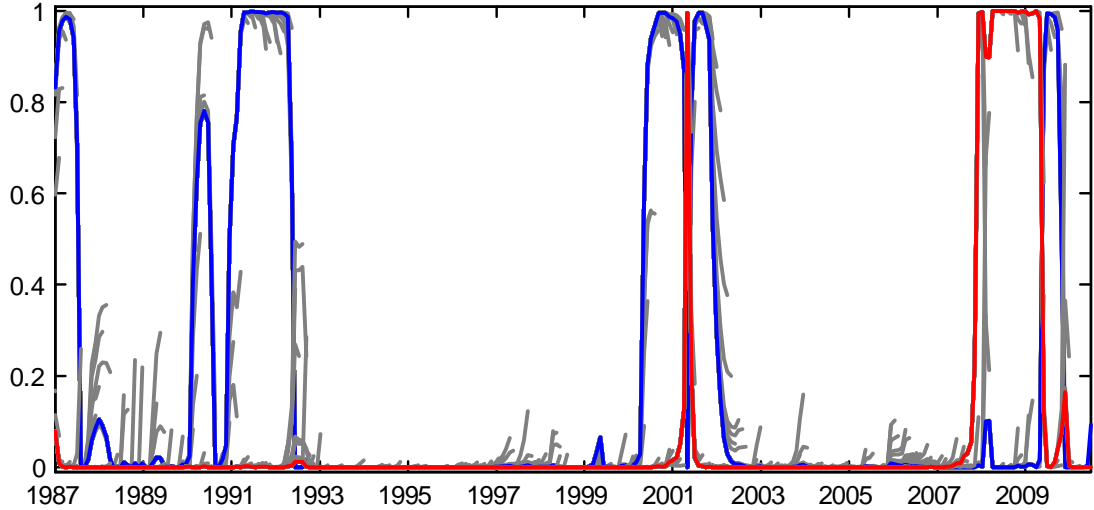


Figure 10: Real-time probabilities; Recursively expanding window; Red: High stress variance high stress coefficients, Blue: Medium stress variance high stress coefficients

We now turn to investigating the potential of this model for macroprudential surveillance. To that end, we estimate the state probabilities in pseudo real-time based on a recursively expanding window. The results are displayed in Figure 10. While the blue and red coloured lines represent the full sample estimates of the state probabilities of regimes 4 and 6 (see also Figure 4), the grey lines are the estimates based on the recursively expanding samples. As can be seen, the estimation of the state probabilities is rather robust. Hardly ever do the grey lines show some indication for a regime switch, that would be implied by a state probability in real-time larger than 0.5. At the beginning of the sample probabilities of being in a high stress regime are sometimes going up, but never reach a value close to 0.5. In other words, if full sample estimates indicate a no systemic stress regime, the state probabilities from the model rarely indicate high systemic stress falsely, and hardly ever do the state probabilities incorrectly signal no systemic stress when the full sample probabilities indicate high systemic stress.

6 Alternative Measures of Financial Stress: Stock Market Volatility

It has often been argued that the VIX or similar general measures of stock price volatilities are useful measures of financial stress, questioning the additional value of constructing a financial or systemic stress index. In order to evaluate whether in our context of investigating the effect of systemic financial instabilities on the economy it is important to appropriately measure systemic financial instability with a broad indicator that a) captures risk and uncertainty in financial markets by including not only market volatilities, but also other measures, in particular risky spreads, and b) captures the systemic dimension of financial stress by taking into account the correlation between the different financial markets and covers a broad range of markets, re-estimate our favourite model from the previous sections substituting the CISS with a measure of realised stock market volatility. Realised stock price volatility is calculated as the square root of average daily squared log price returns. We compute state probabilities, real-time probabilities and IRFs for the model including realised stock price volatility as a variable measuring financial stress. Figure ?? presents the impulse responses to a one standard deviation in stock market volatility. Comparing the response in output growth to that from the model with the CISS indicator (see Figure 5) we find that here the output response is much smaller and much less persistent as for the model with the CISS. Therefore, it underestimates the severity of the real effects of systemic stress. This is not surprising because realised volatility of stock prices does only measure volatility and 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. Overall, we find that it does not capture well the phenomenon we are interested in analysing with using the CISS, namely the pronounced effects of systemic financial stress.

