

# Financial Instability and the Macroeconomy: Measurement, Interdependency and the Role of Monetary Policy

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To  
my wife Jana,  
my sons Ben and Fred,  
and my parents Erna and Günter.

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# CHAPTER 1

## INTRODUCTION

“Money is a veil, but when the veil flutters, real output sputters.”—Gurley  
(1961)

It has become by now conventional wisdom that financial development is critically important for economic growth.<sup>1</sup> Hence, finance is not just a pure veil in which real transactions are shrouded, but a well-developed and smoothly operating financial system rather performs essential functions for the real economy to flourish. Finance helps overcome frictions in the real sector arising from information and transaction costs, thereby influencing economic agents’ savings and investment behaviour and therefore long-run economic growth (Beck 2014).

However, the causal relationship between finance and growth—which actually can run both ways—holds true for good and bad times alike. As the recent crisis vividly reminded us, financial development may also become the root cause of a deep financial and economic crisis. This ambiguous role of finance reflects the fact that the financial sector itself is prone to market failures resulting from informational frictions (e.g., moral hazard and adverse selection). When such financial frictions become dominant and widespread, as it is the case in a systemic crisis, they tend to have severe repercussions for the real economy.

Against this background, policy makers have an essential interest in measuring the stress level in the financial system caused by financial frictions in order to assess its macroeconomic risks, and to consider appropriate timely counteractions.

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<sup>1</sup>See Levine 2005 for an extensive overview of the theoretical and empirical literature on the finance-growth nexus.

There exists a great variety of standard indicators measuring the level of stress in individual market segments, each capturing certain symptoms of the underlying financial friction. For instance, option-implied volatilities provide information about market participants' degree of risk aversion and uncertainty (Bekaert and Hoerova 2014); they can be computed for many important assets such as government bonds, interest rate derivatives, interbank deposits, equities, foreign exchange and many more. The VIX has received particular attention in this context, since the financial press often refers to it as investors' "fear gauge" (Carr and Lee 2009).<sup>2</sup> Other stress indicators are, for instance, CDS and other credit risk spreads, liquidity measures like bid-ask spreads, equity valuation losses but also quantity-based indicators measuring activity in certain primary and secondary markets, for instance. Such indicators have long been used by policy institutions engaged in financial stability surveillance, such as the IMF, the BIS, central banks and other national supervisory authorities. These standard indicators form the backbone of any financial stability report produced by these institutions.

While all these individual indicators are useful for partial analysis, the sheer amount of existing stress measures complicates the task of inferring, for instance, whether stress observed in one particular market segment is either mainly idiosyncratic or instead a more widespread and thus systemic phenomenon. Sometimes you "can't see the wood for the trees".

One way to synthesise the information coming from many individual indicators is the computation of a composite indicator of financial stress, or "financial stress index" as it has become known in the literature. Financial stress indexes quantify the current stress level in the financial system by compressing a certain number of individual stress indicators into a single statistic. While this appears quite obvious, and despite the fact

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<sup>2</sup>The VIX is the Volatility Index of the Chicago Board of Options Exchange, constructed from a portfolio of options on the S&P 500 index.

that composite indicators have been used for other purposes for a long time (e.g., monetary and financial conditions indexes), financial stress indexes have become a popular tool only in recent years. This trend has been spurred by the financial crisis, reflecting the increasing demand from policy authorities to systematically measure, monitor and assess systemic stress and the risks it entails for the economy as a whole.

This dissertation is about a novel financial stress index, an indicator which explicitly aims to emphasise the systemic dimension of financial stress, and how this indicator can be used to assess empirically the dynamic interactions between financial instability, the macroeconomy, and monetary policy as a means of public intervention. Within this context, the estimated impact of financial stress on real economic activity receives particular attention and runs like a common thread through all the three papers forming part of this dissertation.

The real effects of financial instability, and the other macroeconomic relationships I am interested in, are estimated using certain variants of vector autoregression (VAR) models, comprising standard linear, but also non-linear VARs. The linear VAR framework captures, by construction, the average dynamic relationships between the model variables estimated over the entire data sample, thereby ignoring, on the one hand, potential non-linearities associated with subperiods of severe financial instability. On the other hand, linear VARs provide a convenient analytical framework if one is mainly interested in testing many different model variations (involving tests of coefficient restrictions) of higher-dimensional VARs based on rather small samples, as it is the case when dealing with pure euro area data.

The non-linear VARs which I apply are particularly suited, a priori, to deal with usually short-lived, extraordinary but still potentially recurrent situations in which the dynamics of the economy changes suddenly and markedly. Such *phase transitions* (Ace-

moglu, Ozdaglar and Tahbaz-Salehi 2015) typically mark the tipping points at which systemic financial stress starts disrupting the regular functioning of the financial system and the economy as a whole. They can be explained, for instance, as switches between multiple equilibria, brought about by certain mechanisms which propagate and/or amplify an adverse stability shock to an extent that it alters the fundamental patterns of behaviour of economic agents and their interactions in an abrupt fashion. For an overview of such theoretical mechanisms—e.g. occasionally binding credit constraints—see Hartmann, Hubrich and Kremer (2013). Since linear VARs tend to wash out any unusual dynamics which may prevail over limited periods of time, certain non-linear methods are required to identify and characterise the specific economic dynamics observed during episodes of financial instability.

The relevance of the general topic of this dissertation derives from the recent financial and economic crisis. In particular, the recent crisis—by now, alluding to the Great Depression in the 1930s,<sup>3</sup> generally referred to as the Great Recession—has brought to the fore the issue of systemic risk. It can be described “(...) *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 2010a). In fact, all major financial crises can be traced back to certain forms of systemic risk, be it large macro shocks, the unravelling of large-scale financial imbalances, contagion or a combination between them (de Bandt and Hartmann 2000). Once financial stress has become widespread and thus systemic, the regular process of financial intermediation becomes impaired or may even collapse. In the latter case, the large-scale failure of the system to provide financial services to the economy forces severe economic contractions, and the resulting adverse welfare effects may even put political stability at risk.

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<sup>3</sup>The Great Depression of the 1930s, was the longest, deepest, and most widespread depression of the 20th century. To date the Great Depression is commonly used as an example of how far the world’s economy can decline, and it still serves as the “Holy Grail” of macroeconomics (Bernanke 1995).

Notwithstanding the long established insight that financial crises are extremely costly, our knowledge of systemic risk still is rather imperfect and incomplete. The Great Recession put this deficit to the spotlight, and as a consequence policymakers and researchers all around the world stepped up efforts to increase our theoretical and empirical understanding of systemic risk, how it affects the real economy (and vice versa), and which policy tools may be most appropriate to address systemic risk both in advance (crisis prevention) and when it has played out (crisis management). The three papers compiled in this dissertation are supposed to make a modest contribution to close some of the related knowledge gaps.<sup>4</sup>

The first paper, Chapter 2 of this dissertation, tackles systemic risk from a measurement point of view. It thereby contributes to an active research agenda that develops measures of systemic risk viewed from a broad range of different perspectives.<sup>5</sup> In that paper I present and discuss a new financial stress index called Composite Indicator of Systemic Stress, CISS (pronounced /kɪs/), whereby the term “systemic stress” is understood as systemic risk that has materialised. Its distinctive design highlights the systemic dimension of financial stress by applying basic portfolio-theoretic principles to the aggregation of individual stress indicators into the composite indicator. In analogy to the computation of portfolio risk, the CISS aggregates the information from its constituent individual stress indicators by taking into account time-varying correlations

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<sup>4</sup>Much research progress in the mentioned areas has been made since the onset of the recent crisis. For recent overviews see, e.g., Freixas, Laeven and Peydró (2015), Schularick and Taylor (2012), Taylor (2015), ECB (2010b) and ESCB Heads of Research (2014).

<sup>5</sup>For instance, a recent survey article by Bisias, Flood, Lo and Valavanis (2012) on measures of systemic risk distinguishes between macroeconomic measures, network measures, stress tests, forward-looking measures, cross-sectional measures, as well as measures of illiquidity and insolvency. In fact, most measures do not try to measure the level of systemic risk prevailing in the financial system as a whole, but instead focus on core market segments, predominantly the banking sector. For instance, many network and cross-sectional measures of systemic risk—such as the popular concepts of CoVaR and systemic expected shortfall—are applied to identify the systemically most important financial institutions. According to the taxonomy of that survey paper, the CISS would fall under the category of forward-looking measures along with alternative measures of financial stress like the index of financial turbulence proposed by Kritzman and Li (2010).

between them. The CISS is found to peak at all well-known financial stress events in the euro area since 1987. In addition, its information content proves robust to sample variations. In my view, this is an important property of a financial stress index that is supposed to be updated on a regular basis, and one which so far has not yet received sufficient attention in the relevant literature. By now the CISS has become a widely known and used index since its first publication in ECB (2010a).<sup>6</sup> The paper furthermore proposes a parsimonious approach to estimate a critical level of the CISS, i.e. a level at which financial stress strongly affects the real economy and thus becomes fully systemic. For this purpose, I apply a threshold-VAR, where the estimated threshold for the CISS introduces a non-linearity into a bivariate VAR for the CISS and growth in industrial production.

The second paper, Chapter 3 of this dissertation, puts the CISS into a broader macro-model perspective in order to investigate the transmission of financial stress to the real economy in some more detail, as well as to assess the relationship between financial stress and monetary policy which often acts as a first line of defense to combat an emerging financial crisis. For this purpose, I include the CISS in a set of macro variables used in a typical “monetary policy VAR”. Such a small-scale VAR model includes at least a short-term interest rate to capture the instrument setting of conventional monetary

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<sup>6</sup>For instance, the CISS regularly appears as Chart 1 in the Overview Section of the ECB’s Financial Stability Review. It is also shown as the first chart in the Risk Dashboard published by the European Systemic Risk Board (ESRB) (<https://www.esrb.europa.eu/pub/rd/html/index.en.html>). In addition, several central banks applied the CISS concept to the computation of a financial stress index for the financial system of their respective country (see, e.g., Johansson and Bonthron 2013; Banco de España 2013; and Braga, Pereira and Balcão Reis 2014). As an example of an application of the CISS for macro-prudential policy purposes, the CISS has proven useful in the evaluation of a set of indicators that can be used to calibrate the release of counter-cyclical capital buffers in Europe (see Detken et al. 2014). The financial press has been using the CISS on repeated occasions to provide evidence of the overall state of financial stability in the eurozone (e.g., see <http://www.ft.com/intl/cms/s/0/bbf89f04-e8d8-11e4-87fe-00144feab7de.html#axzz3fwf2dIQB>). Last but not least, the CISS has also become part of a standard set of financial stability indicators applied in the academic world (see, e.g., Bekaert and Hoerova 2014, or Boeckx, Dossche and Peersman 2014). Weekly updates of the euro area CISS are available via the ECB’s Statistical Data Warehouse (SDW), Thomson Financial Datastream and Haver Analytics.

policy, a measure of aggregate economic activity and a measure of aggregate inflation. In my model, I use the ECB's interest rate on the main refinancing operations (MRO rate), the annual growth in real GDP and the annual consumer price inflation as the core variables of the system. To these four variables I further add the growth rate of the ECB balance sheet to capture the ECB's stance of unconventional monetary policy measures, as well as the spread between the overnight market interest rate and the MRO rate to better differentiate between liquidity demand and supply shocks. Within this simple linear VAR framework, I first assess the role played by the CISS for the overall dynamics of the system. The CISS turns out to be a major driver behind the dynamics of almost all model variables, including economic growth. Moreover, the strong explanatory power of the CISS also proves robust to the inclusion of alternative variables with known or presumed predictive power in particular for economic activity and inflation. I also find that the CISS impacts real GDP growth and the ECB balance sheet growth rate directly, while its influence on the ECB policy rate occurs only indirectly through its effects on the other model variables, predominantly on economic activity. In contrast to its important role for the dynamics of the system, the other variables are found to have only moderate (MRO rate) or no significant effects on the CISS itself.

The third paper, Chapter 4 of this dissertation, adopts a similar model setup but allows for regime switches in coefficients and error variances, where coefficients and variances can switch regime independently from one another. The regime shifts are driven by exogenous Markov processes. We estimate a five-dimensional Markov-Switching VAR—with inflation, industrial production growth, a three-month money market rate, bank lending growth and the CISS as the endogenous variables—with Bayesian methods and find results which are qualitatively consistent, but quantitatively rather different from those found in the previous chapter. In particular, the CISS shows up as a very strong driver for economic activity in what we call a systemic crisis regime that combines the

highest variances of financial stress shocks with a strong transmission of financial shocks to the real economy. In fact, the dynamic effects of CISS shocks on industrial production growth in this regime look rather similar to the corresponding pattern of responses from the crisis regime determined by the bivariate threshold-VAR. In contrast, in regimes capturing normal times, the effects of the CISS on economic growth appear much more muted.

The final Chapter 5 of this dissertation discusses some policy conclusions which can be derived from the findings of the three previous chapters.



## CHAPTER 2

### CISS – A PORTFOLIO-THEORETIC FRAMEWORK FOR THE CONSTRUCTION OF COMPOSITE FINANCIAL STRESS INDEXES

**Abstract:** This paper introduces a novel indicator of current stress in the financial system as a whole named Composite Indicator of Systemic Stress (CISS). Its specific statistical design is shaped in accordance with standard definitions of systemic risk. The main innovative feature of the CISS is the application of portfolio theory to the aggregation of individual stress indicators into the composite index. Along the lines of how portfolio risk is computed from the risks of individual assets, we propose to compute the level of stress in the system as a whole by aggregating five market-specific subindices of stress - comprising a total of 15 individual stress indicators - on the basis of a time-varying measure of the cross-correlations between them. The CISS thus puts relatively more weight on situations in which stress prevails in several market segments at the same time, capturing the idea that financial stress is more systemic and hence more hazardous for the real economy if instability spreads more widely across the whole financial system. Applied to data for the euro area as a whole, we determine within a threshold VAR model a critical (crisis) level of the CISS at or above which adverse shocks to financial stress tend to depress real economic activity materially.\*

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\*This chapter builds on initial joint work on the CISS project with Daniel Holló and Marco Lo Duca (see Holló, D., M. Kremer and M. Lo Duca, “CISS - A Composite Indicator of Systemic Stress in the Financial System,” *ECB Working Paper* No. 1426, March 2012). I thank Tommy Kostka for outstanding research assistance and for several good ideas which helped improving the CISS. Very helpful comments from Philipp Hartmann, Geert Bekaert, Hans Degreyse, Wolfgang Lemke, Simone Manganelli, Seth Pruitt, Harald Uhlig, Barbara Rossi, Rong Chen, and three anonymous referees are gratefully acknowledged. I finally thank seminar participants at the Euro Area Business Cycle Network 2011 conference “Econometric Modelling of Macro-Financial Linkages” in Florence, the 5th CSDA International Conference on Computational and Financial Econometrics in London, the Board of Governors of the Federal Reserve System, the Sveriges Riksbank, the AEA 2013 Annual Meeting in San Diego, the joint Federal Reserve Bank of Cleveland and Office of Financial Research 2013 conference

## 2.1 Introduction

The recent global financial crisis erupted when growing and increasingly visible strains in the US subprime mortgage market caused liquidity conditions to largely dry up in the markets for securities backed by pools of such mortgages. This eventually forced a European bank, BNP Paribas, to halt redemptions on three of its investment funds with large exposures to such asset-backed securities. That very moment in August 2007 turned local strains in certain US asset markets into an open systemic crisis affecting large parts of the financial system in particular in advanced economies. Financial stress further intensified in September 2008 when Lehman Brothers failed, an event which shifted the crisis into a higher gear. Financial frictions now started to seriously damage the global economy which, in turn, further aggravated the level of strains in the financial system, and so forth. This vicious cycle also widened the scope of the turmoil, now spilling over into emerging markets and precipitating the sovereign crisis in Europe in early 2010. In general, the crisis unfolded erratically, with catalytic events triggering new stress peaks followed by periods of gradual and partial recovery.

While it makes sense to associate financial crises with its main identifying events in such narrative accounts, quantified information about the degree of financial instability prevailing at each point in time arguably allows for a more profound characterisation of crisis episodes. One popular tool to tackle this measurement problem is what has become known as a financial stress index (FSI). FSIs aim to quantify the current state of instability - i.e., the current strength of frictions and strains (“stress”) - in the financial system (or certain parts of it) by aggregating a certain number of individual stress

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indicators into a single composite index. In their property as a coincident indicator of overall financial stability conditions, FSIs serve several purposes. For example, since FSIs usually rely on input data which is recorded at relatively high frequency (e.g., daily or weekly) and available without much delay, they provide information in more or less real time and have thus become a standard tool for those in charge of regularly monitoring financial stability. FSIs also help to better describe, analyse and compare historical crisis episodes. For instance, FSIs provide a framework to delineate the start and end points of crises in a meaningful way and at higher frequencies of observation than what is current practice (see Reinhart and Rogoff 2009, Chapters 1 and 16). They might also improve the information content and the statistical power of early warning models which typically rely on binary crisis indicators as dependent variables (e.g., Illing and Liu 2006; for recent applications of FSIs in early warning models see Misina and Tkacz 2009, and Lo Duca and Peltonen 2013). Last but not least, FSIs may offer a quick summary gauge of the overall impact of policy measures aimed at alleviating financial instability.

In this paper we introduce an innovative financial stress index named Composite Indicator of Systemic Stress (CISS). The main innovative features of the CISS vis-à-vis alternative FSIs rest in its economic foundation on the notion of *systemic risk*. Systemic risk can be defined as the risk that instability becomes so widespread within the financial system that it impairs its functioning to the point where economic growth and welfare suffer materially (de Bandt and Hartmann 2000). We interpret *systemic stress* - which is what the CISS aims to measure - as an ex post measure of systemic risk, i.e. systemic risk which has materialised.

Against this conceptual background, the CISS is designed in such a way that it operationalises both the idea of widespread financial instability and the importance of

financial stress for the real economy. At the level of individual financial stress indicators, the CISS selects 15 mostly market-based stress measures which are categorised into five market segments arguably representing the largest and systemically most important parts of a modern financial system. In order to homogenise the set of raw stress indicators in terms of scale and the underlying unconditional distribution, we transform each of them by applying the probability integral transform, i.e. by replacing each observation of an indicator with its corresponding value from the empirical cumulative distribution function. A separate financial stress subindex is computed for each of the five market segments as the arithmetic mean of in each case three constituent transformed indicators. The resulting subindices are then aggregated into the composite indicator based on portfolio-theoretic principles. We see the application of portfolio theory at the aggregation step as the main conceptual innovation of the CISS compared to alternative FSIs. The portfolio-theoretic framework offers two elementary avenues to incorporate systemic risk aspects. First, analogously to the computation of portfolio risk from the risk of individual assets, the five subindices of segment-specific stress are aggregated by taking into account a time-varying measure of the cross-correlations between them. In this way the CISS puts relatively more weight on situations in which stress prevails in several market segments at the same time, i.e. on situations in which financial instability *spreads widely* across the whole financial system. Second, the portfolio weights (shares) assigned to each subindex can be calibrated in proportion to their systemic importance. In the empirical application of the present paper to data for the euro area as a whole, the weights are determined on the basis of the estimated impact of each subindex of financial stress on economic activity.

The proposed design of the euro area CISS possesses two further idiosyncratic features vis-à-vis most other FSIs, namely its recursive (real-time) computation over expanding data samples, and its enhanced robustness to the addition of new information.

The latter feature is achieved by applying the probability integral transform to the raw stress indicators, thereby relying on the known robustness of order statistics to extreme observations. Both features help to mitigate the risk of reclassifying crisis regimes/events ex post, a risk which may affect in particular those FSIs whose statistical design relies strongly on stable distribution properties of the raw input series in typically small samples. The empirical evaluation of the euro area CISS confirms the robustness of its information content. Furthermore, all peaks in the CISS can be associated to well-known periods of financial stress, and the recent financial crisis clearly stands out as a unique systemic event in the past two and a half decades.

The paper makes a further contribution to the literature on FSIs by proposing the use of econometric approaches to *endogenously* identify different stress regimes. We demonstrate it on the basis of a parsimonious threshold vector autoregressive (TVAR) model that identifies a systemic crisis level of the CISS at or above which financial stress becomes very costly in terms of reduced real economic activity. The results from the TVAR suggest that while shocks in the CISS exert only small output reactions during low-stress regimes, industrial production truly collapses during high-stress regimes in response to a typical adverse shock in financial stress. Similarly, it is only in the high-stress regime that a negative output shock triggers increases in financial stress, supporting the idea that output and financial shocks might reinforce each other in a truly systemic crisis.

The remainder of this paper is organised as follows: Section 2 provides a very brief summary of the related literature. Section 3 motivates and describes the statistical design of the CISS and presents an empirical application to data for the euro area economy as a whole. The euro area CISS is assessed in Section 4 in terms of its robustness properties and its ability to identify well-known periods of financial stress; in addition,

it presents results from the TVAR model to determine endogenously different regimes in the CISS. Section 5 concludes.

## 2.2 Related literature

The paper relates mainly to two strands of literature, the first one discussing different options to construct financial stress indices, and the second one studying the impact of financial distress on aggregate economic activity.