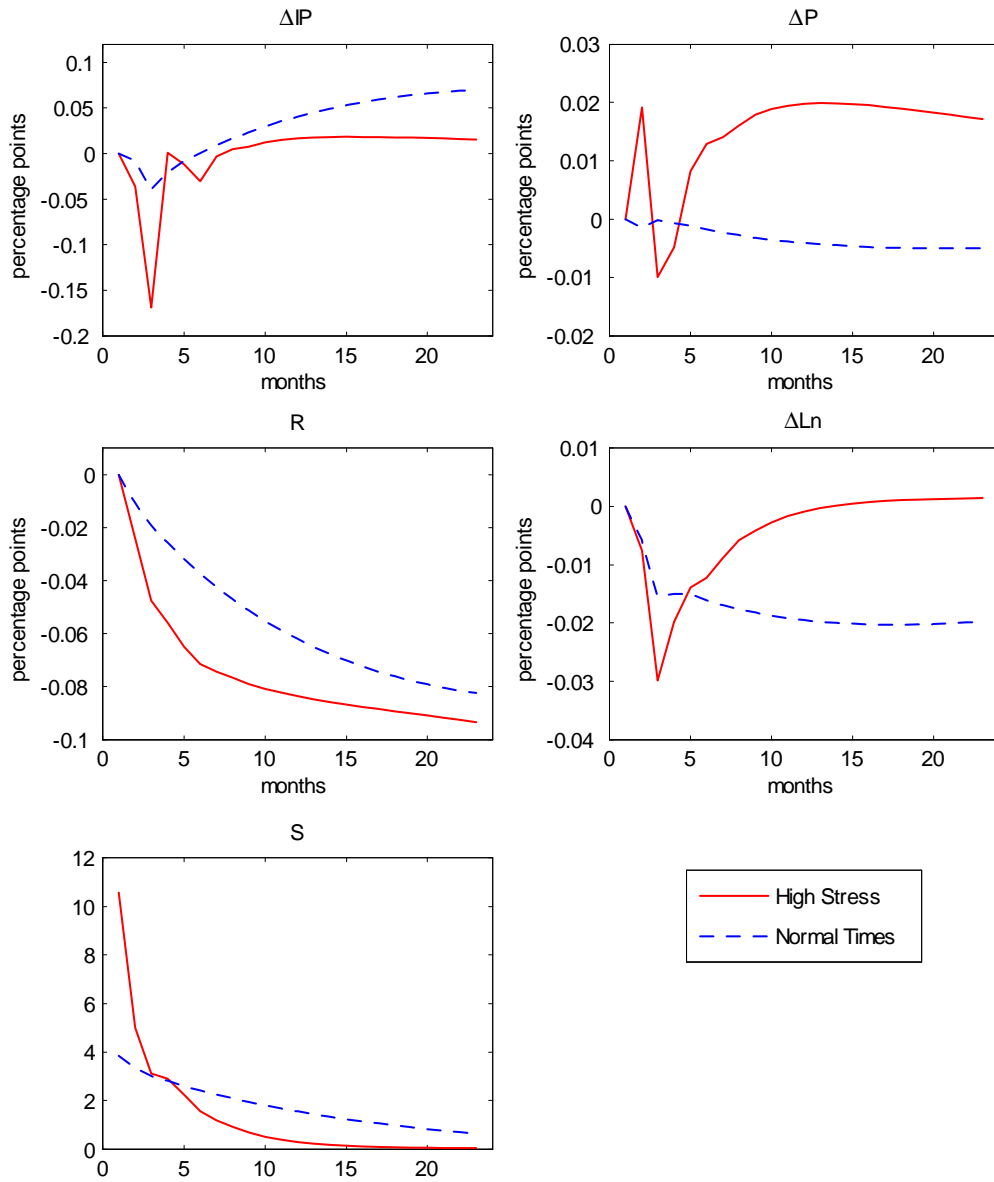


Figure 11: Impulse responses of a financial stress shock in a model with realised stock price volatility as measure of financial stress

7 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 at the transition to high systemic financial stress the macroeconomy changes fundamentally its behaviour. Both the parameters characterising the structural relationships of the economy as well as the error variances characterising the size of shocks change regime. Regular impulse response functions as well as counterfactual exercises indicate that as a consequence of such fundamental non-linearities the recessionary effects of shocks to systemic financial instability become much more pronounced than during tranquil times. Our analysis also suggests that the careful representation of widespread financial instability, the possibility to allow for regime changes and the feedback effects between the variables incorporated in the VAR model are crucial for this result.

Our findings may provide an explanation for why most forecasts missed the severe real effects of the financial crises that started in September 2008. Whilst we do not assess forecast performance in this paper, the approach may have potential to be developed in the future as a tool to better predict the effects of severe financial stress on the main macroeconomic variables. Moreover, it may be usable as a tool for macro-prudential surveillance by deriving the state probabilities embedded in the model for the different regimes. In the end, both monetary and macro-prudential policies may benefit from the availability of empirical macroeconomic tools, like this one, which can realistically capture systemic financial instability and the non-linearities associated with it.

References

- [1] Acharya, V. V. and D. Skeie (2011): “A Model of Liquidity Hoarding and Term Premia in Inter-Bank Markets”, CEPR Discussion Paper No. 8705, December.
- [2] Allen, F. and D. Gale (2000), “Financial Contagion”, *Journal of Political Economy*, Vol. 108, No. 1, pp. 1-33.
- [3] Aoki, K. and K. Nikolov (2012), “Bubbles, Banks, and Financial Stability”, ECB Working Paper No. 1495.
- [4] Barkbu, B., B. Eichengreen and A. Mody (2012), “Financial crises and the multilateral response: What the historical record shows”, *Journal of International Economics*, Vol. 88, No. 2, pp. 422-435.
- [5] Bekaert, G., R.J. Hodrick and X. Zhang (forthcoming), “Aggregate Idiosyncratic Volatility“, NBER Working Paper No. 16058, *Journal of Financial and Quantitative Analysis*.
- [6] Bekaert, G. and M. Hoerova (2013), “The VIX, the Variance Premium and Stock Market Volatility“, mimeo., Columbia University and European Central Bank, March.
- [7] Bernanke, B.S. and M. Gertler (1989), “Agency Costs, Net Worth and Business Fluctuations“, *American Economic Review*, Vol. 79, No. 1, (March): pp. 14-31.
- [8] Bernanke, B.S. (1983), “Nonmonetary Effects of the Financial Crisis in Propagation of the Great Depression”, *American Economic Review*, Vol. 73, No. 3, (June): pp. 257-276.
- [9] Bernanke, B.S. and C.S. Lown (1991), “The Credit Crunch”, *Brookings Paper on Economic Activity*, No. 2, pp. 205-247
- [10] Bianchi, J. (2011), “Overborrowing and Systemic Externalities in the Business Cycle“, *American Economic Review*, Vol. 101, (December): pp. 3400-3426

- [11] Bianchi, F. (forthcoming), “Regime Switches, Agents’ Beliefs, and Post-World War II U.S. Macroeconomic Dynamics“, *Review of Economic Studies*.
- [12] Bloom, N. (2009), “The Impact of Uncertainty Shocks”, *Econometrica*, Vol. 77, No. 3, pp. 623-685.
- [13] Boissay, F. (2011), “Financial Imbalances and Financial Fragility“, ECB Working Paper No. 1317.
- [14] Boissay, F., F. Smets and F. Collard (2013), “Booms and Systemic Banking Crisis”, mimeo, ECB and University of Bern..
- [15] Bordo, M., B. Eichengreen, D. Klingebiel and M. Soledad-Martinez (2001), “Is the Crisis Problem Growing More Severe?“, *Economic Policy*, Vol. 16,32, (April): pp. 51-82.
- [16] Brunnermeier, M.K. and L.H. Pedersen (2008), “Market Liquidity and Funding Liquidity”, *Review of Financial Studies*, Vol. 22, No. 6, pp. 2201-2238.
- [17] Brunnermeier, M.K. and Y. Sannikov (2013), “A Macroeconomic Model with a Financial Sector“, mimeo, Princeton University.
- [18] Cardarelli, R., S. A. Elekdag and S. Lall (2011): “Financial Stress and Economic Contractions”, *Journal of Financial Stability*, Vol. 7, pp. 78-97.
- [19] Christiano, L.J., M. Eichenbaum and C. Evans (1999): “Monetary Policy Shocks: What Have We Learned and to What End?," *Handbook of Macroeconomics*, in: J. B. Taylor and M. Woodford (eds.), *Handbook of Macroeconomics*, Edition 1, Vol. 1, Chapter 2, pp. 65-148 (Amsterdam: Elsevier).
- [20] Davis, E.P. (1995), *Debt Financial Fragility and Systemic Risk* (Oxford: Oxford University Press).