As to the first field, the development of FSIs has become a very active business in recent years, spurred by the analytical demands created by the crisis. For the sake of brevity the following literature review is neither very detailed nor exhaustive but tries to illustrate the broad range of existing methodologies. The ECB working paper version of this article (Holló, Kremer and Lo Duca 2012) provides a more detailed account of the recent literature. The seminal paper is Illing and Liu (2006). They develop a daily financial stress index for the Canadian financial system and propose several approaches to the aggregation of individual stress indicators into a composite stress index. The specification of their preferred FSI was chosen according to which variant performs best in capturing crisis events in the Canadian financial system identified on the basis of a survey among Bank of Canada policy-makers and staff. The preferred FSI comprises 11 financial market variables aggregated on the basis of weights determined by the relative size of the market to which each of the indicators pertains. Caldarelli, Elekdag and Lall (2011) present a monthly financial stress index for 17 advanced economies computed as the arithmetic mean of twelve standardised market-based financial stress indicators, an aggregation method also known as *variance-equal weighting*. Nelson and Perli (2007) and Carlson, Lewis and Nelson (2012) present a weekly financial fragility indicator for the

United States computed in two steps from twelve market-based financial stress measures. The standardised input series are first reduced to three summary indicators, namely a level factor, a rate-of-change factor and a correlation factor. In the second step, the financial fragility indicator is computed as the fitted probability from a logit model with the three summary indicators as explanatory variables and a binary pre-defined crisis indicator as the dependent variable. Refining the last step of the approach by Nelson and Perli (2007), Blix Grimaldi (2010) computes a weekly FSI for the euro area, where the binary crisis indicator is systematically derived from crisis events identified on the basis of a keyword-search algorithm applied to relevant parts of the ECB Monthly Bulletin. Hakkio and Keeton (2009) construct a monthly FSI applying principal components analysis to US data. The idea is that financial stress is the factor most responsible for the observed correlation between the indicators, and this factor is identified by the first principal component of the sample correlation matrix computed from the standardised indicators. The weights of each input series is computed from its loading to the first principal component. The weekly financial conditions index developed by Brave and Butters (2011a, 2011b) also builds on factor analysis but is more complex and sophisticated than its competitors in terms of the number and the heterogeneity of the input data and the statistical indicator design. The computation of the FCI is cast into a dynamic factor model in state-space form which includes a maximum of 100 indicators, where Kalman filtering takes account of the missing data problem resulting from the different sample lengths and frequencies of the input data. The FSI developed by Oet et al. (2011) integrates 11 daily financial market indicators grouped into four sectors. The raw indicators are normalised by applying the probability integral transform similar to what we are doing in the present paper. The transformed indicators are then aggregated into the composite indicator by computing a weighted average with time-varying credit weights which are proportional to the quarterly financing flows in the four markets.

Second, the present paper also relates to the general literature examining empirically the real impacts of financial stress (e.g., Hakkio and Keeton 2009; Cardarelli, Elekdag and Lall 2011; Hatzius et al. 2010; Li and St-Amant 2010; Mallick and Sousa 2011; Carlson, King and Lewis 2011; and van Roye 2011). The regime-dependence of the impact of financial stress on economic activity found in our study broadly corroborates the findings of Davig and Hakkio (2010) from a bivariate Markov-switching model with the FSI developed by Hakkio and Keeton (2009) and a monthly measure of US economic activity as endogenous variables. Hubrich and Tetlow (2015) for the US and Hartmann, Hubrich, Kremer and Tetlow (2015) (which is also Chapter 4 of this dissertation) for the euro area provide qualitatively similar evidence on much stronger impacts of financial stress on economic activity in high-stress regimes within more richly specified small-scale macro-econometric Bayesian VAR models with Markov-switching in coefficients and residual variances, where the latter study uses the CISS to measure financial stress.

### **2.3 Statistical design of the CISS**

The CISS aims to measure the current level of systemic stress in the financial system as a whole. 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 attention to those parts of the financial system - subject to data availability - which can be regarded as both systemically important and sufficiently representative for the system as a whole.



Against this background, the design of the CISS can be viewed as a three-stage aggregation framework, with each stage featuring particular characteristics of systemic risk.<sup>1</sup>

We start with the *intermediate level*, i.e. the second stage, at which five highly aggregated market segments shall represent the main elements of a financial system. These segments capture, in a stylised fashion, the main flows of funds from ultimate lenders/savers to borrowers/spenders, channeling funds either indirectly through financial intermediaries or directly via short-term and long-term security markets. The five segments are: 1. the financial intermediaries sector (comprising banks, insurance companies, pension funds and other financial services providers); 2. the bond market (only sovereign and non-financial corporate issuers); 3. the equity market (only non-financial corporations); 4. the money market (broadly defined as including in principle all forms of short-term wholesale financing in the economy, e.g., interbank and commercial paper markets); and 5. the foreign exchange market (capturing potential stresses affecting cross-border financing activities). The choice of these five market segments can be justified on grounds of their systemic importance. Size, substitutability and interconnectedness are three of the main criteria usually applied to identify systemically important financial institutions and markets. According to the size criterion, it is probably fair to say that the five identified market segments collectively represent the core of any financial system. In addition, the markets and sectors included in the CISS are aggregated to such an extent that in case financial stress disrupts all of them at the same time, no major substitute forms of unimpaired finance presumably exist in the economy.

The interconnectedness criterion brings us to the *top stage* of our aggregation framework where the heart of the paper rests, namely the application of portfolio-theoretical principles to the aggregation of the five market segment-specific indices of financial stress

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<sup>1</sup>For a graphical representation see Figure 1 in Hollo, Kremer and Lo Duca (2012).

into the CISS. The aggregation of the subindices of stress by way of their time-varying cross-correlations operationalises the idea of *widespread financial instability* in a novel fashion. In addition, the variation in the cross-correlations may also capture state-dependent 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 portfolio weights for each subindex of stress offers another route to bring in features of systemic risk.

The population of the five subindices with individual indicators of financial stress takes place at the *lower stage* of the aggregation framework. Each selected indicator captures typical symptoms of financial stress in the market segment it is associated with.

Details on each of the three stages of the statistical indicator design are provided in the subsequent subsections. The empirical implementation of the CISS concept is demonstrated on the basis of data for the aggregate euro area economy.

### **2.3.1 Raw stress indicators**

Financial stress is a rather elusive concept. It is usually operationalised by drawing on the main features associated with financial crises defined as situations in which the normal functioning of a financial system is impaired. The list of typical crisis features includes (see, e.g., Hakkio and Keeton 2009; Fostel and Geneakoplos 2008): increased uncertainty (e.g., about asset valuations and the behaviour of other investors); increased differences of opinion among investors; increased asymmetry of information between borrowers and lenders (intensifying problems of adverse selection and moral hazard); and lower preferences for holding risky assets (flight-to-quality) or illiquid assets (flight-to-liquidity) resulting from stronger risk or uncertainty aversion, for instance (Caballero

and Krishnamurthy 2008).

Although the various stress features are not directly observable, they can be captured by observable stress symptoms like increased asset price volatility, large revaluations for risky assets, wider default and liquidity risk premia, as well as sharp reversals in financing flows linked to financial instruments or institutions perceived as being more risky. However, such symptoms measure the underlying stress characteristics only imperfectly, as the former typically also reflect the impact of other factors than the mentioned crisis features. The identification of individual stress features is further complicated by the fact they are often closely interrelated, with a tendency to reinforce each other as in the case of fire sales and liquidity spirals (Brunnermeier and Pedersen 2009; Krishnamurthy 2010). As a consequence, it is likely that certain financial market indicators - henceforth called raw stress indicators - capture several stress features at the same time.

The literature offers a vast variety of financial quantity and price variables reflecting characteristics of financial stress. Which ones to pick for the construction of a financial stress index appears to be a greatly arbitrary choice. For our purposes, we narrow down the list of candidate raw stress indicators to be included in the CISS by imposing several restrictions:

1. Each of the five segment-specific subindices of stress includes (not more than) three raw stress indicators. The composite indicator thus comprises a total of (at most) 15 individual indicators of financial stress. The same number of indicators per subindex shall ensure that the subindices do not possess different statistical properties by construction. In addition, the three raw indicators in each subindex should convey complementary information on the level of strains in the respective market segment; ideally, the information content of all three indicators should be perfectly correlated only under conditions of extreme stress.

2. To ensure representativeness, the raw stress indicators should cover market-wide developments. We therefore prefer indicators based on broad market indices, but sometimes revert also to certain assets with benchmark status (e.g., government bonds) for the pricing of a wider range of closely related financial instruments.
3. To make the CISS fit for real-time monitoring purposes, all raw stress indicators should be available at a daily/weekly frequency and with a publication lag of a one day at most.
4. Raw stress indicators should carry sufficiently long data histories to comprise at least a few episodes of financial distress.

These restrictions jointly imply that the CISS includes mainly fairly standard price-based financial market indicators available for many countries and over relatively long data samples. We mostly rely on risk spreads and a measure of realised asset return volatility included in all five subindices. Table 2.1 provides details on the computation and the data sources of all individual stress indicators included in the euro area CISS.

As to their information content, asset return volatilities tend to increase with investors' uncertainty about future fundamentals and/or the behaviour and sentiment of other investors (Pastor and Veronesi 2009; Veronesi 2004). Chordia, Sarkar and Subrahmanyam (2005) present evidence that volatility shocks in bond and stock markets tend to predict shifts in liquidity condition in both markets. Stress in the money market is also captured by a euro area equivalent of the US TED spread, i.e. by the yield differential between a three-month unsecured inter-bank market rate and a comparable essentially risk-free Treasury bill rate. This spread reflects liquidity and counterparty risk in the inter-bank market (Heider, Hoerova and Holthausen 2015; Acharya and Skeie 2011) as well as the convenience premium on short-term Treasury paper, and thus captures stress features like flight-to-quality, flight-to-liquidity as well as the price impacts

of enhanced adverse selection problems in times of stress in the banking system. Another variable measuring stress in the inter-bank money market is banks' recourse to the marginal lending facility at national central banks of the Eurosystem. The yield spread between long-term A-rated bonds of non-financial corporations and governments, respectively, measures bond market stress. Drawing on the empirical findings of Feldhütter and Lando (2009) for the US, the ten-year swap spread is arguably a relatively clean measure of the convenience premium embedded in the prices of German government bonds - the presumably safest and most liquid sovereign bonds in the euro area - which, in turn, captures flight-to-liquidity and flight-to-quality effects in this market segment (on the convenience yield in US Treasuries see Krishnamurthy and Vissing-Jorgensen 2012, and Krishnamurthy 2010). Stress in the equity market is captured by the so-called CMAX measuring the maximum cumulated loss in a stock price index over a moving two-year window. It was originally developed to identify crisis periods in international stock markets (Patel and Sarkar 1998). Stress in the equity market is furthermore measured by a time-varying correlation coefficient between stock and government bond returns capturing, amongst others, flight-to-liquidity and flight-to-quality phenomena (Baele, Bekaert and Inghelbrecht 2010). For instance, in times of heightened systemic stress, investors try to shift funds out of more risky stocks into safer government bonds, thereby driving the return correlation between these two asset classes into negative territory. Since our stress measures shall increase with higher levels of stress, we take the negative of the short-term stock-bond correlation (measured as the deviation from a longer trend-correlation). Stress in the financial intermediaries sector is measured by idiosyncratic stock return volatility of the banking sector and the yield differential between A-rated financial and non-financial corporations. A partly novel stress measure of the financial intermediaries segment is obtained by interacting the CMAX of this sector with its inverse price-book ratio. The idea behind this indicator is that any given

large stock market loss puts financial intermediaries the more under stress the lower their current valuation levels as measured by the price-book ratio. Stress in the foreign exchange market is exclusively represented by the realised volatility of three bilateral euro exchange rates.

### **2.3.2 Transformation of raw indicators**

Building a composite indicator of financial stress faces the challenge that prior to aggregation, the rather diverse set of individual financial stress indicators has to be homogenised in terms of their units of measurement and, ideally, distributional properties, by way of statistical transformation. In the vast majority of cases, the literature puts the raw stress indicators on a common scale by standardisation, i.e. by subtracting the sample mean from the raw score and dividing this difference by the sample standard deviation. Standardisation, however, implicitly assumes that the raw variables are normally distributed. The fact that many standard stress indicators violate this assumption (e.g. asset volatilities)<sup>2</sup>, enhances the risk that the results obtained from the use of standardised variables are particularly sensitive to aberrant observations. In that case, updates of the conditional means and the conditional standard deviations—when calculated, for instance, over expanding data samples—can be subject to large revisions if more and more outliers (from the viewpoint of a standard normal distribution) are added to the data set (Hakkio and Keeton 2009), a situation which tends to occur during a new period of severe and protracted financial stress. Such robustness problems related to standardisation can distort the information content of financial stress indicators over time. In an extreme case it might happen that an identified financial stress event dating back several years has to be called off (“event reclassification”) due to the

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<sup>2</sup>For instance, if an asset return is standard normal distributed, its square or averages of its square—an often used measure of asset volatility—would follow a chi squared distribution.

Table 2.1: Individual financial stress indicators included in the CISS

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**Money market**

1. Realised volatility of 3-month Euribor rate.
2. Interest rate spread between 3-month Euribor and 3-month French T-bills.
3. Monetary Financial Institution's (MFI) recourse to the marginal lending facility at Eurosystem central banks, divided by total reserve requirements; MFIs can use the marginal lending facility to obtain overnight liquidity from national central banks against eligible assets and, typically, at an interest rate higher than the prevailing overnight market interest rate.

**Bond market**

4. Realised volatility of German 10-year benchmark government bond index.
5. Yield spread between A-rated non-financial corporations and government bonds (7-year maturity).
6. 10-year interest rate swap spread.

**Equity market**

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

**Financial intermediaries**

10. Realised volatility of idiosyncratic equity return of Datastream bank sector stock price index over the total market index; idiosyncratic return calculated as residual from OLS regression of daily log bank return on log market return over a moving 2-year window.
11. Yield spread between A-rated financial and non-financial corporations (7-year maturity).
12. CMAx of Datastream financial sector stock price index interacted with the sector's book-price ratio; both indicators transformed by their recursive sample CDF prior to multiplication; final indicator obtained by taking the square root of this product.

**Foreign exchange market**

13. Realised volatility of euro exchange rate vis-à-vis US dollar.
14. Realised volatility of euro exchange rate vis-à-vis Japanese Yen.
15. Realised volatility of euro exchange rate vis-à-vis British Pound.

Notes: Realised volatilities computed as weekly averages of absolute daily log return or interest rate changes; all other series, except indicator 8, computed as weekly averages of daily data. All raw equity market data start 4/1/1980 (indicators 7 to 10 and 12); all money market data (indicators 1 to 3) start 8/1/1999; all corporate bond data (indicators 5 and 11) start 3/4/1998; bond market indicators 4 and 6 start 5/1/1990 and 4/3/1987, respectively; all exchange rate data start 6/7/1990.

Sources: All input series, except those of indicator no. 3, are from Thomson Financial Datastream; input data of indicator no. 3 are from the ECB.

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smoothing effect brought about by the impact of additional extreme observations from a more recent financial crisis on the conditional means and standard deviations of the raw stress indicators considered. Applying principal components analysis (PCA) in order to aggregate the standardised indicators into a composite indicator may aggravate the problem of sub-sample robustness, since PCA itself is sensitive to outliers (as it minimises squared distances from the multidimensional mean). These problems of robustness are closely related to the fact that standardisation of the raw indicators only rescales their underlying empirical distribution function but does not change their basic shape. Accordingly, standardisation does not deliver a set of homogeneously distributed transformed indicators, a fact which may bring about other undesired properties of the composite indicator apart from the increased sensitivity to outliers just mentioned; for instance, the dynamics of the composite indicator may be dominated by those components which tend to produce more observations far away from the sample mean by the very nature of their true underlying distribution function.

We address the various inherent challenges of transformation—i.e. the different scales and distributional heterogeneity among the raw indicators, as well as the robustness issue—by applying the probability integral transformation (PIT) to each raw indicator of financial stress. The theorem of the PIT states that for any continuous random variable  $X$  with cumulative distribution function (CDF)  $F_X(x)$ , the random variable defined by  $Y = F_X(X)$  has a uniform distribution over the range  $(0, 1)$  regardless of the form of the original distribution  $F_X(x)$ , i.e.:<sup>3</sup>

$$Y = F_X(X) \sim U(0, 1).$$

In the empirical implementation of the PIT, we have to work with the discrete sample

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<sup>3</sup>See, e.g., Spanos (1999) or Cassela and Berger (2002). The term “probability integral transform” refers to the relationship between the continuous cumulative distribution function  $F_X(\cdot)$  and its corresponding density function  $f_x(\cdot)$ :  $F_X(x) = \int_{-\infty}^x f_x(u) du$ , where  $F_X(x)$  equals the probability that the random variable  $X$  does not exceed the value  $x$ .



analogue of the CDF, the empirical CDF, which we henceforth denote as  $\widehat{F}_n(x)$ , with  $n$  the number of observations included in a given data set of a raw financial stress indicator  $x = \{x_1, x_2, \dots, x_n\}$ . As the first step of the PIT, the observations are ranked in ascending order, giving rise to the ordered set  $\{x_{[r]}, r = 1, \dots, n\}$  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. Each original observation of the raw indicator,  $x_t$ , is now replaced by its corresponding value of the empirical CDF,  $\widehat{F}_n(x_t)$ . The transformed data are collected in  $y = \{y_t, t = 1, \dots, n\} = \{\widehat{F}_n(x_t), t = 1, \dots, n\}$  which denotes the data set of the transformed stress indicator which we may henceforth call a *stress factor*. The transformation value  $y_t$  of any observation  $x_t$  is computed as the ranking number  $r$  of observations not exceeding that particular value  $x_t$ , divided by the total number of observations  $n$  (Spanos 1999, p. 230f.):

$$y_t = \widehat{F}_n(x_t) := \begin{cases} \frac{r}{n} & \text{for } x_{[r]} \leq x_t < x_{[r+1]}, \quad r = 1, 2, \dots, n-1 \\ 1 & \text{for } x_t = x_{[n]} \end{cases} .$$

In the case of tied observations, that is when  $m$  of them have the same value and rank  $r$ , the functional value assigned to each of them is computed as  $((r+1) + (r-m))/n$ . The empirical CDF is hence a function which is non-decreasing and piecewise constant with jumps being  $1/n$  (or  $m/n$  in the case of tied observations) at the observed points.

Equation 2.3.2 does not yet feature the intended real-time character of the CISS. The real-time character implies that past values of the CISS are not revised when new data on the raw indicators becomes available. This situation arises when the composite indicator shall be regularly updated. This property is introduced by applying the PIT recursively over expanding samples. Precisely, the non-recursive transformation as defined in Equation 2.3.2 applies to all observations from the pre-recursion period running from 8 January 1999 to 4 January 2002. All subsequent observations are transformed recursively on the basis of ordered samples recalculated with one new observation added

at a time:

$$y_{n+T} = F_{n+T}(x_{n+T}) = \begin{cases} \frac{r}{n+T} & \text{for } x_{[r]} \leq x_{n+T} < x_{[r+1]}, \quad r = 1, 2, \dots, n, n+1, \dots, n+T-1 \\ 1 & \text{for } x_{n+T} = x_{[n+T]} \end{cases} \quad (2.1)$$

for  $T = 1, 2, \dots, N$ , with  $N$  indicating the end of the full data sample (in the present application,  $N$  represents 24 June 2011).<sup>4,5</sup>

I conclude this section with a brief discussion of some statistical properties of the probability-integral-transformed data. The PIT projects raw stress indicators into stress factors which are unit-free and (approximately) uniform distributed over the range  $(0, 1]$ . This transformation thus has the distinct advantage that, whatever is the original distribution of the raw indicators, the transformed indicators are homogenous in terms of scale and their underlying unconditional distribution function.

In addition, the PIT relies on order statistics which are known to be less affected by extreme observations (Stuart and Ord 1994; Cassela and Berger 2002). This presumed robustness feature of the PIT appears particularly relevant in the present context due to the recursive computation (and updating) of the CISS. Figure 2.1, which displays the transformation for all 15 raw stress indicators computed both recursively and based on the full data sample, broadly corroborates our presumption of robustness. In most cases the differences between the empirical CDFs calculated in real-time and those computed from the full data sample are relatively small. While in a few cases the differences become somewhat more pronounced, they do not affect the strong robustness of the composite indicator against variations of the sample length both in absolute terms and compared

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<sup>4</sup>In fact, the euro area CISS is updated on a weekly basis, and the updates are published on the ECB's homepage (<https://sdw.ecb.europa.eu/browse.do?node=9551138>).

<sup>5</sup>The total number of observations included in the ordered samples varies from indicator to indicator depending on the availability of historical data. The longest sample starts in 4 January 1980 (see Table 2.1) with the total number of observations included in the pre-recursion sample amounting to 1149, while the shortest pre-recursion sample starting in 8 January 1999 is left with 157 observations.

to an alternative, conventional indicator design that involves the standardisation of indicators (see Section 2.4.1).

However, the PIT also comes with a disadvantage. This method of transformation implies the loss of that part of the information which is only contained in the cardinal scale of the original data but not in the ordinal scale of the transformed series. For instance, after standardisation, the distances between two observations of a transformed stress indicators still matter (i.e., it matters how many times one observation exceeds another observation), while this is not the case for the probability integral transformed indicators (i.e., the PIT only pays attention to the relative ranking of two observation within a given data sample). The probability integral transformation therefore trades off gains in indicator homogeneity and statistical robustness against some loss of information when moving from a cardinal to an ordinal measurement scale.