- [21] De Bandt, O. and P. Hartmann (2000), “Systemic Risk: A Survey”, ECB Working Paper No. 35, November.
- [22] De Bandt, O., P. Hartmann and J.-L. Peydro (2009), “Systemic Risk in Banking: An Update”, in A. Berger, P. Molyneux and J. Wilson (eds.), Oxford Handbook of Banking, Oxford University Press.
- [23] Diamond, D. and P. Dybvig (1983), “Bank Runs, Deposit Insurance, and Liquidity”, Journal of Political Economy, Vol. 91, No. 3, pp. 401-419.
- [24] Diamond, D. and R. Rajan (2005), “Liquidity Shortages and Banking Crises”, Journal of Finance, Vol. 60, No. 2, pp. 615-647
- [25] Dubey, P., J. Geanakoplos and M. Shubik (2005), “Default and Punishment in General Equilibrium“, Econometrica, Vol. 73, No. 1, pp. 1-37
- [26] Eika, K.H., N.R. Ericsson, and R. Nymoen (1996), “Hazards in Implementing a Monetary Conditions Index”, Oxford Bulletin of Economics and Statistics, Vol. 58, No. 4, pp. 765–790.
- [27] Estrella, A. and G.A. Hardouvelis (1991), “The Term Structure as a Predictor of Real Economic Activity”, Journal of Finance, Vol. 46, No. 2, pp. 555–576.
- [28] Estrella, A. and F.S. Mishkin (1998), “Predicting U.S. Recessions: Financial Variables as Leading Indicators”, The Review of Economics and Statistics, Vol. 80, pp. 45-61.
- [29] European Central Bank (2010), “Towards Macrofinancial Models with Realistic Characterisations of Financial Instability”, ECB Financial Stability Review, December, pp. 138-146.
- [30] European Central Bank (2012), Report on the First Two Years of the Macro-prudential Research Network, October.
- [31] Evans, M. and P. Wachtel (1993), “Inflation Regimes and the Sources of Inflation Uncertainty“, Journal of Money, Credit and Banking, Vol. 25, No. 3, (August): pp. 475-511.

- [32] Gauthier, C., C. Graham and Y. Liu (2004), “Financial Conditions Indexes for Canada”, Bank of Canada Working Paper, No. 2004-22.
- [33] Gertler, M. and C.S. Lown (1999), “The Information Content of the High Yield Bond Spread for the Business Cycle”, *Oxford Review of Economic Policy*, Vol. 15, pp. 132–150.
- [34] Gilchrist, S. and E. Zakrajsek (2012), “Credit Spreads and Business Cycle Fluctuations”, *American Economic Review*, Vol. 102, No. 4, pp. 1692–1720.
- [35] Goodhart, C., A.K. Kashyap, D.P. Tsomocos and A. Vardoulakis (2012), “Financial Regulation in General Equilibrium“, NBER Working Paper No. 17909.
- [36] Goodhart, C. and D.P. Tsomocos (2007), “*Annals of Finance*”, Vol. 3, No. 1, pp. 37-74.
- [37] Gorton, G.B. and A. Metrick (forthcoming), “Securitized Banking and the Run on Repo”, *Journal of Financial Economics*
- [38] Hamilton, J.D. (1989), “A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle“, *Econometrica*, Vol. 57, No. 2, (March): pp. 357-384
- [39] Harvey, C. (1988), “The Real Term Structure and Consumption Growth”, *Journal of Financial Economics*, Vol. 22, pp. 305-333.
- [40] Hatzius, J., P. Hooper, F. Mishkin, K.L. Schoenholtz and M.W. Watson (2010), “Financial Conditions Indexes: A Fresh Look after the Financial Crisis”, *Proceedings of the U.S. Monetary Policy Forum*, Chicago Booth School of Business, April.
- [41] He, Z. and A. Krishnamurthy (forthcoming a), “Intermediary Asset Pricing“, *American Economic Review*.
- [42] He, Z. and A. Krishnamurthy (forthcoming b), “A Model of Capital and Crises“, *Review of Economic Studies*.