### 2.3.3 Aggregation

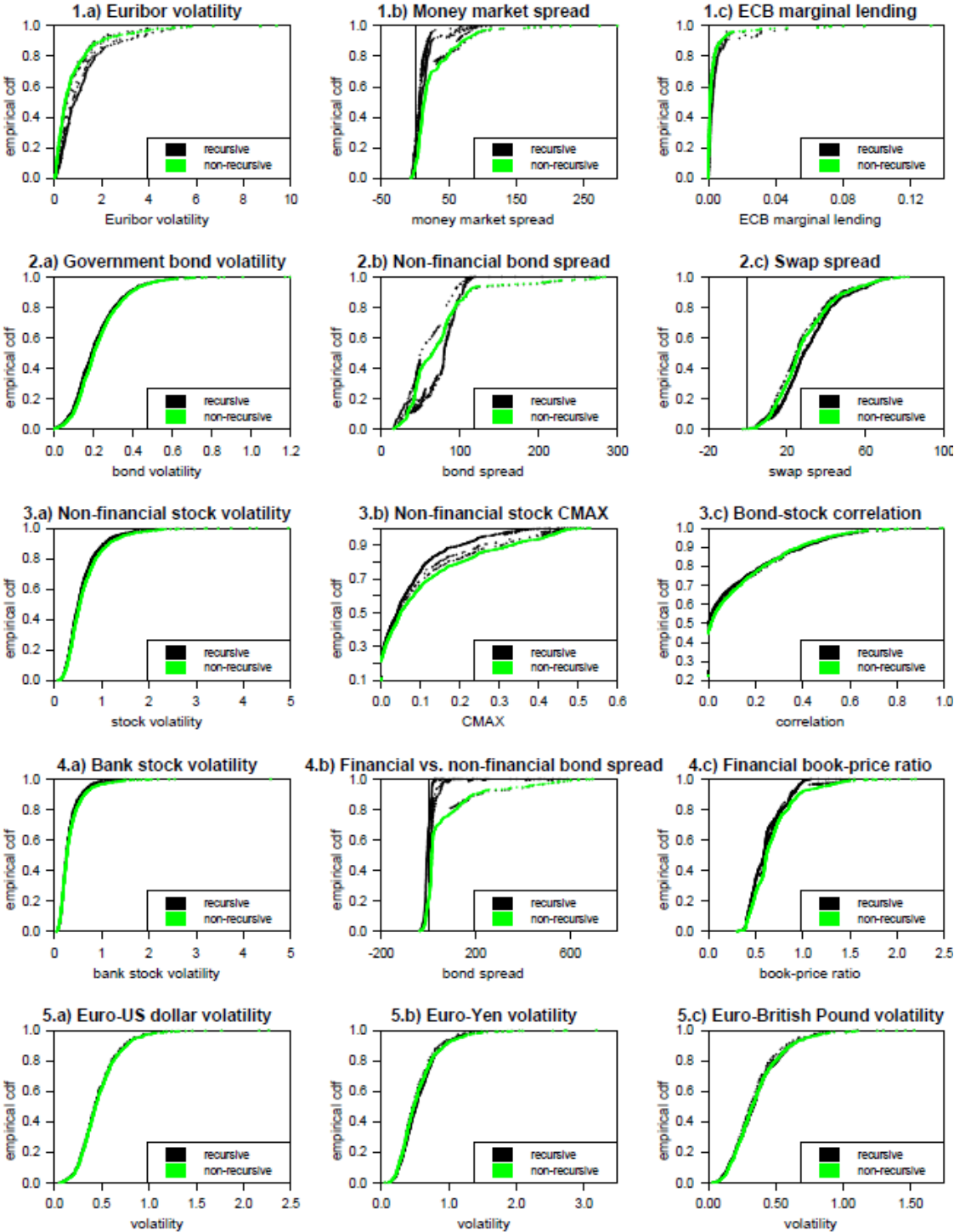
**Subindices.**—We are now equipped with a set of 15 homogenised stress factors  $y_{i,j,t}$ , with  $i = 1, 2, \dots, 5$  indicating the respective market segment and  $j = 1, 2, 3$  denoting the stress factors within each subindex  $i$ . The five subindices of financial stress are calculated as the arithmetic mean of the three constituent stress factors:

$$s_{i,t} = \frac{1}{3} \sum_{j=1}^3 y_{i,j,t}. \quad (2.2)$$

We postpone the discussion of this presumably inconsistent choice of intra-subindex aggregation to the next section, as it requires an understanding of the portfolio-theoretic approach to the aggregation across subindices.

**Composite index.**—The main innovative element of the CISS compared to alternative financial stress indicators is the application of standard portfolio theory to the

Figure 2.1: Recursive versus full-sample transformation of raw stress indicators



aggregation of subindices. The portfolio-theoretic framework offers two elementary avenues to incorporate systemic risk aspects. First, analogously to the computation of portfolio risk from the risk of individual assets, the five subindices of segment-specific stress are aggregated by taking into account the cross-correlations between them. It is essential for our purpose that we allow for time-variation in the cross-correlations. In this way the CISS puts relatively more weight on situations in which stress prevails in several market segments at the same time, i.e. on situations in which financial instability spreads more widely across the financial system. The correlations thus focus on capturing the systemic dimension of stress within the financial system (the *horizontal view* on systemic risk as defined by de Bandt and Hartmann 2000). Second, the weights assigned to each subindex in the composite indicator can be calibrated in proportion to their systemic importance which in turn may be gauged in different ways. For instance, the weights may mirror the relative size of the financial market segment covered by each subindex (size weights) as in Illing and Liu (2006) and Oet et al. (2011). Alternatively, the weights may be determined on the basis of some estimate of the relative impact of financial stress in the different market segments for economic activity (real-impact weights), which is a novel route to address this issue taken in the present paper. In both cases, the calibration of weights provides an opportunity to account for country differences in the structure of financial systems and the associated differences in the transmission of financial stress to the real economy, thereby capturing the *vertical view* on systemic risk which gives an idea about the potential real costs of a financial crisis (de Bandt and Hartmann 2000). Since such structural features of an economy are not set in stone, the weights can in principle also vary over time.

Against this background, the CISS is computed in two variants according to the

following formulas:

$$CISS_t = (w_t \circ s_t)' \Omega_t (w_t \circ s_t) \text{ or} \quad (2.3)$$

$$= \sqrt{(w_t \circ s_t)' \Omega_t (w_t \circ s_t)}, \quad (2.4)$$

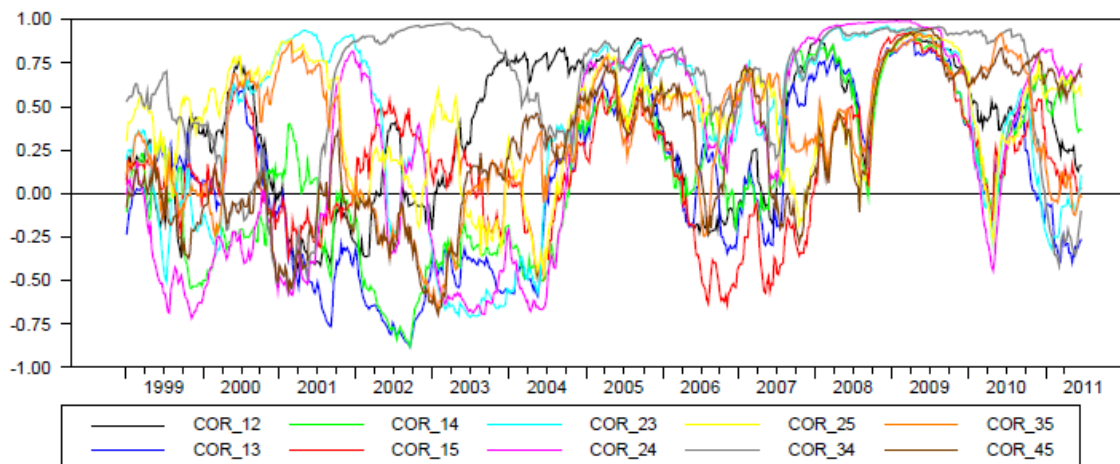
with  $w'_t = (w_{i,t})'$  a  $1 \times 5$  vector of subindex weights, and  $s'_t = (s_{i,t})'$  a  $1 \times 5$  vector of subindices with  $i = 1, \dots, 5$ ;  $w_t \circ s_t$  the element-wise product of both vectors; and  $\Omega_t$  the symmetric  $5 \times 5$  matrix collecting the time-varying cross-correlation coefficients  $\rho_{ij,t}$  between subindices  $i$  and  $j$  as defined below in Equation 2.5. Due to the quadratic form of Equation 2.3, and alluding to the return variance as a measure of portfolio risk, the first variant may be called the variance-equivalent CISS; it is the variant of the CISS which is used in the empirical application in the subsequent sections. The second version of the CISS (Equation 2.4), which simply takes the square root of the right-hand side of Equation 2.3, may accordingly be called the volatility-equivalent CISS. Assuming that  $-1 \leq \rho_{ij,t} \leq 1$ , both variants of the CISS are unit-free indicators bounded by the interval  $(0, 1]$ , just as their constituent stress factors  $y_{ij,t}$ .

**Estimation of cross-correlations.**—For the present purpose the time-varying cross-correlations  $\rho_{ij,t}$  are recursively computed as exponentially-weighted moving averages (EWMA) of subindex covariances  $\sigma_{ij,t}$  and variances  $\sigma_{i,t}^2$ , specified in the form of IGARCH-type models which are asymptotically equivalent to EWMA (Bauwens, Laurent and Rombouts 2006; Engle 2002):

$$\begin{aligned} \sigma_{ij,t} &= \lambda \sigma_{ij,t-1} + (1 - \lambda) \tilde{s}_{i,t} \tilde{s}_{j,t} \\ \sigma_{i,t}^2 &= \lambda \sigma_{i,t-1}^2 + (1 - \lambda) \tilde{s}_{i,t}^2 \\ \rho_{ij,t} &= \sigma_{ij,t} / (\sigma_{i,t} \sigma_{j,t}) \end{aligned} \quad (2.5)$$

for  $i = 1, \dots, 5$ ,  $j = 1, \dots, 5$ ,  $i \neq j$ ,  $t = 1, \dots, N$  with  $\tilde{s}_{i,t} = (s_{i,t} - 0.5)$  denoting demeaned subindices (obtained by subtracting the unconditional population mean of 0.5 rather than the sample-dependent conditional mean). EWMA or IGARCH models

Figure 2.2: Cross-correlations between CISS subindices



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

are used by practitioners to forecast daily or weekly conditional asset price volatilities and correlations (Cuthbertson and Nitzsche 2004; González-Rivera, Lee and Yoldas 2007). The decay factor or smoothing parameter is held constant through time at a value of 0.93 which is similar to the value used by RiskMetrics for weekly data (Engle 2002). This value equals the rounded average smoothing parameter estimated recursively over expanding samples within a five-dimensional IGARCH model for the demeaned subindices.<sup>6</sup> The covariances and variances are initialised (at  $t = 0$ , i.e. 1 January 1999) at their average values over the pre-recursion period 8 January 1999 to 4 January 2002. Figure 2.2 displays the EWMA-estimates of all the cross-correlations between the five subindices of the euro area CISS.

Since the raw stress indicators are transformed by applying the probability integral transform, the estimated cross-correlations represent a time-varying variant of Spearman's rank correlation coefficient. The cross-correlations thus indicate whether the

<sup>6</sup>The multivariate IGARCH model includes only the constant terms in the conditional mean equations.

historical ranking of the level of stress in two market segments is relatively similar or not at any point in time.

**Calibration of the subindex weights.**—For the present purpose, the weights attached to each stress subindex are calibrated in proportion to their relative impact on real economic activity in the euro area. The real impacts are estimated using two different econometric approaches, where the results from in each case four different model specification are combined to achieve some degree of robustness. We also hold the weights constant over time, implicitly assuming that the structural features of the euro area financial system, which determine the way financial stress is transmitted to the real economy, have not undergone major changes over the relatively short sample considered.

We first run conventional bivariate VARs with industrial production and one of the subindices of stress as endogenous variables. The models are estimated on the basis of monthly data (monthly averages for stress indices) with a uniform optimal lag order of two as suggested by standard selection criteria. Two model variants differ only in their respective sample length, with one starting in January 1987 (i.e., including pre-EMU data) and the other one in January 1999 (when the euro was introduced). The two remaining VAR specifications differ in the transformation of the industrial production data (log level and its 12th difference, respectively). We compute cumulated 24-month structural impulse responses of the respective measure of industrial production to a unit shock in each stress subindex. Structural identification of shocks is obtained by applying the usual Cholesky decomposition to the variance-covariance matrix of reduced-form residuals, with the stress subindex ordered first and industrial production second (for a justification of this ordering see Section 2.4.3). The subindex weights associated with each model variant are then determined as each subindex's share in the sum of cumulated



impulse responses across the five subindices.

Linear VARs, however, only measure the mean impact of financial stress on industrial production, since the impulse response functions are computed from the models' least squares estimate of the conditional mean functions. While this can make perfect sense under many circumstances, it might be less suitable in the present context. For instance, financial crises are rare events often associated with unusually severe output losses. This may recommend focussing more on the dependence structure in the lower tails of the conditional distributions when calibrating the subindex weights. Least squares regressions may also provide biased coefficient estimates because of the influence from extreme values in the data brought about by episodes of severe financial stress. Against this background, we also perform single-equation quantile regressions as introduced by Koenker and Bassett (1978). Quantile regressions are based on minimising asymmetrically weighted absolute residuals and are more robust to extreme values and other forms of non-normality in the residual distributions than least squares. Resembling the set up of the VARs, we regress the annual growth in industrial production ( $y_t = \Delta_{12} \log IP_t$ ) on each one of the subindices of financial stress (with lags 0 to 2) along with the lagged endogenous variable (lags 1 and 2). This gives rise to the following linear conditional quantile functions estimated for all stress subindices  $s_{i,t}$ ,  $i = 1, \dots, 5$ , and for the full range of regression quintiles  $\tau = 0.05, 0.10, \dots, 0.95$ :

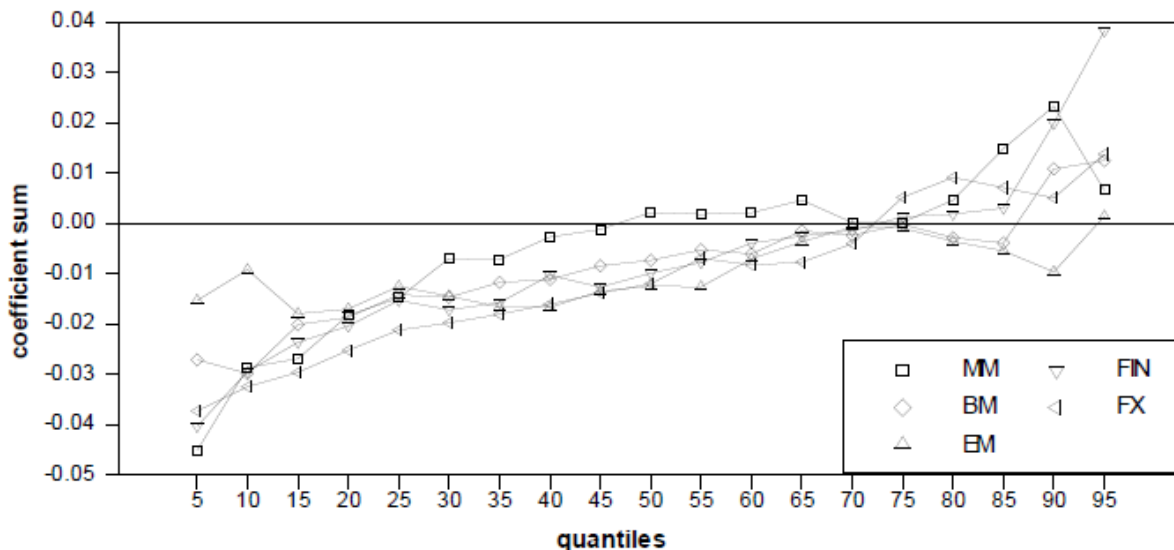
$$Q_{y_i}(\tau|I_t) = \beta_0(\tau) + \beta_1(\tau)y_{t-1} + \beta_2(\tau)y_{t-2} + \beta_3(\tau)s_{i,t} + \beta_4(\tau)s_{i,t-1} + \beta_5(\tau)s_{i,t-2} \quad (2.6)$$

with  $I_t = (y_{t-1}, y_{t-2}, s_{i,t}, s_{i,t-1}, s_{i,t-2})$  being the conditioning information set available at time  $t$ , and  $t = 3, \dots, T$ . Estimating Equation 2.6 for all  $\tau$  yields a set of coefficients characterising the entire distribution of industrial production conditional on each subindex of financial stress. Figure 2.3 plots the coefficient sums  $\bar{\beta}(\tau) = \beta_3(\tau) + \beta_4(\tau) + \beta_5(\tau)$  for the five subindices against the whole range of  $\tau$ -values. The coefficient sums summarise the long-term impact of subindex stress on economic activity. Some notable features emerge

from the coefficient plots: i) In a textbook-style fashion, all estimated impact functions are upward sloping, i.e. the coefficient sums tend to increase for higher quantiles. The strongest negative impacts - in all cases statistically significant - accordingly materialise in the lowest quantiles, in line with what one would expect from a financial crisis point of view. ii) Around median quantiles the estimated coefficient sums become uniformly very small in absolute terms and lose their statistical significance. This indicates that economic activity becomes unrelated to our measures of segment-specific financial stress during periods of normal growth. iii) The coefficient sums turn positive—but in only one case statistically significant at the 95% confidence level—at the highest quantiles. This may suggest that economic boom periods tend to be associated with somewhat higher uncertainty and risk aversion among financial market participants, possibly reflecting investors’ growing concerns about the nature and duration of the boom and the eventual responses of (monetary) policy makers. iv) The impact functions look rather similar across subindices. This notwithstanding, each subindex still possesses some independent predictive power for economic activity. For this purpose we also run quantile regressions pooling all five subindices (with lags 0 to 2) as regressors. It turns out that all of them retain independent and statistically significant explanatory power in particular at the lower quantiles (results not shown).

The real-impact weights are determined from two sets of quantile regressions which differ in the specification of the dependent variable as in the case of the VARs, namely industrial production in log levels and in annual log growth rates. Moreover, in line with the notion of systemic stress, we focus attention on the lower regression quantiles. More precisely, we compute the real-impact weights for both specifications in two ways: we first calculate the average coefficient sums from the 5th to the 30th regression quantiles and determine the relative share of each subindex in the overall sum; the second method computes the weights from each subindex’ maximum absolute impact within the same

Figure 2.3: Quantile regressions for industrial production growth on CISS subindices



The lines represent the coefficient sums (for lags 0 to 2) for each of the CISS subindices, estimated for 19 equally spaced quantile functions.

range of lower quantiles.

The VARs and the quantile regressions thus provide eight different measures of the subindex weights.<sup>7</sup> Averaging across this set of weights leads to the following (rounded) subindex weights applied in the empirical part of this paper: 19 % money market, 22% bond market, 14% equity market, 25% financial intermediaries, and 20% foreign exchange market ( $w'_t = \bar{w}' = (0.19, 0.22, 0.14, 0.25, 0.20)$  in Equations 2.3 and 2.4). However, it turns out that the differences in the CISS when computed with real-impact weights or with equal weights are generally minor (see Figure A.2 in Holló, Kremer and Lo Duca 2012).

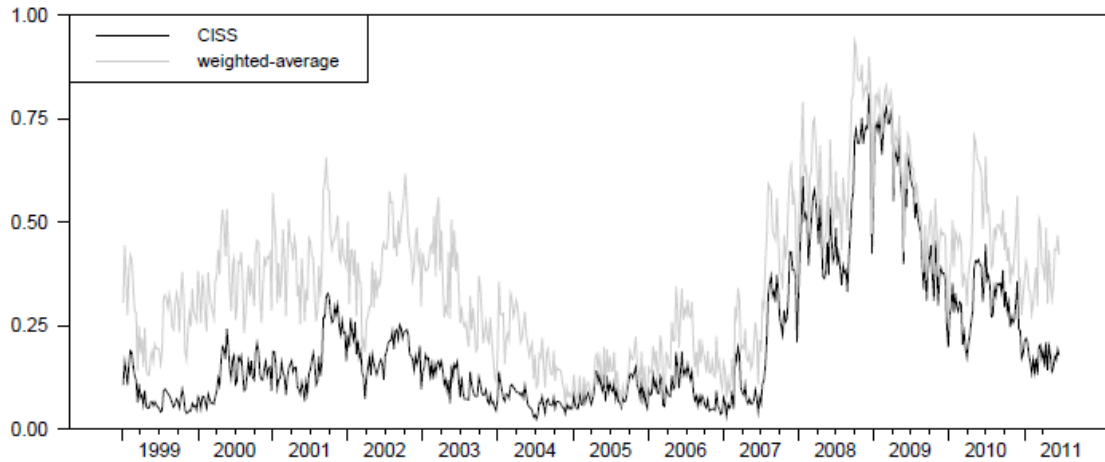
<sup>7</sup>Detailed results from the VARs and the quantile regressions are available upon request.

### 2.3.4 The euro area CISS

We have now compiled all the ingredients necessary to compute the CISS for the euro area economy according to Equation 2.3. The resulting time series of weekly data from January 1999 is plotted in Figure 2.4 as the black line. Within the portfolio-theoretic aggregation framework, the square of the simple weighted average of the five subindices, i.e.  $(\sum_{i=1}^5 w_i s_{i,t})^2$ , emerges as a special case. If all subindices were perfectly correlated all the times, the CISS and the squared weighted average would coincide. The weighted average (the grey line in Figure 2.4) thus actually serves as an upper bound of the CISS. The CISS and its perfect-correlation counterpart indeed almost overlap when correlations are generally very high. This happened, for instance, in the run-up to the crisis around 2005 at very low levels of the CISS, as well as in the aftermath of the Lehman bankruptcy at very high levels of financial stress (see Figure 2.2). Most of the time, however, correlations are quite diverse and relatively moderate such that the CISS assumes much lower levels in normal times than the simple-average composite indicator. This, in turn, suggests that the CISS helps to better identify periods of collectively high and thus systemic stress by reducing the importance of situations in which higher levels of stress remained confined within a smaller subset of the financial system. For instance, the burst of the equity market boom in early 2000 led to a protracted period of heightened stress levels in the equity markets, but it did not affect much the other system segments as evidenced by the high dispersion of the cross-subindex correlations around that time (see Figure 2.2).

The difference between the weighted average of subindices and the CISS can also be used to derive a decomposition of the CISS into the contributions coming from each of the subindices and the overall contribution from all the cross-correlations. Such a decomposition may appear particularly attractive for regular monitoring exercises

Figure 2.4: CISS versus the squared weighted-average of subindexes (perfect-correlation case)



Weekly data from 8 Jan. 1999 to 24 June 2011.

as part of the financial stability surveillance functions performed by macro-prudential authorities (see European Central Bank 2011).

We still owe a discussion of the choice to take arithmetic means of three stress factors to compute the subindices of financial stress. It can be argued that within the portfolio-theoretic framework of the CISS, the arithmetic means imply perfect correlation between all three subindex components and thus run counter to our idea of stress factors providing complementary information. This inconsistency notwithstanding, the arithmetic mean also has its respective merits for our purposes. For instance, within our three-stage aggregation framework, applying EWMA-based correlation-weights also *within* subindices would further smooth out the CISS because of the double-smoothing entailed by applying correlation-weights also *between* subindices at the final stage.<sup>8</sup> In addition, data limitations would in many cases obviate the application of portfolio-

<sup>8</sup>The problem of the double-smoothing can be avoided by computing the CISS with a two-stage framework instead of the three-stage setup chosen in the present paper. The "two-stage CISS" merges the second and the third stage by computing the full  $15 \times 15$  matrix of correlations between all transformed individual stress indicators, thereby avoiding the need to compute subindices of stress for the different market segments before computing the correlations. The two-stage CISS will be presented in currently ongoing research conducted by me.

weighting or PCA within subindices; it often happens, for example, that one only finds one or two constituent stress factors to populate a certain subindex when composing a CISS for economies with less developed financial systems, but also for advanced countries in the more distant past when data coverage was thinner.

## **2.4 Assessment of the euro area CISS**

Assessing the performance of FSIs is an inherently complicated task. First of all, the CISS, just as any other existing FSI, is far from being an ideal composite indicator in the sense that neither the selection of raw stress indicators, their transformation, nor their weighting are determined on the basis of an underlying structural model. The measurement problem is further aggravated by the fuzziness of the concepts of systemic risk and financial (in)stability, the complexity of modern-world financial systems, and the difficulties in empirically identifying certain features of financial stress. The construction of composite stress indicators thus involves many arbitrary and subjective choices. Any FSI therefore limits attention to only a few segments of the financial system, and draws on a broad array of largely imperfect measures of financial stress. In addition, reflecting the fact that financial crises are rare events (according to Reinhart and Rogoff 2009, crises occur on average about once every five years or so world wide), the data samples of FSIs are typically rather short, covering merely a few crisis episodes which severely impairs the statistical reliability of empirical analyses. The vast discrepancy between the degrees of freedom available in constructing and in testing FSIs, respectively, makes it extremely difficult to assess whether a particular indicator performs well both in absolute terms (What is a good indicator?) and in relative terms (Which indicator is better?). Against the background of these caveats, this section assesses the performance of the CISS on the basis of economic plausibility checks as well as a few statistical/econometric

criteria. In order to enlarge the set of historical crisis-like episodes, we base the analysis on a version of the euro area CISS extended backward until January 1987, i.e. including 12 years of data from the pre-EMU period (for details see Holló, Kremer and Lo Duca 2012).

### 2.4.1 Robustness

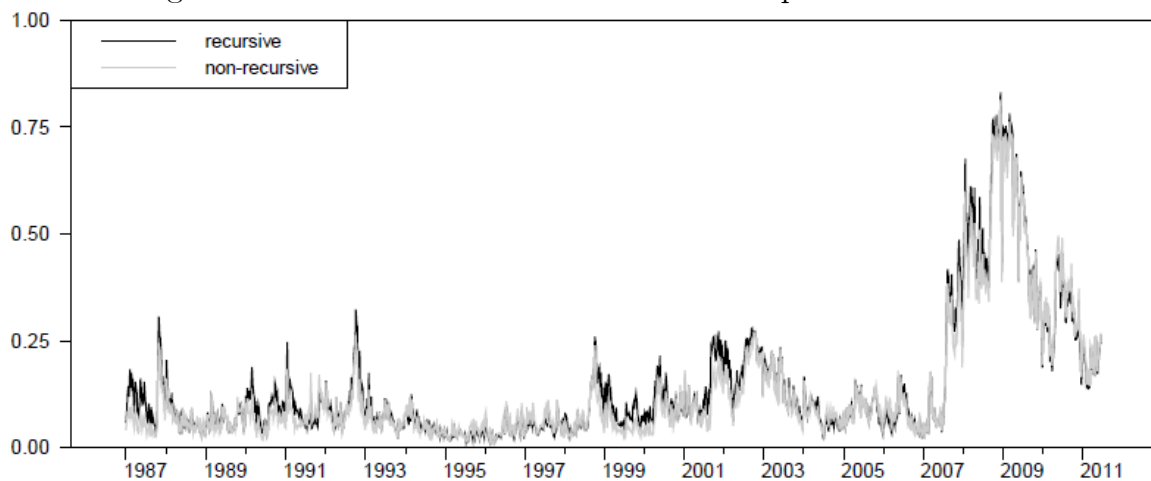
The signals issued by any FSI should be stable over time in order to avoid the so-called event reclassification problem. For instance, assume that in a particular point in time an indicator suggests that the prevailing level of stress is unusually high by historical standards. It is then desirable that the indicator still classifies this period as a particularly stressful episode say ten years hence, i.e. when ten years of data are added to the sample. Otherwise no robust historical comparison can be made, and the calculation of certain threshold levels for the indicator would not make sense either.

In order to limit the event reclassification problem from the outset, we opt for a procedure that transforms the raw indicators based on order statistics as discussed in Section 2.3.2. Figure 2.5 illustrates the robustness of the (backward-extended) CISS when computed recursively over an expanding data window (black line; recursion starting in January 1990!) and non-recursively (grey line) based on the full sample information. The two time series track each other remarkably closely. The average absolute difference amounts to only 0.015 (standard deviation: 0.022) with a mean error of 0.010. The largest deviation between the two differently computed indicators occurs in February 2008 with a value of 0.076. We therefore conclude that the CISS is a markedly robust statistic in the time dimension, implying that it is hardly affected by the event reclassification problem.<sup>9</sup>

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<sup>9</sup>This conjecture of recursive robustness receives support from ongoing own research based on the

Figure 2.5: CISS with recursive versus full-sample transformation



The version of the CISS labelled “non-recursive” uses full-sample information in the probability integral transformation of the raw stress indicators. The “recursive” CISS is the standard version which applies the transformation recursively, i.e. only using data available up to each point in time. In this example, the recursion starts in Jan. 1990. Weekly data from 2 Jan. 1987 to 24 June 2011.

As a second statistical robustness check, we compute the CISS for a range of values of the smoothing parameter  $\lambda$  that governs the speed at which the cross-correlations adjust to latest information. In Holló, Kremer and Lo Duca (2012) we compare the time series for three  $\lambda$ -values, namely 0.89, 0.93, and 0.97 (see Figure 7 therein). As expected, the CISS with the lowest smoothing parameter displays wider swings, and it spikes somewhat more pronouncedly in response to large stress shocks than our preferred CISS with an intermediate  $\lambda$ -value of 0.93. Conversely, setting the smoothing parameter to a higher level produces a CISS with dampened swings and spikes. All in all, however, the differences produced by different smoothing parameters are relatively low and, importantly, they do not alter the general pattern of behaviour of the CISS. Its basic information content, namely the broad classification of financial stress events

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euro area two-stage CISS. In this research I demonstrate that the differences between the recursively and non-recursively computed CISS are statistically insignificant. The opposite result, i.e. statistical significance of the sometimes wide gaps between the recursive and non-recursive indicator, holds true for an alternative financial stress index computed on the basis of the same set of raw stress indicators, but transformed by standardisation and merged into a composite indicator by applying principal components analysis. Results are available upon request.



or regimes, thus remains robust.

### 2.4.2 Identification of stress events

The most widely adopted criterion to evaluate financial stress indicators is their performance in identifying well-known past episodes of financial stress (stress events). Illing and Liu (2006) developed a probabilistic evaluation framework to determine which financial stress indicator concept performs best among a broader set of candidates. Their evaluation framework rests on a survey of experts to identify the most critical stress events for the Canadian economy out of 40 pre-selected potentially stressful events since the early 1980s. On the basis of the survey results, the authors construct a binary stress event indicator (crisis dummy) for use in the empirical analysis. Their preferred financial stress indicator is the one which matches best the survey results balancing Type I errors (failure to report a high-stress event) against Type II errors (falsely reporting a high-stress event).

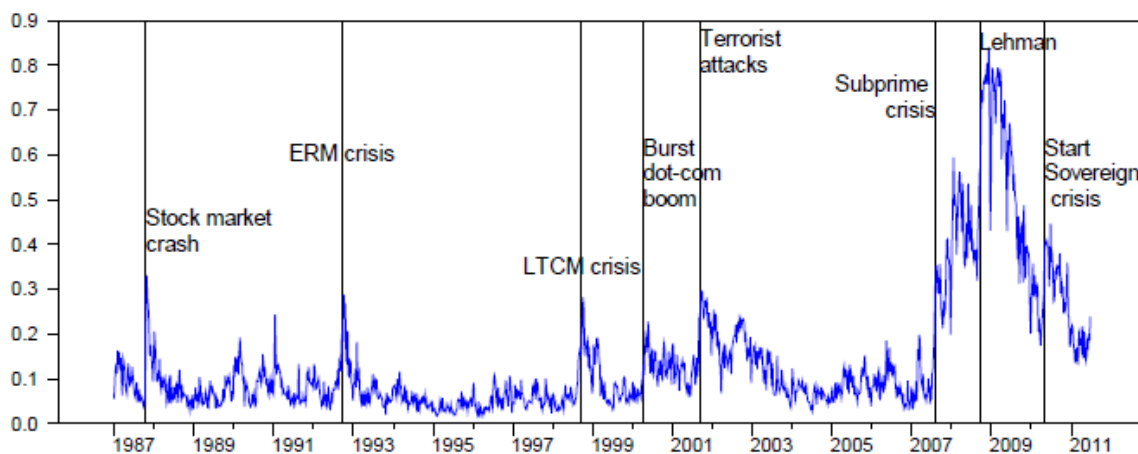
While the event-based criterion appears rather obvious and straight-forward, it also suffers from some conceptual and measurement problems. First, in a certain sense it relies on knowing a priori what the indicator is supposed to identify in the first place, namely episodes of systemic stress. Second, in particular when the data of the stress index is available at a higher frequency (say monthly or even weekly), the criterion requires knowing when a stress episode begins and, even more difficult, when it ends. Third, the mere focus on well-known stress events excludes a priori those episodes which cannot be associated with specific triggering events, but which rather build up gradually over time as a result of cumulated smaller pieces of bad news. The so-called dot-com boom and bust episode around the turn of the millennium may exemplify such a case. Hence, evaluation approaches relying on *crises defined by events* are likely to miss such

more hidden periods of systemic stress, while *crises defined by quantitative thresholds* determined on the basis of financial stress indicators are less prone to such Type I errors (on these two crises definitions see Reinhart and Rogoff 2009). In the light of these problems, we argue against relying too strongly on a formalised version of the event-criterion when studying the performance of FSIs.

We rather prefer a narrative approach like in Hakkio and Keeton (2009) to find out whether peaks in the CISS can be plausibly associated with well-known crisis events. Figure 2.6 illustrates that the sharpest spikes in the CISS indeed tend to occur around very popular events which caused, at least temporarily, severe stress in the global financial system (for a full account of the most important stress events identified by the CISS see Holló, Kremer and Lo Duca 2012). The first major stress event in the sample is the stock market crash in October 1987. On October 19, the US stock market experienced its largest one-day loss in market valuations ever, causing extreme stress in the financial industry worldwide. However, stress subsided relatively quickly when market participants realised that financial firms had been able to remain financially sound (Cardarelli, Elekdag and Lall, 2011). About five years later the European financial system was shaken by the collapse of the European Exchange Rate Mechanism (ERM). Tensions in the currency markets culminated in the British Pound and the Italian Lira eventually withdrawing from the ERM on September 16 and 17, 1992, respectively. But the financial turmoil caused by the ERM crisis again turned out rather short-lived with the CISS reverting quickly back to pre-crisis levels. It took another six years for financial stress to return to Europe in the context of the global market reactions to the Russian debt moratorium in August 1998 and the subsequent collapse of the hedge fund Long-Term Capital Management (LTCM) in September 1998.

The next period of elevated stress appears to be closely related to the downturn in

Figure 2.6: CISS and major financial stress events in the global and European financial markets



Weekly data from 8 Jan. 1999 to 24 June 2011.

high-tech stocks in early 2000. More widespread tensions occurred in the wake of the strong initial losses in the high-tech segment. The CISS remained relatively high in general over the subsequent two years fed by the continued “crash in instalments” in technology stocks (by October 2002, the NASDAQ had lost about 75% of its peak level in early March 2000) and recessions in core parts of the global economy. The terrorist attacks in the US on September 11, 2001, caused a sharp abrupt increase in the CISS in between. Investors soon realised, though, that their initial fears about the potential financial and real economic impacts of the attacks were exaggerated such that the global financial system recovered relatively quickly from this severe shock.

However, none of those previous events pushed the CISS towards similarly high levels reached during the most recent financial and economic crisis. The CISS first signalled an extreme level of stress in August 2007, when BNP Paribas suspended three investment funds that invested in asset backed securities linked to subprime mortgage debt which had become virtually illiquid. Spreading announcements of severe losses incurred by banks, mortgage lenders and other financial institutions lifted the CISS further up,

and it peaked again in response to the collapse of Bear Stearns in March 2008. The CISS experienced its largest jump in September 2008 when Lehman Brothers filed for bankruptcy protection and AIG was rescued to avoid bankruptcy. The index reached its historical maximum in November 2008 when the US plan to buy toxic assets under the Troubled Asset Relief Program (TARP) was abandoned, which undermined global market confidence. After November 2008 the CISS signalled a steady decline in financial stress until mid-April 2010 when serious concerns about sovereign credit risk in the euro area emerged.

To sum up, it appears that all extreme peaks in the CISS can be associated with specific financial stress events, suggesting that it does not suffer from type II errors. It is harder to judge whether it also performs well on the dimension of type I errors, i.e. whether there are severe crises which it failed to indicate. Potential candidates in this regard are the global bond market crisis and the Mexican peso crisis both in 1994 and the Asian crisis in 1997, for instance. The CISS suggests that these events did not trigger significant systemic stress in the euro area financial system as a whole, but rather represented more isolated tensions in specific market segments and other parts of the world economy. This view is broadly consistent with findings from the international contagion literature (e.g., Bekaert, Harvey and Ng 2005). Overall, developments in the CISS appear in general rather plausible, not least because it singles out very clearly the recent financial and economic crisis as the by far most stressful period over the past quarter of a century of available data for the euro area, comparable probably only to the Great Depression.

### 2.4.3 A threshold VAR to identify systemic crises

Financial stress indices like the CISS may help identify stress levels in the financial system which indicate elevated risks of heading towards, or having entered, a systemic crisis. Since systemic crises are regularly associated with severe contractions in economic activity, identifying such risks as early as possible is of major interest to policymakers. The literature suggests several ways to tackle this problem. One approach is to benchmark the current level of stress against levels observed during historical crises known to have caused such serious economic disruptions. An alternative is to identify quantitative thresholds or regimes for the FSI at hand on the basis of statistical or econometric methods. The most widely used approach is to classify financial stress as severe if the index exceeds its historical mean by one or more standard deviations (e.g., Illing and Liu 2006; Cardarelli, Elekdag and Lall 2011). This approach, however, manifests several shortcomings. First, it assumes that the sample means and standard deviations are stable properties of the stress index. However, this may not be the case in particular for those FSIs which use standardisation of the input series and data compression methods like principal components analysis to compute the composite index. Temporal instability of the first two moments of the index distribution may give rise to the event reclassification problem as discussed above. This risk appears particularly pronounced in the present case since in times of crisis, the new data added to the sample usually take on extreme values. Second, this approach also suffers from the ad hoc nature of the identified threshold, in the sense that it is not obvious how many standard deviations the index should exceed its mean in order to signal systemic stress.

To overcome these shortcomings, we propose applying econometric regime-switching models in order to endogenously identify periods of extreme financial stress. The basic idea behind such approaches is that the dynamics of the financial system and its inter-

actions with the real sector may be subject to multiple equilibria depending on whether the economy is in a state of financial crises and non-crisis (Hansen 2000). This may reflect the fact that the interaction between externalities (e.g., contagion), information problems (e.g., adverse selection) and certain special features of the financial sector (e.g., the existence of maturity mismatches and high leverage) can lead to powerful feedback and amplification mechanisms driving the system from a state of relative tranquility to a state of turmoil, also altering the system's normal laws of motion. In order to identify such regime changes, Holló, Kremer and Lo Duca (2012) identify three different level-regimes of the euro area CISS based on an autoregressive Markov-switching model.

In this paper we apply a threshold VAR (TVAR) model that captures, in a stylised fashion, regime-dependent dynamic interactions between financial stress and the real economy. The regimes are identified on the basis of an estimated threshold of the CISS based on the idea that financial stress becomes a cause of major concern when it adversely impacts on the real economy, thereby integrating the *vertical view* of our favoured definition of systemic risk. According to this viewpoint, we would expect that economic activity drops sharply whenever the CISS reaches a certain critical level. One major advantage of such an estimated threshold level of the CISS and the corresponding regime classification consists in its direct economic interpretation.

In general, threshold regression models represent a class of regime-switching which assumes that state transitions are triggered any time an observable variable crosses a certain threshold level (Franses and van Dijk 2000). We assume a priori that the CISS is the relevant threshold variable and that at most two regimes and therefore one single threshold exists. We follow Tsay (1998) and identify potential threshold effects within a bivariate TVAR with the CISS ( $C_t$ ) and annual growth in industrial production ( $y_t$ ) as the endogenous variables. Anticipating a shortage of degrees of freedom in the high-

stress regime recommends a specification of the TVAR as parsimonious as possible. Hence, we also opt for the shortest lag-order suggested by standard specification tests. While information criteria (weakly) prefer a higher lag order (four lags), an exclusion F-Test suggests that a VAR with two lags may suffice. The basic regression setup is as follows:

$$x_t = \alpha^H + \Phi_1^H x_{t-1} + \Phi_2^H x_{t-2} + \epsilon_t^H \quad \text{if} \quad z_{t-d} > \tau \quad (2.7)$$

$$x_t = \alpha^L + \Phi_1^L x_{t-1} + \Phi_2^L x_{t-2} + \epsilon_t^L \quad \text{if} \quad z_{t-d} \leq \tau \quad (2.8)$$

with  $x_t = (C_t, y_t)'$  a two-dimensional vector;  $\alpha^s$  and  $\Phi_j^s$  the vector of intercepts and the two matrices collecting the slope coefficients, respectively, for states  $s = \{H, L\}$  (with  $H$  and  $L$  standing for high-stress and low-stress regimes, respectively) and lags  $j = \{1, 2\}$ . The threshold variable is denoted  $z_{t-d}$  with  $d \in \{1, \dots, d_0\}$  and  $d_0 = 2$  the maximum threshold lag or *delay* foreseen. The threshold parameter is labelled  $\tau$  and the vector  $\epsilon_t^s$  contains the state-dependent regression errors with variance-covariance matrices  $\Sigma^s$ . As mentioned above, the once or twice lagged CISS plays the role of the threshold variable exciting the switches in regimes any time it crosses the threshold  $\tau$ .

Tsay (1998) proposed a two-step conditional least squares procedure to estimate this TVAR under the assumption that the lag order, the number of states and the threshold variable are all known. It is furthermore assumed that  $z_{t-d}$  is stationary and continuous with a positive density function on a bounded subset of the real line. As the first step, for given  $d$  and  $\tau$ , the model parameters  $\alpha^s$ ,  $\Phi_j^s$  and  $\Sigma^s$  can be estimated by ordinary least squares. Given the parameter estimates, Tsay (1998) developed test procedures to determine  $d$  and  $\tau$  simultaneously. The main criterion of the selection procedure is Tsay's  $C(d)$ -Statistic testing for statistically significant threshold effects in the VAR. The  $C(d)$ -Statistic is asymptotically chi-squared distributed, and results for  $d = 1$  and  $d = 2$  (i.e., the once and twice lagged CISS as the threshold variable) are shown in Table

Table 2.2: Testing for threshold delay and threshold values

$d$	Tsay (1998)-Test				Hansen (2000)-Test		
	$C(d)$ -Stat	$p$ -value	$\tau$	AIC	$F$ -Stat	$p$ -value	$\tau$
1	20.03	0.0166	0.2960	-2741	13.46	0.0000	0.2957
2	19.24	0.0402	0.3233	-2766	12.59	0.0000	0.2747

$d$  denotes the threshold delay and  $\tau$  the threshold value. AIC is the Akaike information criterion. The  $C(d)$ -Statistic tests for a threshold in the  $d$ -lagged CISS within a bivariate TVAR(2) for the CISS and annual industrial production growth. The  $F$ -Statistic tests for a threshold effect in the production growth equation only. Estimation with monthly data Jan. 1987 to June 2011.

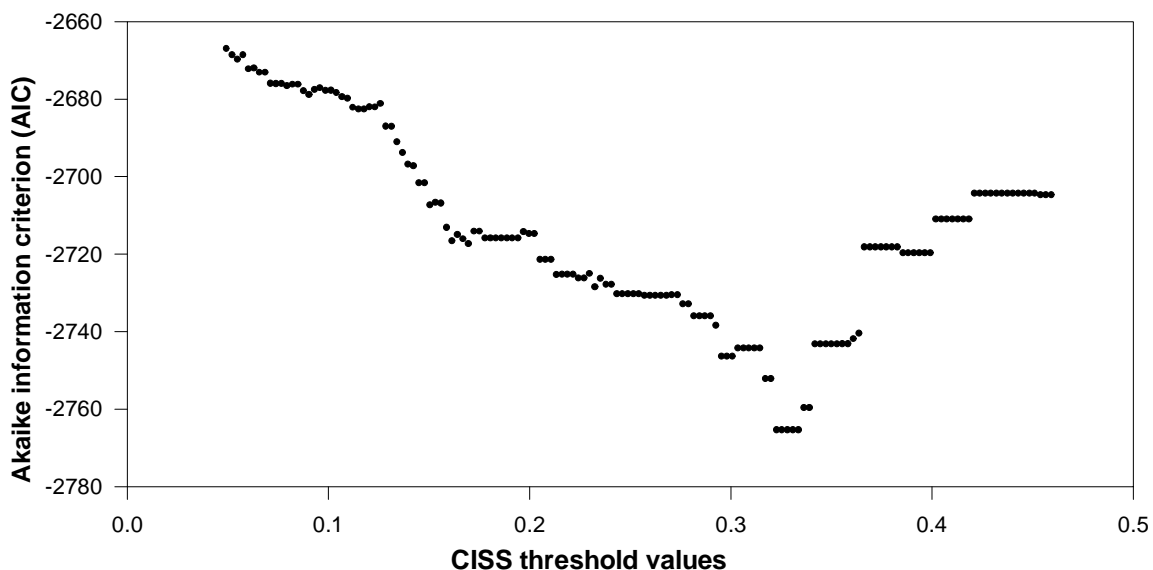
2.2. In both cases the  $C(d)$ -Statistic clearly rejects the null hypothesis of no-threshold effects (linear VAR against TVAR) with  $p$ -values below the 5%-confidence level. The optimal threshold value for each  $d$  is determined by a grid search procedure (over a range of CISS values) which minimises the Akaike information criterion (AIC). The optimal specification is found to be a TVAR(2) model with the twice lagged CISS ( $d = 2$ ) as the threshold variable and an estimated threshold value of 0.3233 (Figure 2.7 plots the results of the grid search procedure). This is suggested by the fact that the AIC is lower for  $d = 2$  than for  $d = 1$  (see the fifth column in Table 2.2).