- [43] Hoggarth, G., R. Reis and V. Saporta (2002), "Costs of Banking System Instability: Some Empirical Evidence", *Journal of Banking & Finance*, Vol. 26, No. 5, (May): pp. 825-855.
- [44] Hollo, D., M. Kremer and M. Lo Duca (2012), "CISS - A Composite Indicator of Systemic Stress in the Financial System ", ECB Working Paper No. 1426, March.
- [45] Hubrich, K. and Tetlow, T. (2012), "Financial Stress and Economic Dynamics: The Transmission of Crises", Federal Reserve Board, Finance and Economics Discussion Series, No. 2012-82, October.
- [46] Illing, M. and Y. Liu (2006), "Measuring Financial Stress in a Developed Country: an Application to Canada", *Journal of Financial Stability*, Vol. 2, No. 4, pp. 243-265.
- [47] Ivashina, V. and D. Scharfstein (2010), "Bank Lending during the Financial Crisis of 2008", *Journal of Financial Economics*, Vol. 97, pp. 319-338.
- [48] Justiniano, A. and G.E. Primiceri (2008), "The Time-Varying Volatility of Macroeconomic Fluctuations", *American Economic Review*, Vol. 98, No. 3, (June): pp. 604-641.
- [49] Kindleberger, C.P. (1978), *Manias, Crashes and Panics: A History of Financial Crises* (New York: Basic Books).
- [50] Kiyotaki, N. and J. Moore (1997), "Credit Cycles", *Journal of Political Economy*, Vol. 105, No. 2, (April), pp. 211-248.
- [51] Kliesen, K.L., M.T. Owyang and E.K. Vermann (2012), "Disentangling Diverse Measures: A Survey of Financial Stress Indexes", *Federal Reserve Bank of St. Louis Review*, September/October, pp. 369-398.
- [52] Korinek, A. (2012), "Systemic Risk-Taking: Amplification Effects, Externalities, and Regulatory Responses", mimeo, University of Maryland.

- [53] Lindgren, G. (1978), “Markov Regime Models for Mixed Distributions and Switching Regressions“, *Scandinavian Journal of Statistics*, Vol. 5, No.2, pp. 81-91.
- [54] Lorenzoni, G., (2008), “Inefficient Credit Booms“, *Review of Economic Studies*, Vol. 75, No. 3, (July): pp. 809-833.
- [55] Martinez-Miera, D. and J. Suarez (2012), “A Macroeconomic Model of Endogenous Systemic Risk Taking”, CEPR Discussion Paper, No. 9134, September.
- [56] Matheson, T.D. (2012), “Financial Conditions Indexes for the United States and euro area”, *Economics Letters*, Vol. 115, pp. 441-446.
- [57] Mayes, D. and M. Viren (2001), “Financial Conditions Indexes”, Bank of Finland Discussion Paper, No. 2001-17.
- [58] Mendoza, E.G. (2002), “Credit, Prices, and Crashes: Business Cycles with a Sudden Stop“, In *Preventing Currency Crises in Emerging Markets*, NBER Conference Report Series, S. Edwards and J.A. Frankel, editors, pp. 335-392.
- [59] Meng, X. L. and Wong, W. H. (1996), “Simulating Ratios of Normalizing Constants via a Simple Identity: A Theoretical Exploration”, *Statistica Sinica*, 6, pp. 831-860.
- [60] Morris, S. and H.S. Shin (2012), “Contagious Adverse Selection”, *American Economic Journal: Macroeconomics*, Vol. 4, No. 1, January, pp. 1-21.
- [61] Mueller, U. (2010), “Marginal Data Densities”, Princeton University, manuscript.
- [62] Nelson, W.R. and R. Perli (2007), “Selected Indicators of Financial Stability”, in *Risk Measurement and Systemic Risk*, Proceedings of the Fourth Joint Central Bank Research Conference, European Central Bank, Frankfurt am Main, April, pp. 343-372.
- [63] Reinhart, C.M., and K.S. Rogoff (2009), *This Time Is Different: Eight Centuries of Financial Folly* (Princeton, NJ: Princeton University Press).