As a robustness check, we also perform Hansen's (2000) test for thresholds in a single-equation regression of output growth on a constant, two of its own lags and the CISS with the same lag length. This regression can thus be regarded as one equation of the bivariate TVAR model. Hansen developed an F-Test for the existence of threshold effects. The test results are shown in the last three columns of Table 2.2, clearly suggesting the existence of statistically significant threshold effects with threshold values very similar to those from the Tsay-procedure.

Equipped with a fully specified and estimated TVAR model we are now in a position to assess whether the effects of the identified threshold of the CISS are both qualitatively and quantitatively consistent with our expectation that particularly high levels



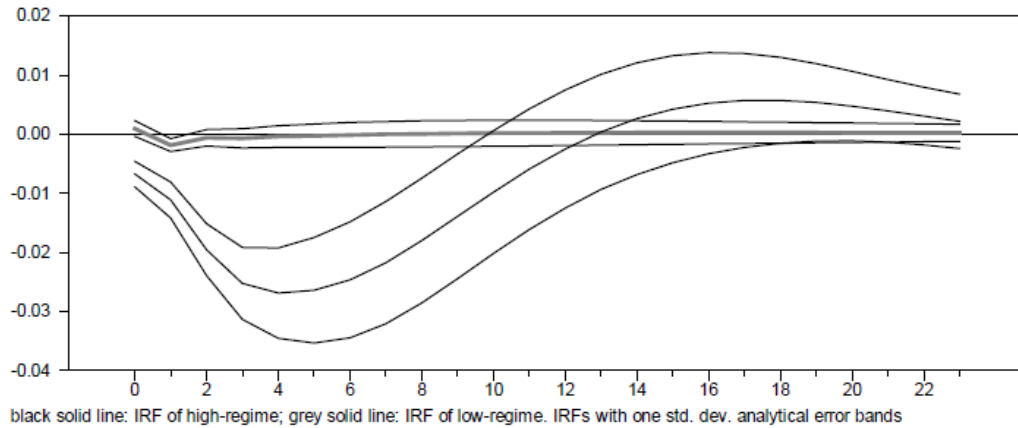
Figure 2.7: Threshold estimation based on the AIC for the null hypothesis VAR(2) vs TVAR(2)



of financial stress tend to depress economic activity. Visual inspection of a scatter plot relating output growth to the twice lagged CISS seems to vindicate this expectation (see Figure A.4 in Holló, Kremer and Lo Duca 2012). While at lower levels of the CISS (non-crisis times) the scatter plot appears purely random, at higher levels of the CISS a clear negative relationship emerges between industrial production growth and financial stress.

In order to substantiate this claim further we compute the impulse response functions (IRFs) from the estimated TVAR-coefficients separately for the high-stress and the low-stress regimes. Of course, computing conventional IRFs in non-linear VARs ignores their history- and shock-dependence in such setups and are therefore valid only under certain assumptions (Koop, Pesaran and Potter 1996). Figure 2.8 displays the two state-dependent IRFs of industrial production growth for a uniform one-standard deviation structural shock in the CISS from the high-stress regime. The dotted lines around the IRFs represent analytical one-standard-deviation error bands (Lütkepohl 1990). The

Figure 2.8: Regime-dependent impulse response functions for output growth to CISS shocks



Impulse response functions (IRF) from a bivariate threshold-VAR model with 2 lags, one threshold (two regimes) and the CISS and annual growth in industrial production for the euro area as endogenous variables. High-stress regime occurs when the CISS (twice lagged) stands at or above a threshold value of 0.3233, and the low-stress regime prevails below the threshold. IRFs for orthogonalised innovations (Cholesky factorisation) with CISS ordered first. IRFs of the low-stress regime rescaled to the typical size (one standard deviation) of CISS innovations from the high-stress regime. Estimation based on monthly data from Jan. 1987 to June 2011.

structural innovations are obtained from the triangular Cholesky-factorisation of the variance-covariance matrix of residuals. The endogenous variables are ordered in such a way (CISS first, output second) that shocks in the CISS can have a contemporaneous impact on economic output but not conversely. This structural shock identification can be justified from an information perspective, for instance. Owing to the lag in the publication of the euro area industrial production index (released in the second third of the second month following the reference month), one may argue that the output innovation of a given month cannot be perfectly predicted by financial market participants, in turn implying that they cannot be fully reflected in contemporaneous asset prices either. In addition, it may appear plausible to assume that CISS shocks tend to originate mainly from within the financial sector particularly during crisis times, and that producers react quickly to increased uncertainty with a rapid drop in aggregate output reflecting a (temporary) pause in their investment and labour hiring decisions (as

in Bloom 2009). However, since our favoured structural identification scheme may not always properly describe the true causal ordering, the IRFs may be better interpreted as an upper bound (in absolute terms) of the output reactions to shocks in the CISS. This notwithstanding, the qualitative results from the impulse-response analysis remain robust to a reverse ordering of variables.

Figure 2.8 indeed confirms our expectations that the real economic impacts of financial stress are in fact dramatically different across the two regimes. While shocks in the CISS do not exert statistically significant reactions in output over whatever horizon during low-stress regimes, industrial production virtually collapses in response to a large positive CISS shock in the high-stress regimes. The maximum impact is reached after four months, when annual output declines by about 2.7% in response to an initial shock in the CISS of 0.06. It takes about a year for the marginal effects to taper off. Similarly, it is only during high stress regimes that, for instance, a negative output shock leads to a subsequent increase in financial stress (see Table 2.3 and Figure A.5 in Holló, Kremer and Lo Duca 2012, for the full set of IRFs in the high-stress regime). Taken together, these mutual reaction patterns seem to suggest that when hit by a sufficiently large (financial or real) shock, an economy faces the risk of entering a vicious downward spiral with financial and economic stress reinforcing each other over time, a finding which could be explained theoretically by some financial accelerator mechanism (e.g., as in Bernanke, Gertler and Gilchrist 1999).

In contrast, during normal times with low financial stress the CISS may become a negligible quantity as evidenced by the absence of statistically significant cross-equation relationships in this regime according to standard exclusion F-Tests. Accordingly, in the low-stress regime the bivariate VAR more or less degenerates into a set of two independent autoregressions. The IRFs point in the same direction.

Table 2.3: Parameter estimates of the TVAR(2) model

	High-stress regime		Low-stress regime	
	$C_t$	$y_t$	$C_t$	$y_t$
Constant	0.2171 (2.8863)	0.0650 (3.5790)	0.0161 (3.5123)	0.0019 (1.1221)
$C_{t-1}$	0.9296 (5.3965)	-0.0938 (2.2556)	0.9022 (14.7494)	-0.0401 (1.7711)
$C_{t-2}$	-0.4106 (1.9639)	-0.0749 (1.4846)	-0.0652 (0.9948)	0.0386 (1.5936)
$y_{t-1}$	-2.2133 (2.6935)	0.8239 (4.1551)	0.1273 (0.8282)	0.5827 (10.2482)
$y_{t-2}$	1.8947 (2.7918)	-0.0932 (0.5693)	-0.1073 (0.7051)	0.3510 (6.2343)
$\sigma$	0.0594	0.0126	0.0337	0.0125
Exclusion F-tests (p-value)				
lagged $C$	15.63 (0.0000)	8.49 (0.0014)	336.69 (0.0000)	1.59 (0.2069)
lagged $y$	3.90 (0.0330)	82.89 (0.0000)	0.34 (0.7093)	553.33 (0.0000)

TVAR(2) denotes bivariate threshold-VAR for the CISS ( $C_t$ ) and annual growth in industrial production ( $y_t$ ), with 2 lags and one threshold for the CISS with 2 lags. High-stress regime occurs when the lagged CISS is at or above the estimated threshold. Estimation based on monthly data from Jan. 1987 to June 2011.

We conclude this section with adding some words of caution. Any econometric analysis of financial stress indicators in the time series dimension must suffer from the low number of crisis events and the resulting lack of statistical degrees of freedom. Financial crises are rare events, and even more so are the truly systemic ones with effects as devastating as in the case of the present crisis. Hence, the results obtained from the threshold VAR are clearly dominated by the dynamics observed during the recent crisis and therefore may not claim generality.

## 2.5 Conclusions

The recent financial and economic crisis revealed considerable gaps in the theoretical underpinning and the empirical toolkits available to analyse and monitor financial stability in general and systemic risk in particular. Academics and financial authorities all around the globe have been stepping up efforts to improve the suit of tools and models in this field accordingly. This paper contributes to this branch of literature by proposing a new composite indicator of systemic financial stress, called CISS, which aims to measure the contemporaneous state of instability in the financial system as a whole; it can therefore be interpreted as a measure of systemic risk which has materialised already. The main distinguishing features of the CISS are its explicit foundation on standard definitions of systemic risk and, as its main methodological innovation, the application of portfolio-theoretic principles to the aggregation of individual financial stress indicators into the composite indicator. We also propose a parsimonious econometric approach to estimate a critical level of the indicator as the endogenous outcome of a threshold VAR. Its statistical robustness to computation over expanding samples ensures that past signals issued by the CISS remain valid also at later points in time. The CISS can be updated quickly on a weekly basis and is thus particularly suitable for real-time surveillance tasks as typically conducted in central banks and other macroprudential authorities.

As to the way forward, several companion projects are ongoing or can be envisaged. For instance, an expansion of the geographical coverage of the CISS promises to lead to a better understanding and assessment of its indicator properties, for instance through econometric analysis that also exploits the cross-country dimension. In a single-country context, the dynamic interactions between financial stress and the real economy should be more thoroughly investigated within richer non-linear econometric model setups as in Hubrich and Tetlow (2015) and Hartmann, Hubrich, Kremer and Tetlow (2015).

In addition, the development of adequate evaluation criteria for running horse races between different financial stress indices would be highly welcome by the profession.

## CHAPTER 3

# MACROECONOMIC EFFECTS OF FINANCIAL STRESS AND THE ROLE OF MONETARY POLICY: A VAR ANALYSIS FOR THE EURO AREA

**Abstract:** This paper analyses a macro-financial VAR model for the euro area that includes—apart from conventional measures of output, inflation and monetary policy—a composite indicator of systemic financial stress, namely the CISS index, and total assets of the ECB balance sheet capturing the stance of unconventional monetary policy. I find that the CISS contributes significantly to the dynamics of the macroeconomy, and exerts a strong influence on monetary policy when looking at both policy rates and the ECB balance sheet. The significance of the CISS appears robust against the inclusion of a broad set of real and financial control variables. Based on tests of direct versus indirect (Granger-)causality patterns proposed in Hsiao (1982), I also find that unlike unconventional policy as measured by ECB balance sheet growth, the policy rate does not seem to react directly to variations in financial stress, but rather indirectly through the impact of financial stress on macroeconomic conditions. These different patterns of reaction are broadly consistent with the ECB’s “separation principle”. The estimated effects of the ECB’s standard and non-standard policy measures on inflation and economic growth are moderate, although an easier stance in both policy tools helps calm financial stress.<sup>‡</sup>

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<sup>‡</sup>This chapter is a revised version of the article published under the same title in *International Economics and Economic Policy*, Vol. 13, 2016, pp. 105–138 (<http://link.springer.com/article/10.1007/s10368-015-0325-z>). I thank the journal editor, Paul J.J. Welfens, my discussant Cillian Ryan (University of Birmingham), and seminar participants at the joint bdrv Research Institute/EIWW at the University of Wuppertal International Conference 2014 in Düsseldorf, the 35th International Symposium on Forecasting in Riverside, and the 2nd Annual Conference of the International Association for Applied Econometrics (IAAE) in Thessaloniki for

### 3.1 Introduction

Financial systems perform essential functions for an economy to create sustainable growth, employment and social welfare. This basic matter of fact becomes all too evident in systemic financial crises, when financial instability gets so severe and widespread that the process of financial intermediation virtually grinds to a halt, causing major losses in economic activity, rises in unemployment and, sometimes, even social and political instability. The recent Great Financial Crisis and the associated Great Recession are prime examples of such a major systemic event, being generally regarded as second only to the Great Depression of the 1930s. Systemic crises bear the risk that strains in the financial and real sectors reinforce each other without a self-correcting mechanism at play that could reverse the vicious circle. Stopping such adverse dynamics and stabilising the financial system therefore seems to require bold and often unconventional policy interventions by public authorities including central banks.

Against this background, this paper models empirically the dynamic interactions between financial instability and the macroeconomy, and assesses the role played by standard and non-standard monetary policy measures within this context. To this end, I estimate an otherwise standard macro-financial multivariate time series model (a vector autoregression model (VAR)) applied to euro area data that includes—apart from conventional measures of economic output, inflation and monetary policy—a composite indicator measuring the state of systemic financial stress or instability, namely the *Composite Indicator of Systemic Stress* (CISS), as well as the size (total assets) of the European Central Bank’s (ECB) balance sheet as endogenous variables. The latter variable shall capture the overall stance of the various forms of unconventional monetary policy measures taken by the ECB during the crisis in pursuit of its political mandate.

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fruitful discussions and comments. However, the views expressed in this paper are mine and do not necessarily reflect those of the European Central Bank or the Eurosystem.



The structural shocks are identified by applying the recursive Cholesky decomposition with the conventional ordering of real macro variables before financial and monetary policy variables. However, it turns out that all the main results of the model are robust to different orderings.

I find, first, that the CISS is an important predictor for the core variables in the system, namely for output growth, monetary policy interest rates and, but less so, for inflation. This predictive ability is confirmed by standard exclusion tests, impulse-response functions, forecast error variance decompositions, and by counterfactual simulations. Block exogeneity tests suggest that the predictive power remains robust to the inclusion of a broad set of real and financial control variables, thereby ruling out spurious causality of the CISS for macroeconomic developments, conditional on this specific set of controls.

Second, the monetary policy rate and the ECB balance sheet growth rate are found to respond significantly to CISS shocks with the expected signs, i.e. the policy rate decreases and the balance sheet expands in reaction to an unpredicted increase in financial stress. Applying the tests of direct and indirect (Granger-)causality put forward in Hsiao (1982), I furthermore find that the monetary policy rate responds to variations in the CISS only indirectly, whereas the ECB balance sheet reacts directly. The indirect lagged reaction of the policy interest rate seems to reflect some genuine information contained in the CISS about the expected course of the economy. This pattern of direct responses of the ECB balance sheet in combination with indirect reactions of the policy rate to variations in financial stress may lend support to the view that the ECB's standard and non-standard monetary policies during the crisis were effectively guided by its declared "separation principle."

Third, the cumulated structural policy rate shocks suggest that the stance of con-

ventional monetary policy may have become constrained by the zero lower bound in 2013.

Fourth, an expansionary stance in the ECB's conventional and unconventional monetary policy tools seems to provide some moderate support to economic activity over the medium-term, whereas no visible impact on inflation is found. In addition, an easier monetary policy also helps calm financial stress.

The paper contributes to three main strands of literature. The first one estimates the macroeconomic effects, foremost the output losses, associated with periods of financial instability as captured by specifically designed composite financial stress indices. The effects are usually estimated within bivariate or higher-dimensional macro-financial VAR models. Examples are Davig and Hakkio (2010) and Hubrich and Tetlow (2015) for the United States; Holló, Kremer and Lo Duca (2012), Mallick and Sousa (2013) and Hartmann, Hubrich, Kremer and Tetlow (2015) for the euro area; van Roye (2014) for Germany; Aboura and van Roye (2013) for France; Li and St-Amant (2010) for Canada; as well as Cardarelli, Elekdagb and Lall (2011), Doovern and van Roye (2014) and Mittnik and Semmler (2014) in multi-country settings. While some of these papers study the robustness of the macroeconomic effects of financial stress over time by applying regime-switching methods, none assesses the robustness of the respective financial stress index's explanatory power against the inclusion of alternative indicators of financial stress, financial conditions or the business cycle.

Second, the paper adds empirical evidence to the question as to whether central banks tend to respond to financial stress by changing monetary policy interest rates accordingly. From the papers just listed, Hubrich and Tetlow (2015) address this issue explicitly for the U.S. case. For a short overview of the broader literature see Adrian and Liang (2014). Some of the most relevant papers cited therein are briefly summarised

in Section 3.5.1. The value added of my paper rests on exploring the robustness of the estimated impacts of financial stress on the ECB's setting of monetary policy interest rates against the addition of competing explanatory variables from the financial and real sphere. My paper also distinguishes between potential direct and indirect effects of financial stress on the policy rate from the perspective of an implicit reaction function estimated as part of the VAR.

Third, this paper also complements the literature that estimates the macroeconomic effects of unconventional monetary policy measures (see, e.g., Lenza, Pill and Reichlin 2010; Peersman 2011; Giannone, Lenza, Pill and Reichlin 2012; Kapetanios, Mumtaz, Stevens and Theodoridis 2012; Fahr, Motto, Rostagno, Smets and Tristani 2013; Ciccarelli, Maddaloni and Peydro 2013; Gambacorta, Hofmann and Peersman 2014; and Boeckx, Dossche and Peersman 2014). In contrast to existing studies, this paper focuses on the robustness of the central bank's balance sheet reaction to financial stress, as well as on the potential feedback effects of unconventional monetary policy on financial stability conditions.

The paper is organised as follows. Section 3.2 describes the rationale, the design and some basic features of the CISS as a composite measure of financial (in-)stability. Section 3.3 details the specification of the benchmark VAR model for the euro area, and the identification of the structural shocks. Section 3.4 presents the first set of results which focuses on the strength and the robustness of the predictive power of the CISS. Section 3.5 discusses how the ECB reacts to financial instability by changing its conventional and unconventional monetary policy stance, and how the identified standard and nonstandard monetary policy shocks feed back to financial stress and the real economy. Section 3.6 summarises a few caveats to the empirical analysis before Section 3.7 concludes.

## 3.2 Measuring systemic financial instability

The main contribution of this paper rests, first, on an adequate empirical representation of systemic financial (in-)stability and, second, on a meaningful integration of the proposed measure of financial instability into an empirical macro model.

As to the first point, I employ the CISS recently developed by me and two collaborators at the ECB (Holló, Kremer and Lo Duca 2012; see also Chapter 2 of this dissertation).<sup>1</sup> The CISS is part of the family of so-called financial stress indexes (see Illing and Liu 2006, and Kliesen, Owyang and Vermann 2012, for overviews). Such indices aim to quantify the current state of financial instability, i.e. the prevailing level of frictions and strains (“stresses”) in the financial system, by aggregating a certain number of individual stress indicators into a single composite indicator.

The design of the CISS concentrates on capturing the *systemic* dimension of financial instability. It does so by, first, covering the main classes of financial markets and intermediaries in a systematic fashion and, second, by considering the time-varying dependence of stress between these major segments of the financial system. First of all, the scope of the CISS is broad, comprising five aggregate market segments covering the main channels by which the funds of savers are reallocated to borrowers, whether those funds are channeled indirectly through financial intermediaries or directly via short-term and long-term markets. These segments include: (1) financial intermediaries; (2) money markets; (3) bond markets; (4) equity markets; and (5) foreign exchange markets. Each of the five market segments is populated with three representative stress indicators that tend to capture typical crisis symptoms, such as risk and liquidity spreads, volatili-

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<sup>1</sup>The CISS project formed part of the Macro-prudential Research Network (MaRs) among researchers of the European System of Central Banks. The network aimed to develop core conceptual frameworks, models and tools to provide analytical support to macro-prudential supervision in the European Union (see [http://www.ecb.europa.eu/home/html/researcher\\_mars.en.html](http://www.ecb.europa.eu/home/html/researcher_mars.en.html)).

ties, and cumulative price losses. Aggregation of each set of three constituent stress measures—after appropriate transformation to harmonise their scale and probability distribution<sup>2</sup>—results in five segment-specific subindices of financial stress.

The way the subindices are aggregated into a composite indicator is the main distinguishing feature of the CISS. In the same way that portfolio risk is computed from individual asset risks, the subindices are aggregated by taking into account the time-varying (rank)-correlations between them. The time variation in the correlations means that relatively more weight is applied during periods in which stress prevails in several market segments at the same time. In this way, the CISS is specifically designed to describe how widespread and severe instability in the financial system has become at any one time. It is presumably when stress is widespread that it has implications for the broader macroeconomy. Indeed, a conventional definition of systemic risk says that it is “(...) *the risk that instability becomes so widespread within the financial system that it impairs its functioning to the point where economic growth and welfare suffer materially*” (de Bandt and Hartmann 2000).

The final indicator, as constructed from euro area data, is shown in Section 3.5 as the grey shaded areas in Figures 3.3 and 3.6. One can easily see that the recent crisis stands out in comparison with previous stress events in terms of both the levels reached and the duration of high readings.<sup>3</sup>

Regarding the second issue, namely the integration of the CISS into an empirical macro framework, I assume that the dynamics of systemic financial stress and its interaction with certain macro and monetary policy variables can be modeled as a linear

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<sup>2</sup>Each of the raw indicators is transformed using its empirical cumulative distribution function (ecdf), that is each observation is replaced by its ecdf value. This transformation is also called the probability integral transform (see, e.g., Spanos 1999). All transformed indicators are bounded by the interval (0,1] and uniform distributed. See Hollo, Kremer and Lo Duca (2012) and Chapter 2 of this dissertation for details.

<sup>3</sup>See Figure 2.6 for a longer times series of the euro area CISS starting back in 1987.

multivariate stochastic time series process. I therefore simply add the CISS to the list of endogeneous variables of an otherwise standard macro-financial VAR in order to address the research questions put forward in this paper. Such an approach remains agnostic when it comes to the origins and specific transmission channels of financial instability. However, regardless of the origins, for financial stress to cause major disruptions in the economy, it must eventually be widespread. Thus, integrating a composite indicator of systemic stress into a VAR can have the advantage that it builds on what systemic crises have in common, namely instability that spreads widely across markets and institutions.

### 3.3 Specification and identification of the VAR

#### 3.3.1 Specification

The general starting point for the empirical analysis is the reduced-form representation of a linear VAR with exogenous variables (VARX):

$$y_t = C + A_1 y_{t-1} + \dots + A_p y_{t-p} + B_1 x_{t-1} + \dots + B_p x_{t-p} + \varepsilon_t \quad (3.1)$$

with  $t = 1, \dots, T$  and  $T$  being the sample size;  $y$  is an  $n \times 1$  vector of endogeneous variables,  $x$  is an  $m \times 1$  vector of exogenous variables,  $C$  is an  $n \times 1$  vector of regression constants,  $A_l$  (with elements  $a_{ij,l}$ ) and  $B_l$  (with elements  $b_{ij,l}$ ) are  $n \times n$  and  $n \times m$  matrices respectively of regression coefficients for lags  $l = 1, \dots, p$  and  $p$  the number of lags included in the model;  $\varepsilon$  is an  $n \times 1$  vector of reduced-form shocks with assumed distribution  $\varepsilon_t \sim i.i.d. N(0, \Omega)$ . The coefficients  $C$ ,  $A_l$  and  $B_l$  are estimated by running ordinary least squares regressions equation by equation, and the variance-covariance matrix is estimated from the sample residuals as  $\Omega = (1/T) \sum_{t=1}^T \varepsilon_t \varepsilon_t'$ . The VARX model will be used to perform the block exogeneity tests in Section 3.4.

The benchmark model—from which most of the results presented in this paper are derived—is estimated for euro area data at the monthly frequency, and covers the period from the introduction of the euro in January 1999 to December 2013. The model has four lags ( $p = 4$ ) and contains six endogenous variables ( $n = 6$ ), but no exogenous variables ( $m = 0$ ), yielding a standard linear VAR in reduced form:

$$y_t = C + A_1 y_{t-1} + \dots + A_p y_{t-p} + \varepsilon_t. \quad (3.2)$$

Three of the endogenous variables represent a block of core variables included in all standard monetary policy VARs of the literature: a measure of the aggregate price level, a measure of aggregate economic activity and a short-term interest rate measuring the stance of conventional monetary policy. Prices are measured by the seasonally adjusted *Harmonised Index of Consumer Prices* (HICP), economic activity by the seasonally adjusted real gross domestic product (GDP), and conventional monetary policy by the marginal interest rate applied by the ECB in the Eurosystem’s main refinancing operations (MRO), i.e. its regular open market operations. The original quarterly real GDP data is interpolated into the monthly frequency by state-space methods, using industrial production as an interpolator variable and assuming that the interpolation error can be described as a log-linear ARIMA(1,1,0) process as in Litterman (1983).<sup>4</sup>

These core model variables are complemented by three additional endogenous variables which are less common in the literature: (i) the square root of the CISS as the proposed summary measure of financial instability<sup>5</sup>; (ii) total assets of the ECB’s balance sheet as a measure of, among other things, the overall stance of the various forms of unconventional monetary policy measures taken by the ECB; and (iii) the spread be-

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<sup>4</sup>Estimation is implemented using the procedure DISAGGREGATE.SRC in WinRATS version 8.0.

<sup>5</sup>I take the square root of the CISS to control for potential nonlinearities arising from the quadratic form of the formula with which the CISS is computed. The square root of the CISS is what has been called the “volatility-equivalent” CISS versus its standard “variance-equivalent” form as published by the ECB (see Hollo, Kremer and Lo Duca 2012). However, all the basic messages of the empirical analysis presented in this paper do not alter when using the standard CISS instead.

tween the *euro overnight index average* (EONIA) and the MRO rate, where the EONIA measures the effective interest rate prevailing in the euro interbank overnight market. This spread shall help interpret the identified structural monetary policy shocks. All raw data are taken from the ECB's Statistical Data Warehouse.<sup>6</sup>

While Boeckx, Dossche and Peersman (2014) use consumer prices, real GDP and ECB total assets in log levels, I prefer to transform these variables by taking annual log differences. Annual differences control for potential (remaining) additive seasonality in the data and, more importantly, remove the upward drift in the log levels of these series. Although coefficients are consistently estimated for a VAR in non-stationary log levels, all the standard errors and derived test statistics are not. This would likely pose a more serious problem in the block exogeneity tests performed in the next section than in the case of using annual differences.

### 3.3.2 Identification

The regression residuals are unidentified and generally correlated with each other which prevents us from giving them a structural economic interpretation. In order to achieve an economic interpretation of the prediction errors, we have to impose certain identifying restrictions on them. In this paper, I identify the structural shocks using the well-known Cholesky decomposition.<sup>7</sup> It starts with the unique triangular factorisation of the variance-covariance matrix of the regression innovations:  $\Omega = ADA'$ , with  $A$  being a lower triangular  $n \times n$  matrix with 1s along the principal diagonal and  $D$  a diagonal  $n \times n$  matrix. The structural shocks  $u_t$  can be computed from the residuals  $\varepsilon_t$  as  $u_t = A^{-1}\varepsilon_t$  such that elements  $d_{ii}$  of  $D$  denote the variances of the structural shocks  $u_{it}$ . Since  $D$  is

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<sup>6</sup>Regular updates of the weekly CISS can be obtained via this link: <http://sdw.ecb.europa.eu/browse.do?node=9551138>.

<sup>7</sup>For an overview of different identifying assumptions see Christiano, Eichenbaum and Evans (1999).



diagonal, one set of identifying restrictions assumes that the structural shocks, i.e. the fundamental economic shocks, are orthogonal to each other.<sup>8</sup> The matrix  $A$  imposes the remaining restrictions to just-identify the system of shocks. Its triangular form implies a recursive shock identification such that the order in which the endogenous variables enter the VAR becomes relevant.

To illustrate that point, we premultiply both sides of the equation  $u_t = A^{-1}\varepsilon_t$  by  $A$  to yield  $Au_t = \varepsilon_t$ . It can be seen that the lower off-diagonal coefficients  $a_{ij}$  measure the contemporaneous impact of a structural shock in the  $j$ -th variable on the reduced-form shock of the  $i$ -th variable. The first structural shock  $u_{1t}$  is identical to the residual  $\varepsilon_{1t}$  from the first equation of the VAR. The second structural shock  $u_{2t}$  can now be obtained as the residual of a linear projection of  $\varepsilon_{2t}$  on the first structural shock  $u_{1t} = \varepsilon_{1t}$ :  $E(\varepsilon_{2t}|u_{1t}) = a_{21}u_{1t}$ . Given the recursive structure of the system, the remaining structural shocks  $u_{jt}$  can be estimated from the OLS regressions  $E(\varepsilon_{jt}|u_{1t}, u_{2t}, \dots, u_{j-1t}) = a_{j1}u_{1t} + a_{j2}u_{2t} + \dots + a_{j,j-1}u_{j-1t}$  (see Hamilton 1994).

The structural shocks for the benchmark VAR are identified largely in line with the most common practice in the literature (see Christiano, Eichenbaum and Evans 1999 for an overview of different identification approaches and their economic rationale). I first assume that the variables in the “real economy block” (inflation and real GDP growth) do not respond contemporaneously to the financial variables (but with a lag of at least one month), where the latter include the CISS and the series forming the “monetary policy block” (MRO rate, ECB balance sheet growth and the EONIA-MRO rate spread). By contrast, the monetary policy variables are allowed to react instantaneously to shocks in inflation, output and the CISS, implicitly assuming that current realisations of these variables are part of the information set available to the ECB’s decision making body, the Governing Council, when it sets its monetary policy instruments in a

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<sup>8</sup>The structural shocks are thus distributed as  $u_t \sim i.i.d. N(0, D)$ .

given month. These assumptions imply that the real-block variables are ordered before all the financial variables, and that the CISS appears before the policy block. Within the real sector block, I order inflation before real GDP growth.<sup>9</sup> Finally, the monetary policy block follows the order MRO rate, ECB balance sheet and the EONIA-MRO rate spread according to two main arguments. First, I assume that in each month the MRO rate is set independently of factors moving the size of the ECB balance sheet, such as banks' liquidity needs or the ECB's acquisition of certain assets. On the one hand, this assumption implies that conventional monetary policy is determined without regard to the factors behind the decisions concerning unconventional monetary policy, at least within a given month. On the other hand, allowing central bank assets to react instantaneously to MRO rate shocks caters for any endogenous reaction of banks' liquidity demand to the new interest rate conditions. Second, at any given level of the MRO rate, changes in central bank liquidity supply as a consequence of ECB non-standard policy measures would normally induce an inverse reaction in the EONIA rate and its spread to the MRO rate (see Boeckx, Dossche and Peersman 2014, and Fahr et al. 2013, for similar lines of reasoning). The final order of the endogenous variables of the benchmark VAR is thus: inflation (P), real GDP growth (GDP), CISS, MRO rate (MRO), ECB balance sheet growth rate (BS), and EONIA-MRO rate spread (SP).

The corresponding estimate of the triangular decomposition matrix  $A$  which identifies the structural shocks  $u_t$  is shown in Equation 3.3. It contains the estimated coefficients  $a_{ij}$  and, underneath in parantheses, the associated  $p$ -values of their statistical significance. Only six out of 15 coefficients (printed in bold), all pertaining to the monetary policy block, are statistically different from zero at a 7% significance level. While the MRO rate reacts to independent contemporaneous shocks in inflation and output with the expected positive sign, the innovations in ECB total assets increase with shocks

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<sup>9</sup>Given the low and insignificant correlation between their reduced-form residuals (see the estimate of coefficient  $a_{21}$  in Equation 3.3), this assumption is inconsequential.

in the CISS and decrease with structural shocks in the MRO rate, again in line with theoretical considerations.

$$\begin{pmatrix}
 1 & 0 & 0 & 0 & 0 & 0 \\
 -0.119 & 1 & 0 & 0 & 0 & 0 \\
 (0.41) & & & & & \\
 -1.920 & -0.064 & 1 & 0 & 0 & 0 \\
 (0.43) & (0.96) & & & & \\
 \mathbf{9.020} & \mathbf{5.439} & -0.206 & 1 & 0 & 0 \\
 (0.05) & (0.02) & (0.14) & & & \\
 -1.782 & -0.684 & \mathbf{0.098} & \mathbf{-0.078} & 1 & 0 \\
 (0.30) & (0.44) & (0.07) & (0.01) & & \\
 \mathbf{7.138} & -1.270 & -0.130 & \mathbf{-0.148} & -0.198 & 1 \\
 (0.07) & (0.53) & (0.28) & (0.02) & (0.25) & 
 \end{pmatrix}
 \begin{pmatrix}
 u_{P,t} \\
 u_{GDP,t} \\
 u_{CISS,t} \\
 u_{MRO,t} \\
 u_{BS,t} \\
 u_{SP,t}
 \end{pmatrix}
 =
 \begin{pmatrix}
 \varepsilon_{P,t} \\
 \varepsilon_{GDP,t} \\
 \varepsilon_{CISS,t} \\
 \varepsilon_{MRO,t} \\
 \varepsilon_{BS,t} \\
 \varepsilon_{SP,t}
 \end{pmatrix}.
 \tag{3.3}$$

With an estimate of  $A$  we can compute the structural form of the VAR:

$$A^{-1}y_t = A^{-1}C + A^{-1}A_1y_{t-1} + \dots + A^{-1}A_p y_{t-p} + u_t. \tag{3.4}$$

### 3.4 Results I: The predictive power of the CISS

In this section, I first present and discuss some general features of the estimated benchmark VAR, before studying in greater detail the overall performance, direct versus indirect transmission channels, and the robustness of the CISS, as a driving force of macroeconomic dynamics.

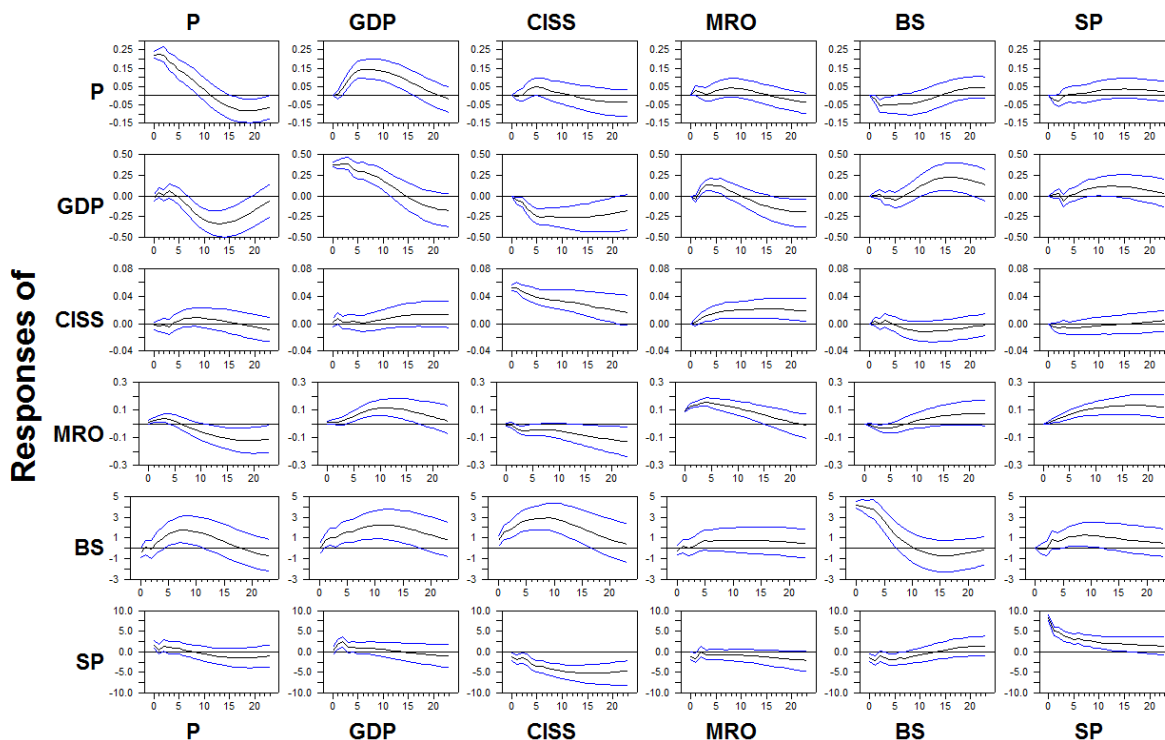
### 3.4.1 Overall effects within the benchmark VAR

The dynamic interactions between the endogenous variables of a multivariate VAR—i.e. a VAR with more than two variables—are generally quite complex. The complexity arises since the lags of practically all variables can enter the equation of any other variable, creating room for a great variety of potential *direct*, *indirect* and *feedback* effects in a model as highly dimensioned as the benchmark VAR at hand. The VAR methodology offers several analytical tools to study the *net* effects that a certain shock exerts on a model variable through all potential transmission channels. The most common tools are impulse response functions (IRFs) and forecast error variance decompositions (FEVDs). An IRF describes the responses of a variable  $i$  at time  $t + s$  with  $s = 0, \dots, h$  (with  $h$  denoting the longest prediction horizon) to a positive one-standard deviation structural shock in variable  $j$  as a one-time impulse at date  $t$ .<sup>10</sup> An IRF is thus a sequence of dynamic multipliers. A FEVD tells us the contribution of a structural shock in variable  $j$  to the forecast error variance of a variable  $i$  at horizon  $t + s$  with  $s = 0, \dots, h$ . The IRFs and the FEVDs produce complementary information since both use the same input data, namely the coefficients of the vector moving average (VMA) representation of a VAR. Since the IRFs and the FEVDs are derived from the structural form of the VAR, they both depend on the particular method applied to identify the shocks. In the present case, they depend on the particular order in which the model variables enter the Cholesky decomposition. However, all conclusions derived from the IRFs and the FEVDs presented in this paper are robust to different variable orderings thanks to the generally rather weak contemporaneous correlations between the reduced-form model

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<sup>10</sup>The matrix  $P = AD^{1/2}$  is known as the Cholesky factorisation of  $\Omega$ . Like  $A$ ,  $P$  is lower triangular, though whereas  $A$  has 1s along the principal diagonal, the Cholesky factor has the square roots of the elements of  $D$ , that is the standard deviations of the structural shocks  $u_t$ , along the principal diagonal. The structural shocks from the Cholesky decomposition are obtained as  $v_t = P^{-1}\varepsilon_t = D^{-1/2}u_t$  such that  $v_t \sim i.i.d. N(0, I_n)$ . Thus,  $v_{jt}$  is just  $u_{jt}$  divided by its standard deviation  $\sqrt{d_{jj}}$ . This decomposition is used to compute impulse response functions to one-standard-deviation shocks rather than one-unit shocks in  $u_t$ .

Figure 3.1: Impulse response functions from the benchmark VAR



residuals as reflected in the few significant coefficients of the  $A$ -matrix in Equation 3.3.

Figure 3.1 displays the full set of IRFs from the six-dimensional structural VAR. The response variables are plotted row-wise and the impulse variables column-wise. The black lines are the mean responses and the blue lines around them represent the 10th and the 90th percentile error bands computed by Monte Carlo integration. Concerning the real sector block, GDP growth declines after a few months in response to a positive inflation shock, while inflation gradually increases to a shock in real GDP growth. This pattern may suggest that the price equation captures predominantly aggregate supply shocks, while the innovations in the equation for real GDP are driven mainly by aggregate demand shocks.

The IRF-plots in the third column substantiate the claim that the CISS plays a

significant role as a driver of macroeconomic dynamics. While its dynamic effects on inflation are rather muted, real GDP growth responds rather strongly to financial stress shocks. For instance, a typical CISS shock of about 0.05 causes a downward revision in the predicted path of annual growth in real GDP by 0.25% one year hence. Everything else held constant, the cumulated shocks in the CISS observed in August 2007 (+0.20) as well as in September and October 2008 (0.08 and 0.10, respectively) would have shaved off as much as around 2% of predicted output growth over a one-year horizon. All three variables in the monetary policy block of the VAR likewise respond significantly to financial stability shocks with the expected signs. The MRO policy rate decreases and the ECB's balance sheet expands in reaction to an unpredicted increase in the CISS. The responses of the money market spread (SP) indicate that the EONIA rate drops more strongly than the MRO rate in reaction to an increase in financial stress. The concurrent expansion of the ECB balance sheet apparently tends to go along with—*ceteris paribus*—an increase in the supply of central bank liquidity, an interpretation which is likewise supported by the significant negative reactions of the spread to positive balance sheet shocks. In the opposite case, the parallel responses of ECB balance sheet growth to shocks in the EONIA-MRO spread suggest that the latter capture liquidity demand shocks, among other things.

The FEVD confirms the powerful contribution of the CISS to the VAR dynamics. Table 3.1 shows the decomposition for all variables over forecast horizons of one month, three months, 12 months and 24 months. We can see that the structural innovations of the CISS contribute by 24% and 26% to the forecast error variance of real GDP growth over a 12-month and a 24-month horizon respectively, which is stronger than the contributions of aggregate supply shocks (14% and 22% resp.), and only somewhat weaker (at least for the longer horizon) than the contributions coming from aggregate demand shocks (52% and 28% resp.). Regarding monetary policy, the CISS contributes

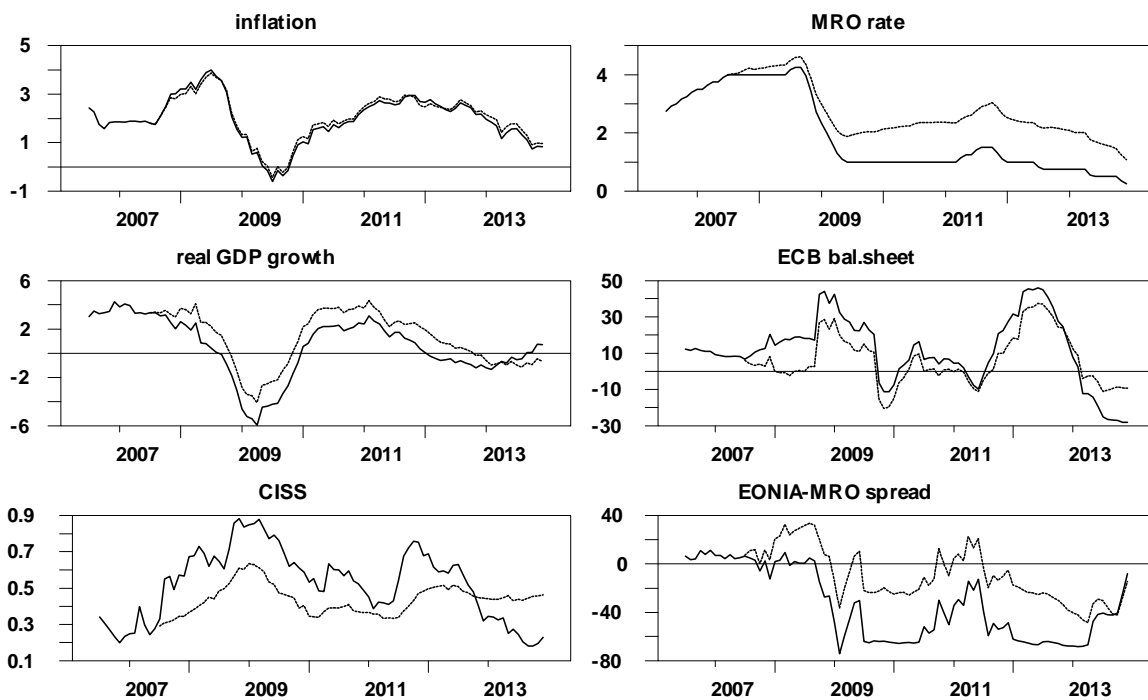
by 14% to the 24-month-ahead forecast error variance of the MRO rate, which is quite substantial given that five out of six shocks exert material impacts. CISS innovations are even the dominant factor behind the 24-month-ahead forecast error variances of the ECB balance sheet growth rate (33%) and the EONIA-MRO rate spread (56%).