- [64] Schularick, M. and A.M. Taylor (forthcoming), “Credit Booms Gone Bust: Monetary Policy, Leverage Cycles and Financial Crises, 1870-2008”, NBER Working Paper No. 15512, American Economic Review.
- [65] Sims, C., D. Waggoner and T. Zha (2008), “Methods for Inference in Large Multi-Equation Markov-Switching Models”, Journal of Econometrics, Vol. 146, 2, (October), pp. 255-274.
- [66] Sims, C. and T. Zha (2006), “Were there Regimes Shifts in U.S. Monetary Policy?”, American Economic Review, Vol. 96,1 (March), pp. 54-81.
- [67] Swiston, A. (2008), “A U.S. Financial Conditions Index: Putting Credit where Credit Is Due”, IMF Working Paper, WP/08/161, June..
- [68] Trichet, J.C. (2011), “Intellectual Challenges to Financial Stability Analysis in the Era of Macroprudential Oversight”, Banque de France Financial Stability Review, No. 15, February, pp. 139-149..

A Appendix: Composite Indicator of Systemic Stress (CISS)

In this appendix we provide more technical details about the construction of the CISS. As described in Section 2, the CISS comprises 15 mostly market-based individual financial stress indicators equally split into five categories, namely the financial intermediaries sector, money markets, equity markets, bond markets and foreign exchange markets. Among the individual measures capturing the main symptoms of financial stress in the various market segments are realised asset return volatilities (weekly average of absolute daily return changes, included in all five subindices), risk spreads (e.g., AA-rated long-term non-financial and financial corporate bond spreads, the 10-year swap spread of German Bunds, and the differential between a three-month unsecured inter-bank market rate and a comparable Treasury bill rate), the time-varying

stock-bond correlation, banks' marginal lending at national central banks of the Eurosystem (scaled by total reserve requirements) and a measure of cumulated stock market losses over a two-year window. For details on all individual stress measures see Table 1 in Hollo, Kremer and Lo Duca (2012).

As a first step to the aggregation into the composite index, all individual stress indicators are transformed by means of their empirical cumulative distribution function (CDF) involving the computation of order statistics. To be more precise, let us denote a particular data set of a raw stress indicator x_t as $x = (x_1, x_2, \dots, x_n)$ with n the total number of observations in the sample. The elements of x are now arranged in ascending order. The ordered sample is denoted $(x_{[1]}, x_{[2]}, \dots, x_{[n]})$ with $x_{[1]} \leq x_{[2]} \leq \dots \leq x_{[n]}$ and r referred to as the *ranking number* assigned to each element of x . The order statistic $x_{[n]}$ accordingly represents the sample maximum and $x_{[1]}$ the sample minimum, respectively. In the transformation, each value of an indicator at time t is first replaced by its ranking number $r(t)$ in the ordered sample of size $n(t)$ 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 $n(t)$ in the respective sample such that the transformed value $r(t)/n(t)$ corresponds to the r/n -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 $(0, 1]$. This particular transformation method has been chosen on robustness grounds. It is well known that location and dispersion measures of an empirical distribution function which are based on order statistics tend to be more robust to aberrant observations (e.g., outliers) than the arithmetic mean and the standard deviation, respectively. The transformation thus trades off gains in statistical robustness against losses of the marginal information contained in the original cardinal scale of the raw stress indicators.

The transformation yields a set of 15 homogenised stress factors, systematically grouped into five market categories. For each market category a separate financial stress subindex is computed by taking the arithmetic average of its three constituent stress factors.

The main methodological innovation of the CISS is the application of basic portfolio theory to the aggregation of the subindexes into the composite indicator. The portfolio-theoretic aggregation takes into account the time-varying cross-correlations $\rho_{ij,t}$ between subindices i and j (collected in the cross-correlation matrix Σ_t) calculated as exponentially weighted moving averages with the smoothing parameter or decay factor set to 0.93. Since the raw stress indicators are transformed by means of order statistics, the cross-correlations may be interpreted as a time-varying variant of Spearman's rank correlation coefficient. The cross-correlations are thus a mainly descriptive device, indicating whether the historical ranking of the level of stress in two market segments is relatively similar or dissimilar in any point in time. The CISS is then computed as follows:

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

with $w = (w_1, w_2, w_3, w_4, w_5)$ being the vector of subindex weights which are assumed constant and for the present purpose set at equal weights, i.e. each subindex receives a weight of 0.2 (i.e., 20%); $s_t = (s_{1,t}, s_{2,t}, s_{3,t}, s_{4,t}, s_{5,t})$ represents the vector of subindexes. Inheriting the basic properties of its constituent input series, the CISS turns out to be continuous and unit-free and bounded by the half-open interval $(0, 1]$.

y the half-open interval $(0, 1]$.