Table 3.1: Forecast Error Variance Decomposition for the benchmark VAR

variable	step	std. err.	contribution of variable (in %)					
			P	GDP	CISS	MRO	BS	SP
P	1	0.202	100.000	0.000	0.000	0.000	0.000	0.000
	3	0.357	95.120	1.017	0.021	0.671	2.390	0.781
	12	0.610	56.883	33.365	2.054	2.481	4.271	0.946
	24	0.699	52.797	32.517	3.606	3.076	5.329	2.674
GDP	1	0.345	0.331	99.669	0.000	0.000	0.000	0.000
	3	0.612	0.464	95.666	1.850	1.669	0.112	0.239
	12	1.309	14.243	51.818	24.457	4.107	2.554	2.821
	24	1.895	22.037	28.359	26.323	8.817	10.796	3.668
CISS	1	0.047	0.334	0.107	99.560	0.000	0.000	0.000
	3	0.081	0.326	0.843	97.031	0.903	0.118	0.779
	12	0.141	2.038	0.834	82.141	11.739	2.156	1.092
	24	0.174	2.120	4.563	69.892	19.538	3.019	0.867
MRO	1	0.086	1.634	0.958	0.363	97.045	0.000	0.000
	3	0.205	4.118	0.927	2.292	90.148	0.864	1.651
	12	0.564	4.103	18.008	5.175	52.757	1.523	18.434
	24	0.901	14.389	14.825	14.137	23.632	5.883	27.135
BS	1	3.934	1.181	0.002	2.423	0.189	96.205	0.000
	3	6.921	0.415	2.923	9.945	0.153	86.541	0.022
	12	13.637	8.886	13.879	31.901	2.100	38.345	4.889
	24	15.772	8.507	19.316	32.747	2.847	30.455	6.129
SP	1	7.958	4.061	0.057	1.889	1.324	2.411	90.257
	3	11.055	3.802	5.949	4.955	2.101	4.750	78.443
	12	17.824	2.580	3.828	36.751	2.074	5.972	48.795
	24	25.170	3.802	2.326	56.186	4.583	4.469	28.635

I also run a counterfactual experiment that simulates the behaviour of the VAR variables from July 2007 (i.e. the month before the start of the subprime crisis) to December 2013, under the assumption of zero innovations in financial stress. Figure 3.2 indicates that if there were no exogeneous variations in the CISS, real GDP growth and

Figure 3.2: Counterfactual simulation with the benchmark VAR assuming zero CISS shocks



solid line: actual series; dotted line: simulated series; simulation period: July 2007 to December 2013

the MRO rate would have been considerably higher, and swings in the ECB balance sheet growth rate would have been more muted.

### 3.4.2 Direct versus indirect effects

It is less common in the literature to disentangle the net effects, measured by IRFs and FEVDs, into the various possible direct and indirect dynamic relationships between certain variables of a VAR. I argue that in the present context such a perspective offers interesting insights. For this purpose, I apply the definitions of different causality patterns and the related testing schemes proposed by Hsiao (1982). Hsiao's causality patterns build on the standard concept of Granger-causality (Granger 1969). Assume we have a tripartite partition of a vector of variables  $y_t = (y_{1,t}, y_{2,t}, y_{3,t})'$  where the  $y_{i,t}$  can



also represent subvectors of variables. A variable  $y_{1,t}$  is said to Granger cause a variable  $y_{2,t}$  if past realisations of  $y_{1,t}$  help predict  $y_{2,t}$  one step ahead conditional on the set of available information  $\Theta_t$ . In the case of a standard VAR the conditioning information set only includes lags of the endogenous variables  $\Theta_t = Y_t = \{y_{i,s} : s < t, i = 1, 2, 3\}$ . For ease of exposition I drop the time subindex from now on. Let  $\sigma^2(y_2|Y)$  denote the mean square error of the minimum mean square linear prediction error of  $y_2$  conditional on  $Y$ , and  $Y - Y_i$  is defined as the set of elements in  $Y$  without the elements in  $Y_i = Y_{i,t} = \{y_{i,s} : s < t\}$ . Hsiao defines the following causality patterns:

**Definition 1 (Direct Causality).** If  $\sigma^2(y_2|Y) < \sigma^2(y_2|Y - Y_1)$ , then we say  $y_1$  causes  $y_2$  directly relative to  $Y$ , denoted by  $y_1 \Rightarrow y_2$ .

**Definition 2 (Direct Feedback).** If  $y_1 \Rightarrow y_2$  and  $y_2 \Rightarrow y_1$ , then we say that direct feedback occurs between  $y_1$  and  $y_2$ , denoted by  $y_1 \Leftrightarrow y_2$ .

**Definition 3 (Indirect Causality).** If  $\sigma^2(y_2|Y) = \sigma^2(y_2|Y - Y_1) < \sigma^2(y_2|Y - Y_3) < \sigma^2(y_2|Y - Y_1 - Y_3)$  and  $\sigma^2(y_3|Y) < \sigma^2(y_3|Y - Y_1)$ ,  $\sigma^2(y_3|Y_1 + Y_3) < \sigma^2(y_3|Y_3)$ , then we say that  $y_1$  causes  $y_2$  indirectly, denoted by  $y_1 \rightarrow y_2$ .

**Definition 4 (No Causality).**  $y_1$  does not cause  $y_2$  when either (i)  $\sigma^2(y_2|Y) = \sigma^2(y_2|Y - Y_1 - Y_3)$  or (ii)  $\sigma^2(y_2|Y) = \sigma^2(y_2|Y - Y_1)$  and  $\sigma^2(y_3|Y) = \sigma^2(y_3|Y - Y_1)$ , denoted by  $y_1 \nrightarrow y_2$ .

**Definition 5 (Spurious Causality).** When condition (ii) of no causality holds, but  $\sigma^2(y_2|Y) = \sigma^2(y_2|Y - Y_1) < \sigma^2(y_2|Y - Y_3) < \sigma^2(y_2|Y - Y_1 - Y_3)$  and  $\sigma^2(y_1|Y) < \sigma^2(y_1|Y - Y_3)$ ,  $\sigma^2(y_1|Y_1 + Y_3) < \sigma^2(y_1|Y_1)$ , we say spurious causality from  $y_1$  to  $y_2$  occurs.

All these conditions can be tested as standard zero restrictions on the VAR coefficients  $a_{ij,l}$ . For instance, in the case of a three-dimensional VAR with  $y = (y_1, y_2, y_3)'$ , direct causality  $y_1 \Rightarrow y_2$  (Definition 1) involves testing the null hypothesis:  $H_0 : a_{21,l} = 0$ ,  $l = 1, \dots, p$ . Direct non-causality  $y_1 \not\Rightarrow y_2$  rules out the predictive power of  $y_1$  for  $y_2$  one-step-ahead. However,  $y_1$  can still predict  $y_2$  indirectly ( $y_1 \rightarrow y_2$ , Definition 3) at horizons beyond one-step-ahead if  $y_1$  contains direct predictive power for  $y_3$ , for instance, which in turn may be directly causal for  $y_2$  ( $y_1 \Rightarrow y_3 \Rightarrow y_2$ ). Both Definitions 3 and 5—covering the cases of indirect versus spurious causality—state that past  $y_1$  will not help predict present  $y_2$  when past  $y_3$  are used, but will help predict present  $y_2$  when past  $y_3$  are not used. However, in the case of indirect causality  $y_1$  drives  $y_3$  which in turn causes  $y_2$ . In contrast, spurious causality assumes that  $y_3$  is the primary driving force for both  $y_1$  and  $y_2$ . Past  $y_1$  only serves as a proxy for the missing  $y_3$ .

In a rather high-dimensional VAR like my benchmark model, many such direct and indirect transmission channels may exist, and may either reinforce or compensate each other. While the IRFs estimate the total or net effects of all these different channels, I now assess which direct and/or indirect causality patterns may be behind the strong overall predictive power of the CISS within the benchmark VAR.<sup>11</sup> The test statistics reported in Table 3.2 identify patterns of direct (Granger-)causality only. Precisely, the  $F$ -tests test—for each equation separately—the statistical significance of zero restrictions on all included lags of one variable in the reduced-form model equation of another variable.<sup>12</sup> The  $p$ -values are derived from a parametric bootstrapping procedure to

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<sup>11</sup>However, Dufour and Tessier (1993) point out that the duality of non-causality restrictions on the coefficients of the autoregressive and the moving-average representation of a VAR does not hold in multivariate systems. Even if  $y_1$  does not cause  $y_2$  in the sense of Granger, the innovations of  $y_1$  may account for a sizeable proportion of the variance of  $y_2$ . Conversely, even if the latter proportion is zero, it is quite possible that  $y_1$  is found to Granger-cause  $y_2$ .

<sup>12</sup>I prefer to report the exclusion  $F$ -tests based on the reduced-form model and thus to limit attention to the analysis of Granger causality rather than mingling it with assumptions about instantaneous causality between the variables as reported in equation 3, since the latter depends on the structural identification scheme. Exclusion  $F$ -tests based on the structural VAR form could be obtained by adding to each equation the contemporaneous values of those variables which precede the variable at hand in

Table 3.2: Testing for direct causality in the benchmark VAR

equation $i$	exclusion of variable $j$					
	P	GDP	CISS	MRO	BS	SP
P	173.73 (0.000)	<b>6.27</b> (0.001)	2.42 (0.070)	1.61 (0.233)	1.62 (0.207)	1.17 (0.363)
GDP	<b>4.73</b> (0.002)	225.32 (0.000)	<b>2.76</b> (0.044)	<b>4.59</b> (0.004)	1.14 (0.376)	<b>2.95</b> (0.031)
CISS	1.00 (0.453)	1.45 (0.263)	114.63 (0.000)	1.22 (0.383)	2.02 (0.122)	0.66 (0.637)
MRO	<b>2.73</b> (0.044)	2.36 (0.079)	2.31 (0.074)	1294.68 (0.000)	1.81 (0.156)	<b>3.51</b> (0.016)
BS	<b>2.67</b> (0.049)	1.21 (0.352)	<b>3.62</b> (0.012)	1.24 (0.351)	184.80 (0.000)	1.95 (0.131)
SP	0.41 (0.818)	<b>2.93</b> (0.035)	1.13 (0.384)	2.50 (0.064)	1.06 (0.416)	67.64 (0.000)

Notes: Entries are the  $F$ -test statistic of the joint zero restriction on all lags of variable  $j$  (column-wise) in the equation of variable  $i$  (row-wise):  $H_0: a_{ij,l} = 0$  for all  $l = 1, \dots, 4$  with bootstrapped (10,000 draws)  $p$ -values below in brackets, based on the benchmark VAR.

ensure better small sample properties of the test. However, in general, the bootstrapped  $p$ -values turn out to be only slightly more conservative than their analytical counterparts. The bold printed entries in Table 3.2 are statistically significant at the 5%-level.

I find a total of ten relationships which qualify as direct causality according to the 5% significance level. Four among them establish direct feedback relationships between real GDP growth and inflation ( $GDP \Leftrightarrow P$ ) and between real GDP growth and the EONIA-MRO rate spread ( $GDP \Leftrightarrow SP$ ). The remaining cases of direct causality are:  $P \Rightarrow MRO$ ,  $P \Rightarrow BS$ ,  $CISS \Rightarrow GDP$ ,  $CISS \Rightarrow BS$ ,  $MRO \Rightarrow GDP$  and  $SP \Rightarrow MRO$ . Hence, the CISS emerges as directly causal for real GDP growth and the growth rate of the ECB balance sheet. As one would expect, economic growth tends to slow down and the ECB balance sheet tends to expand in response to higher financial stress.

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the order of the vector of endogeneous variables.

From a monetary policy perspective, the identified direct causality patterns suggest two potential routes of indirect causality between the CISS and the MRO rate, both operating through the CISS's direct causality for real GDP growth: (i)  $CISS \Rightarrow GDP \Rightarrow P \Rightarrow MRO$ , and (ii)  $CISS \Rightarrow GDP \Rightarrow SP \Rightarrow MRO$ . The first route may work through the impact of changes in aggregate demand on inflation which, in turn, tends to trigger a response in the policy rate. The second route may progress via changes in expected monetary policy as reflected in changes in the EONIA-MRO rate spread (indicating tighter or looser central bank liquidity conditions) which tend to be confirmed, on average, by subsequent actual MRO rate moves.

Since Definition 3 requires a partition of the vector of variables into three non-empty subsets, I cannot test these two indirect causality relationships separately within the benchmark VAR. What I do instead is test for indirect causality  $CISS \rightarrow MRO$  via the remaining four variables  $P, GDP, BS$  and  $SP$  jointly as a block. Table 3.3 reports the test statistics and the associated  $p$ -values of the four conditions establishing indirect causality according to Definition 3. The first one, row (1), requires the absence of direct causality between the CISS and the MRO rate; the corresponding null hypothesis cannot be rejected at the 5% significance level, a result already established in Table 3.2. The second condition in row (2) demands a significant loss in the predictive power when dropping all other variables (collected in vector  $y_3$ ) apart from the CISS and own lags of the MRO rate. The null of equal predictive power can be rejected at a 1% significance level. The third condition, row (3), requires direct predictive power of the CISS for the MRO rate when excluding all other variables from the MRO rate equation. A  $p$ -value of 0.014 suggests that this condition also holds true. The last condition stated in row (4) requires significant predictive power of the CISS for the block of variables in vector  $y_3$ . The corresponding 16 zero-restrictions can be clearly rejected even at the 1% significance level. Hence, all conditions for indirect causality of the CISS for the MRO

Table 3.3: Testing for indirect causality of the CISS for the MRO rate

test condition from Definition 3	benchmark VAR	
	(1) test-statistic	(2) <i>p</i> -value
(1) $\sigma^2(y_2 Y) = \sigma^2(y_2 Y - Y_1)$	$F(4, 139) = 2.31$	0.061
(2) $\sigma^2(y_2 Y) < \sigma^2(y_2 Y - Y_3)$	$F(16, 139) = 2.19$	0.008
(3) $\sigma^2(y_2 Y - Y_3) < \sigma^2(y_2 Y - Y_1 - Y_3)$	$F(4, 155) = 3.21$	0.014
(4) $\sigma^2(y_3 Y) < \sigma^2(y_3 Y - Y_1)$	$F(16, 139) = 2.28$	0.005

Notes: The table provides the test statistics for the separate tests of the four conditions establishing indirect causality  $CISS \rightarrow MRO$  as defined in Definition 3. The variables are defined as:  $y_1 = CISS$ ,  $y_2 = MRO$ ,  $y_3 = (P, GDP, BS, SP)$  for the benchmark VAR.

rate are fulfilled.

The same set of tests also suggests indirect causality between the CISS and the spread ( $CISS \rightarrow SP$ ) via variables  $P, GDP, MRO$  and  $BS$  (with *p*-values of (1) 0.346, (2) 0.064, (3) 0.008 and (4) 0.000 for the four conditions set out in Table 3.3). In contrast, indirect causality between the CISS and inflation ( $CISS \rightarrow P$ ) cannot be fully established. First, the null hypothesis of direct causality can only be marginally rejected at a 5% level with a *p*-value of 0.052. Second, while conditions (2) and (4) can be confirmed with a *p*-value of 0.004 in both cases, condition (3), which requires Granger causality of the CISS for inflation in a bivariate VAR setting, is clearly violated with a *p*-value of 0.376.

Summing up, tests for direct and indirect causality confirm the substantial predictive power of the CISS within the benchmark VAR as suggested by the IRFs and the FEVD. The CISS is found to be directly causal for real GDP growth and the ECB balance sheet growth rate. Indirect causality of the CISS can be established for the MRO rate and the EONIA-MRO rate spread. The evidence for the CISS's role as a driver of inflation is somewhat mixed and thus not fully clear.

On the other hand, no other variable helps directly predict developments in the CISS; the ECB balance sheet growth rate comes closest to statistical significance with a  $p$ -level of 12% (see Table 3.2).<sup>13</sup> Capturing direct and indirect effects, the IRFs and the FEVD suggest that, if at all, only the MRO rate may possess some predictive power for financial stress; the remaining variables produce no discernible net effects on the CISS whatsoever.

### 3.4.3 Robustness, or looking for spurious effects

As the final piece of evidence presented in this section, I assess the robustness of the CISS's predictive power to the inclusion, one at a time, of a broad set of real and financial variables with established or presumed predictive power for macroeconomic developments. In order to strengthen the case, I only consider the explanatory power with respect to the core model variables, i.e. inflation, real GDP growth and the monetary policy interest rate. The robustness tests are performed on the basis of a VARX model as described in general terms in Equation 3.1. The vector of endogenous variables now only contains inflation, real GDP growth and the MRO rate ( $n = 3$ ). The CISS and one of the control variables constitute, in that order, the vector of exogenous variables ( $m = 2$ ). Within this framework, the explanatory power of the CISS for the core model variables can be assessed on the basis of standard block exogeneity tests. In the present case, the block exogeneity test has, as its null hypothesis, that the lags of the CISS do not enter the block of equations for the endogenous variables.<sup>14</sup> This

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<sup>13</sup>A block exogeneity test of the CISS with respect to the remaining variables delivers a  $p$ -value of 0.10. Interpreting this result as evidence against one-step ahead predictability would imply that the CISS is *Granger causally prior* to the other model variables, which in turn implies that the other model variables do not help predict the CISS even beyond the one-step-ahead forecast horizon (see Doan and Todd 2010, and Jarocinski and Mackowiak 2013).

<sup>14</sup>Hence, the null hypothesis states that the three endogenous variables as a block are exogenous with respect to the CISS.

can be expressed as zero restrictions on the coefficient matrices  $B_l$ :  $H_0 : b_{i1,l} = 0$  for all  $i = 1, 2, 3$  and  $l = 1, \dots, p$  with  $p = 4$ .<sup>15</sup> The Likelihood Ratio test statistic is computed as:  $(T - mc)(\ln |\Omega_r| - \ln |\Omega_u|)$ , where  $T$  denotes the number of observations,  $mc$  is a small-sample correction suggested by Sims (1980)<sup>16</sup>,  $\Omega_r$  is the variance-covariance matrix from the restricted regression and  $\Omega_u$  the one from the unrestricted regression. This likelihood ratio is asymptotically distributed as  $\chi^2(12)$  with degrees of freedom equal to the number of restrictions ( $n \cdot p$ ).

Table 3.4 reports the results for two sets of block exogeneity tests. The first set (columns 1 and 2) tests for block exogeneity of the core variables with respect to the CISS for the case when no control variable is included (row 1), and for the cases when a certain control is added (rows 2 to 14). The second set of block exogeneity tests (columns 3 and 4) reverses the question, asking whether a certain control variable helps to predict the core model variables conditional on the inclusion of the CISS as a competing exogenous variable (rows 2 to 14). This second set of tests provides evidence on the strength, i.e. the predictive power, of each control variable. A data description of the control variables can be found in Appendix A.

The results from the block exogeneity tests with respect to the CISS can be generalised as follows: The CISS displays a strong robustness to the inclusion of a broad range of forecasting variables from the real and financial sphere. For instance, when including significant short-term predictors of economic developments like surveys on expected inflation and the business climate, the CISS retains its strong joint predictive power for consumer price inflation, real GDP growth and the MRO rate (see rows 3, 5 and 6). In addition, an index measuring policy uncertainty in EU countries emerges as

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<sup>15</sup>The number of lags ( $p$ ) for the endogenous and exogenous variables is set to four, the same number of lags as used for the benchmark VAR.

<sup>16</sup>Sims (1980) suggests using a correction equal to the number of regressors in each unrestricted equation in the system. In the present case, the correction equals  $(n + m)p = 20$ .

Table 3.4: Robustness tests for the predictive power of the CISS

		testing for block exogeneity w.r.t.			
		CISS		control variable	
control variable		(1)	(2)	(3)	(4)
		$\chi^2(12)$	$p$ -value	$\chi^2(12)$	$p$ -value
(1)	—	30.46	0.00	n.a.	n.a.
(2)	commodity price index	31.96	0.00	57.11	0.00
(3)	Consensus inflation forecast	29.19	0.00	29.68	0.00
(4)	unemployment rate	26.10	0.01	12.23	0.43
(5)	Consensus real GDP forecast	26.41	0.01	12.75	0.39
(6)	business climate index	23.83	0.02	24.92	0.02
(7)	policy uncertainty index	20.52	0.06	25.50	0.01
(8)	bank loans	33.74	0.00	32.77	0.00
(9)	effective euro exchange rate	34.92	0.00	15.44	0.22
(10)	10-year government bond yield	29.09	0.00	5.42	0.94
(11)	term spread	29.40	0.00	6.96	0.86
(12)	BBB corporate bond spread	21.68	0.04	27.26	0.01
(13)	high yield corporate bond spread	27.61	0.01	27.40	0.01
(14)	option-implied stock volatility	16.72	0.16	19.93	0.07

a significant predictor, but it reduces the explanatory power the CISS only marginally (row 7). Regarding financial variables, growth in bank loans to the non-financial sector, corporate bond spreads, and implied stock market volatility (VSTOXX) are also found to have a strong marginal predictive power which, again, does not affect the power of the CISS substantially (see rows 8, 12, 13 and 14).<sup>17</sup> No independent predictive power for our core model variables is found for the unemployment rate, Consensus real GDP growth forecasts, the euro effective exchange rate, the 10-year government bond yield and the term spread (rows 4, 5, 9, 10 and 11), which all leave the predictive power of the CISS basically unaffected.

<sup>17</sup>The case of the VSTOXX may appear different, though, since the  $p$ -value of the block exogeneity test with respect to the CISS increases to 16%. However, within the full benchmark VAR, the CISS clearly retains its predictive power when including the VSTOXX with a  $p$ -value of the block exogeneity test of 0.001. In addition, when testing for block exogeneity of the core variables with respect to the VSTOXX without including the CISS, the VSTOXX turns out to be statistically insignificant even at the 10% level. Its predictive power seems to depend on the presence of the CISS. In general, the fact that the block exogeneity zero restrictions cannot be rejected for both variables when the VSTOXX is included along with the CISS, may also point at problems of multicollinearity.