B Appendix: Markov-Switching BVAR Model

- TO BE ADDED -

C Appendix B: Counterfactuals on Financial Stress Shocks

To shed more light on the difference in the response of the macroeconomy to a financial stress shock between high stress times and more tranquil times, we investigate the effects of setting a financial stress shock to zero in a historical context. Figure 12 presents the counterfactual for setting the financial stress shocks to zero in normal times. We find that this hardly has any impact on the economy, in particular not on loan growth and growth of industrial production. In contrast, carrying out the same experiment for the episode of high financial stress in 2008 (see Figure 13) leads to a difference in the path of output growth of 10 percentage points. In the absence of shocks in the CISS financial stress remains more or less at the same level, output growth declines much less than it would have in the presence of financial stress shocks and the same is true for loan growth and inflation. Monetary policy also needs to be less accommodative in such a situation.

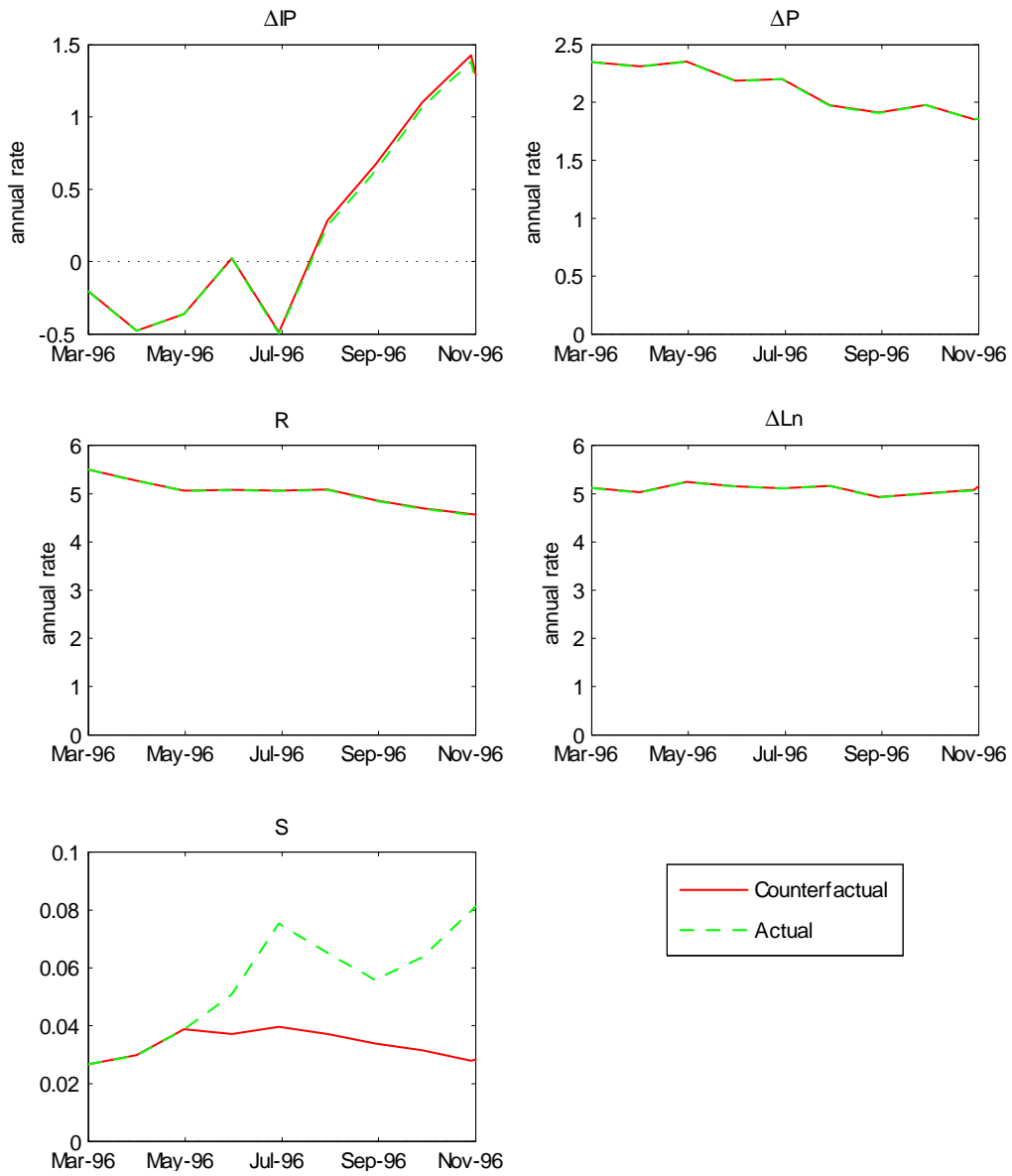


Figure 12: Counterfactual experiment, financial stress shock set to zero, starting May 1996, normal times

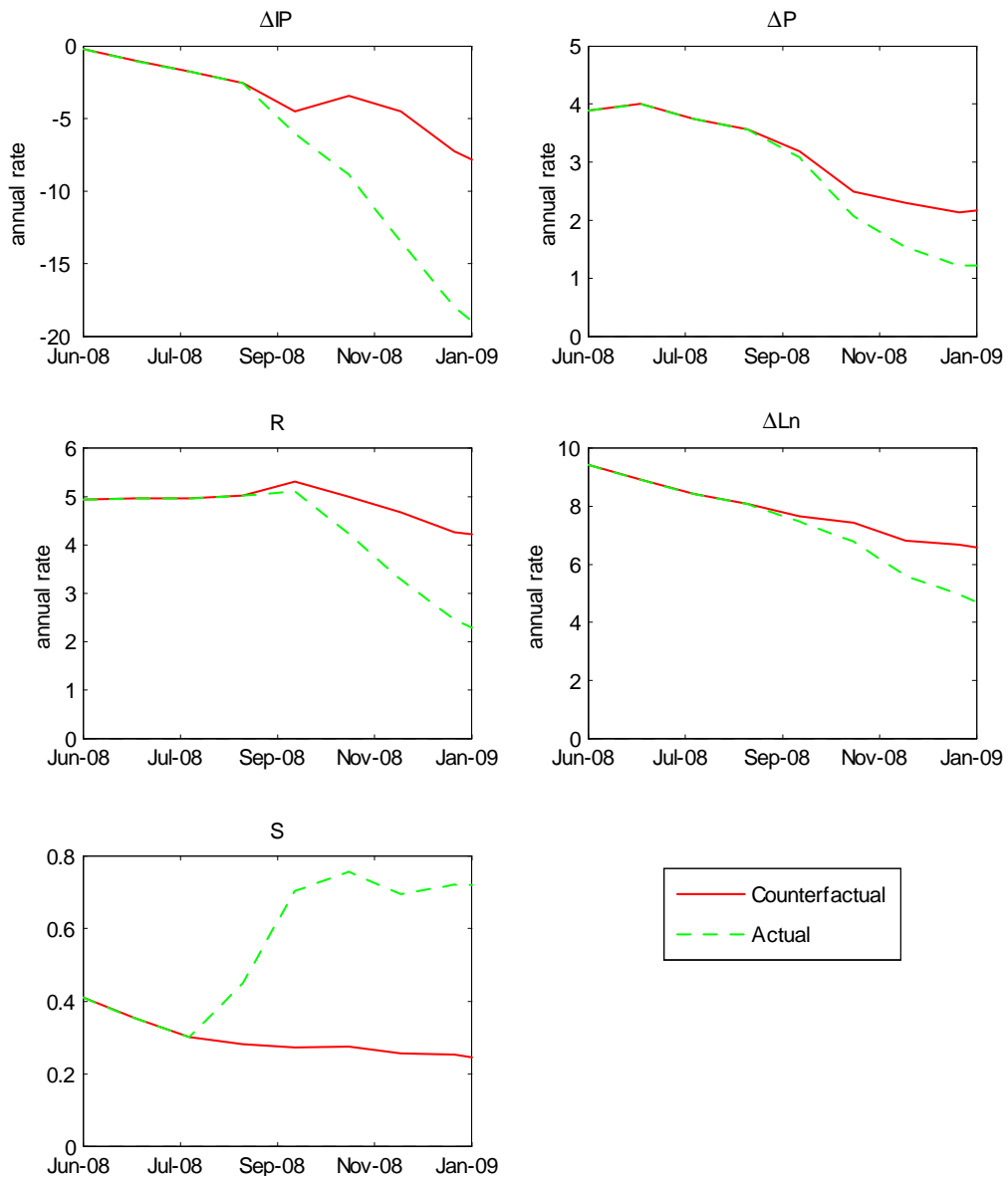


Figure 13: Counterfactual experiment, financial stress shock set to zero, July 2008, high systemic stress episode