Performing the same exercise for the full benchmark VAR model, i.e. adding the ECB balance sheet growth rate and the EONIA-MRO rate spread to the set of core model variables, reveals an even more robust predictive power of the CISS. In that case, all block exogeneity tests of these five variables with respect to the CISS, and conditional on a specific control variable, can be rejected even at the 1% significance level.

The two sets of block exogeneity tests reported in Table 3.4 can be interpreted as tests of two conditions for spurious causality as defined in Definition 5. Assume that  $y_1$  is still the CISS,  $y_2$  is now a three-dimensional vector including P, GDP and MRO, and  $y_3$  represents a control variable. Recall the first condition stated in Definition 5:  $\sigma^2(y_2|Y) = \sigma^2(y_2|Y - Y_1) < \sigma^2(y_2|Y - Y_3) < \sigma^2(y_2|Y - Y_1 - Y_3)$ . The entry in row (1) and column (1) in Table 3.4 confirms that the latter part of this condition is fulfilled, namely that the CISS has significant predictive power for the core model variables when no control variable is used (the information set is restricted to  $Y - Y_3$ ). However, the first part of the condition is clearly violated for all control variables (individually) since the CISS retains its predictive power for the core variables when adding lags of one control variable at a time to the list of regressors, i.e. when expanding the information set from  $Y - Y_3$  to  $Y$ . We obtain  $\sigma^2(y_2|Y) < \sigma^2(y_2|Y - Y_1)$ , which says that the CISS is found to be directly causal for the block of core variables conditional on the expanded information set. Hence, we can rule out spurious causality of the CISS—relative to this specific set of control variables—without having to test further restrictions implied in Definition 5.

### 3.5 Results II: Monetary policy and financial instability

The literature distinguishes between systematic and unsystematic monetary policy. The former describes that part of the variation in a monetary policy instrument which reflects policy makers' systematic responses to variations in the state of the economy. This systematic component is typically formalised with the concept of a feedback rule, or reaction function. In general such a rule associates the policy instrument  $S_t$  in a systematic way, i.e. via a general function  $f(\cdot)$ , with certain data collected in the information set  $\Theta_t$  which shall represent policy makers' knowledge about the past, current and future state of the economy available to them when setting the policy instrument at time  $t$ . But not all variations in central bank policy can be accounted for as a systematic reaction to the state of the economy. The unaccounted variation is formalised with the notion of an exogenous monetary policy shock  $u_t^s$ .<sup>18</sup> Such a shock arises, first, when a change in the policy instrument is either under or overestimated on the basis of available information or, second, when the instrument is not changed although data updates on the state of the economy would have called for a policy action according to the policy rule  $f(\Theta_t)$ . In each period of time, the policy instrument can now be expressed as the sum of its systematic and unsystematic components (Christiano, Eichenbaum and Evans 1999):

$$S_t = f(\Theta_t) + u_t^s.$$

In the present case,  $S_t$  can be either the MRO rate, the ECB's main conventional or standard monetary policy instrument, or the growth rate in total assets of the ECB's balance sheet which is meant to capture the ECB's unconventional or non-standard

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<sup>18</sup>For an economic interpretation of such shocks see Christiano, Eichenbaum and Evans (1999) who describe possible sources of exogenous variations in monetary policy, such as (i) exogenous shocks to the preferences of the monetary authority (for instance due to stochastic shifts in the relative weight given to certain data which, in turn, could reflect shocks to the preferences of the members of the decision-making body), or to the weights by which their views are aggregated; (ii) strategic considerations with respect to the policy expectations held by private economic agents; and (iii) technical factors, e.g. measurement errors in the preliminary data available to policy makers at the time they make their decisions, a point raised by Bernanke and Mihov (1998).

monetary policy stance. Within the benchmark structural VAR framework, the reaction function  $f(\Theta_t)$  is a linear projection of the policy instruments on  $p$  lags of all endogenous variables as well as—according to the structural identification as summarised in Equation 3.3—on the time  $t$  realisations of inflation, real GDP growth and the CISS.<sup>19</sup>

It is important to note that in the present context such estimated policy rules or reaction functions are mere *descriptions* of how the policy instruments are set in response to economic variables. They are not to be interpreted as rules in a prescriptive, normative sense (Taylor 1999). Accordingly, what I do in the remainder of this section is to describe whether and how the ECB reacted in a systematic fashion with its conventional and unconventional monetary policy instruments to changes in the state of the economy, with a particular focus on the state of financial (in)stability as measured by the CISS indicator. I also assess the estimated effects of the two different types of monetary policy shocks, but I do not aim to draw normative conclusions as to whether the ECB’s monetary policy over the sample period has been optimal or not in any particular sense.

### 3.5.1 Conventional monetary policy

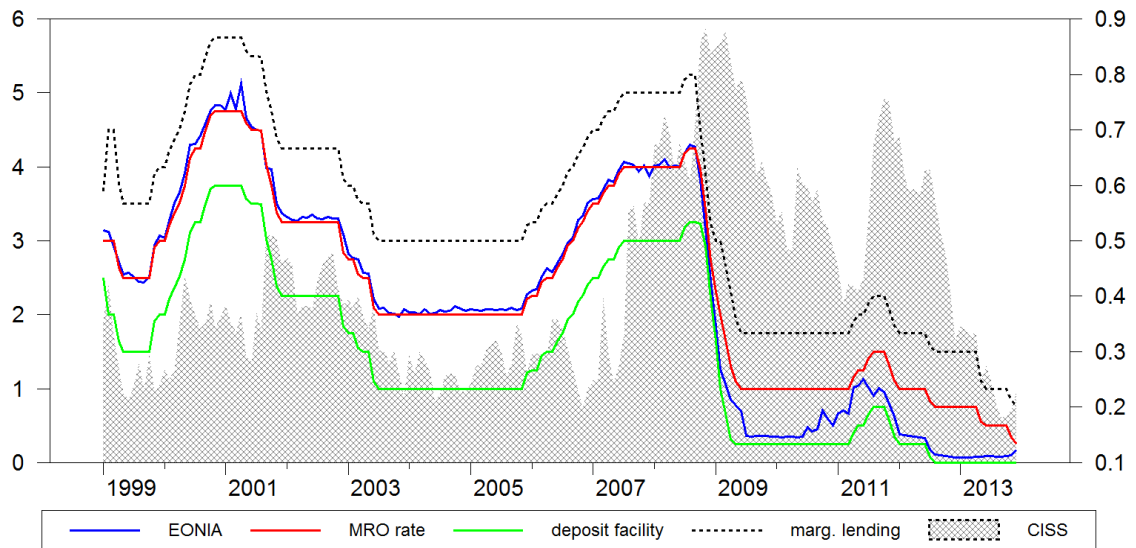
The ECB’s framework to implement monetary policy aims to steer very short-term market interest rates in line with the Governing Council’s preferences as revealed, among other things, in the setting of its main policy rates. In the pre-crisis period, up to October 2008, the ECB geared its main refinancing operations (MRO) towards neutral liquidity conditions so that the EONIA rate stayed relatively close to the MRO minimum bid rate.<sup>20</sup> The marginal lending facility rate and the deposit facility rate provide the

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<sup>19</sup>For the balance sheet instrument the contemporaneous MRO rate is also treated as predetermined.

<sup>20</sup>The weekly MROs were based on a variable rate tender until October 2008, with a minimum bid rate equal to the interest rate below which the Eurosystem would not accept any bids. Thereafter, a fixed rate tender procedure was introduced and the minimum bid rate became the rate at which all bids were allotted (ECB 2014).

Figure 3.3: Key ECB policy rates and the overnight interbank rate



Note: Monthly data; Jan. 1999 - Dec. 2013

upper and lower bounds, respectively, of an effective interest rate corridor which limits fluctuations of the EONIA. Since the meltdown of the global financial system in October 2008, the ECB moved to tender operations with fixed rate full allotments, creating conditions of excess liquidity such that the EONIA was no longer steered towards the MRO rate but, instead, moved closer to the ECB's deposit facility rate (see Figure 3.3). But the MRO rate still represents a key policy rate not least because it continues to determine the cost at which banks usually obtain central bank liquidity from the ECB.

As alluded to above, the fourth equation of the reduced-form benchmark VAR may be interpreted as a backward-looking variant of the ECB's reaction function, in the sense that it is implicitly assumed that the MRO rate is determined only on the basis of past information about the VAR variables. The direct causality tests reported in Table 3.2 suggest that this standard policy tool reacts directly to past real GDP growth and the lagged EONIA-MRO rate spread (apart from own lags) according to the 5% significance level; at a 10% level, responses to lagged inflation and past realisations of

the CISS would also become significant. Furthermore, the outcome of the structural identification indicated that the MRO rate reacts directly to contemporaneous inflation and output growth (see the fourth row of the  $A$ -matrix in Equation 3.3).<sup>21</sup> However, we have also shown that the MRO rate reacts indirectly to financial stress via changes in the economic outlook which, in turn, are further transmitted to the monetary policy rate through their impact on inflation and money market interest rate conditions.<sup>22</sup>

The net effects of all direct and indirect transmission channels are again summarised in the IRFs and the FEVD pertaining to the MRO rate. Overall, the outcome from these exercises confirm the results of the partial analysis of the policy rate reaction function. The panels in the fourth row of Figure 3.1 and the variance decomposition for the MRO rate as shown in Table 3.1 suggest that shocks in all variables except the ECB balance sheet exert a sizeable impact on the policy rate. For instance, in response to a positive aggregate supply shock, the policy rate is first kept stable for a couple of months before it is gradually reduced in parallel with the onsetting decline in economic activity. Aggregate demand shocks, in contrast, seem to trigger quicker policy responses than supply shocks as revealed in the much stronger contribution to the forecast error variance of the MRO rate at a one-year horizon. As highlighted in the previous section, unexplained increases in financial stress lead to a gradually stronger easing of conventional monetary policy down the road. Eventually, CISS innovations add 14% to the forecast error variance of the MRO rate 24-month-ahead, which is basically identical to the contributions from aggregate supply and demand shocks. Only own shocks (23%) and shocks in the EONIA-MRO rate spread (27%) obtain a larger share over this horizon. The persistent hump-shaped response pattern to own shocks may

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<sup>21</sup>In the present context “contemporaneous” information ignores the issue of publication lags in order to simplify the analysis.

<sup>22</sup>The absence of direct causality may suggest that the CISS is unlikely to emerge as a significant explanatory variable in estimated augmented (dynamic) Taylor rules if endogeneity issues are not properly dealt with.

indicate a preference for interest rate smoothing on the side of the ECB in line with the empirical findings from the general literature on Taylor-like interest rate rules. The MRO rate responds very strongly to shocks in its spread against the EONIA rate, with positive spread innovations giving rise to gradual increases in the policy rate. This response pattern is likely to reflect market participants' anticipatory behaviour concerning future developments in monetary policy rates as mirrored in tighter current interbank liquidity conditions.

Given that own shocks explain less than one forth of the medium-term forecast error variance of the MRO rate, and given that the explanatory power and the direction of the impact of the other endogenous variables on the MRO rate are significant and in line with theoretical predictions, one may argue that the few endogenous variables included in the benchmark VAR already capture reasonably well the information about the state of the economy and the financial system to which the Governing Council of the ECB reacted *on average* with its interest rate policy. In particular, monetary policy makers did not only take into account latest developments in inflation and output, as well as market anticipations about future policy, when deciding about the path of its policy rates, but they also seemed to react in a systematic fashion, though indirectly, to financial stress conditions. This indirect lagged policy reaction seems to reflect some genuine information contained in the CISS about the expected course of the economy, i.e. information which is not reflected in the concurrent dynamics of typical macroeconomic state variables like inflation, output and some of the control variables. In addition, in times of severe financial stress—such as it occurred in the context of the U.S. terrorist attacks in September 2001 and in the aftermath of the Lehman debacle in September 2008—the ECB like other central banks may have eased its interest rate policy beyond what would have been commanded by the immediate outlook for output and inflation<sup>23</sup>;

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<sup>23</sup>See Baxa, Horvath and Vasicek (2013).

it may have done so in order to preserve financial stability and thus to fend off tail risks to price stability over the medium term.

Such adjustments of monetary policy rates to emerging financial disruptions are a common finding in the literature. For instance, Bekaert and Hoerova (2014) decompose the VIX index, an equity-implied volatility measure, into a risk and an uncertainty component. In principle, both components capture certain symptoms of financial stress, but they find that standard Taylor-rule residuals are particularly strongly correlated with the uncertainty component. Adrian, Moench and Shin (2010) estimate a macro risk premium by combining certain spreads from fixed income securities (term spread, credit spreads) that perform well in predicting real economic activity. They show that this risk premium is closely associated with the balance sheet growth of broker dealers and shadow banks in particular, which are therefore interpreted as measures of financial intermediary risk appetite. They finally document within a VAR framework that the degree of risk appetite measured this way helps predict real GDP growth, but also the federal funds target rate, and that the funds target rate, in turn, partly determines the future level of risk appetite. This interdependency might offer an interesting channel for preemptive monetary policy geared towards achieving both macroeconomic and financial stability. Gilchrist and Zakrajsek (2012) measure strains in the U.S. financial system by the excess bond premium which is derived from a decomposition of a corporate credit spread index and which likely captures variations in the average price of bearing corporate credit risk. They find that adverse shocks in this measure of financial stress cause substantial negative consequences for future economic activity, and that the federal funds rate declines significantly in response to such shocks as well. It is argued that the excess bond premium provides a timely gauge of the effective risk aversion of the financial sector, and that increases in risk aversion lead to a decline in asset prices, a contraction in the general supply of credit and, consequentially, to a slowdown in economic activity

and lower inflation. In Gilchrist and Zakrajsek (2011), the authors demonstrate that a central bank that augments a standard Taylor rule with a credit spread dampens the negative consequences of financial disruptions on real economic activity without materially compromising on its inflation objective, a finding similar to that of Curdia and Woodford (2010).

The cumulated policy rate shocks provide an estimate of the overall policy stance prevailing over certain periods.<sup>24</sup> Figure 3.4 plots the sum of the structural MRO rate shocks from the benchmark VAR (the grey shaded area around the zero line) together with the MRO rate over the entire sample period. I offer the following cautious interpretation of these facts.<sup>25</sup> With the swift and strong reduction of the MRO rate (to a then new low of 1%) in response to the fallout from the Lehman default, the ECB was able to maintain a roughly neutral policy stance until about mid-2010. Subsequently, and despite the fact that policy rates were held constant, the improvement in the economic outlook and the lower levels of stress produced a relatively easy monetary policy stance (i.e. negative shock sums) which the ECB partly corrected with its two rate hikes in April and July 2011. In response to the intensification of the sovereign debt crisis in the summer of 2011 and the ensuing deterioration in economic activity and declining inflation, the ECB gradually lowered the MRO rate to a mere 0.25% by December 2013. This notwithstanding, the overall easing stance gradually vanished and remained at a neutral level throughout 2013. Apparently, the ECB's conventional monetary policy

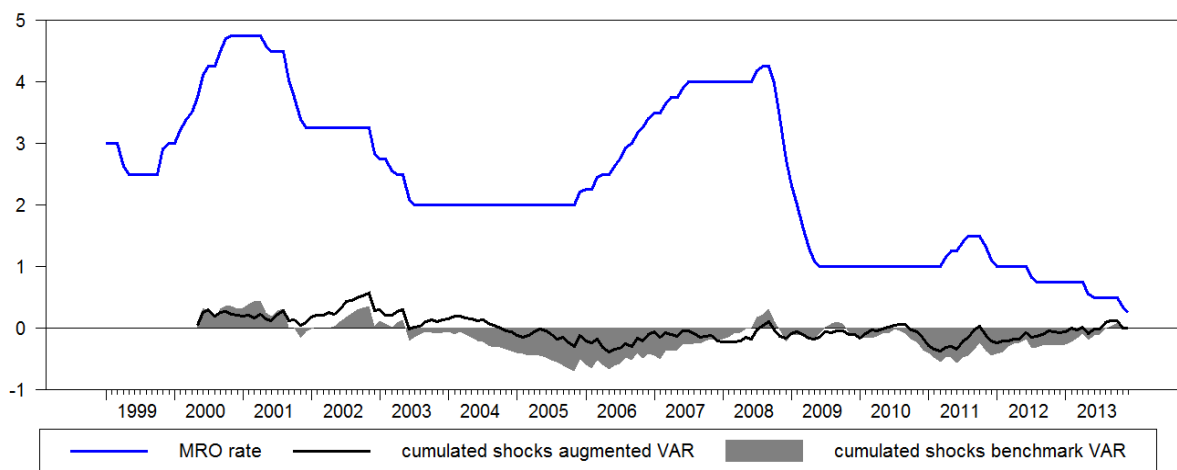
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<sup>24</sup>This interpretation assumes that the MRO rate predicted by the lagged endogenous variables approximates a short-term equilibrium rate. Positive or negative deviations of the actual MRO rate from that short-term neutral rate therefore determine whether the policy stance is contractionary or expansionary, respectively. A long-run natural interest rate could be computed from the steady-state solution of the VAR model.

<sup>25</sup>This interpretation is subject to several caveats. For instance, the regression format restricts the overall sum of shocks to be equal to zero. Hence, the procedure implicitly assumes that on average the policy stance is neutral. In addition, whether the cumulated policy shocks can represent the prevailing overall policy stance also depends on the appropriate choice of the starting date of the cumulation. Since the cumulated shock series starts at a value of zero, the starting date should coincide with a period in which the policy stance can be considered as neutral. In the present case, I let the summation start at the earliest possible date.



Figure 3.4: Measuring the stance of conventional monetary policy



became constrained by the zero lower bound towards the end of the sample period.

I also compute structural MRO rate shocks from a VAR augmented by three control variables which prove significant when being added to the MRO rate equation, namely the annual log change in the effective euro exchange rate, the BBB non-financial corporate bond spread and the business climate index. The series of the resulting shock cumulant is plotted as the black solid line in Figure 3.4. In general, the sums of shocks from the benchmark and the augmented VAR are rather similar. This notwithstanding, the cumulated shocks from the benchmark VAR would suggest a more pronounced easing stance in the years immediately preceding the outbreak of the financial crisis in August 2007. In contrast, since the height of the crisis in late 2008, the two series paint a rather similar picture of the monetary policy stance.

Finally, I ask which effects are brought about by the ECB's conventional monetary policy. This question can be addressed by looking at the dynamic responses of the benchmark VAR variables to structural MRO rate shocks plotted in the fourth column of Figure 3.1. A one-standard deviation shock in the MRO rate (about 8 basis points)

first moderately increases real GDP growth before the effect turns negative after about a year. There is no significant impact on inflation over a two-year horizon, and the dynamic effects on the ECB's balance sheet growth rate and the EONIA-MRO rate spread are likewise negligible. However, policy rate shocks exert rather significant effects on financial stress. For instance, when the ECB lowers the MRO rate “by surprise,” the CISS also declines, indicating that policy easing in times of heightened financial stress helps to reduce these very strains. Over a two-year horizon, shocks in the policy rate contribute about 20% to the prediction error variance of the CISS.

### **3.5.2 Unconventional monetary policy**

During the various stages of the financial crisis, the ECB—like many other major central banks—implemented several non-standard policy measures with the ultimate aim of mitigating the risk of further adverse consequences of the crisis on the macroeconomy and its policy objectives. The non-standard measures deployed to achieve this goal differed across economic areas, though, since they generally served different specific purposes tailored to the specific circumstances prevailing in the respective economies at each point in time.

The measures adopted by the ECB were generally designed to support the monetary policy transmission process in a context of dysfunctional markets. The ECB has thus interpreted its non-standard measures as complements to its standard interest rate policy, complements which are necessary to ensure that standard policy can have its intended effects. Several measures were designed to address a crisis phenomenon which was specific to the euro area, namely the emergence of financial fragmentation along national borders (Cœuré 2013). The fragmentation of financial markets inhibited a smooth and uniform transmission of conventional monetary policy impulses across the different

member states which further aggravated arising divergences between the cost of funding for banks, sovereigns and, ultimately, also private firms and households across different euro area countries.<sup>26</sup>

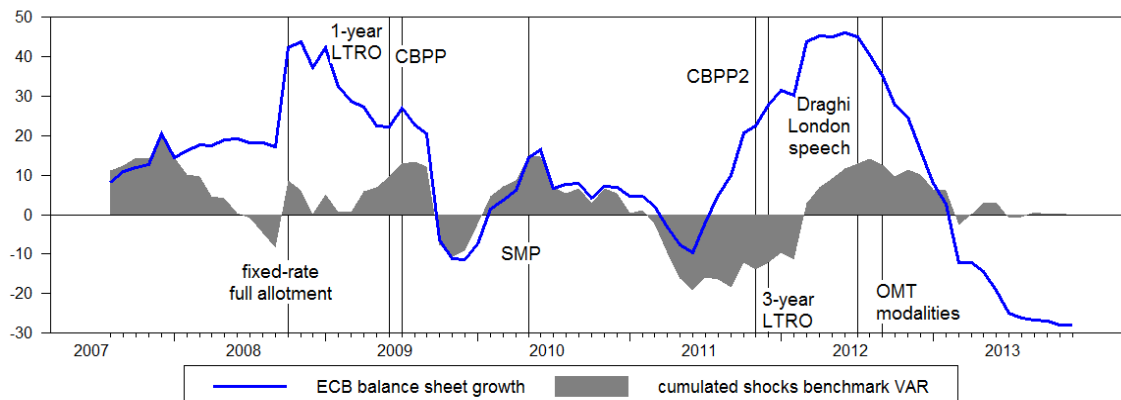
In order to counter impairments of the transmission process which were rooted in the money market, the ECB decided in October 2008 to conduct all liquidity-providing operations through a fixed rate tender procedure with full allotment. This measure insured that banks' liquidity needs were fully accommodated subject to the availability of sufficient eligible collateral. The de facto endogenous determination of banks' refinancing at a given policy rate resulted in a first marked expansion of the ECB balance sheet (see Figure 3.5). Later on, the ECB also lengthened the maturity of its long-term refinancing operations (LTROs) first to six months (February 2009), then to one year (June 2009), and finally, to three years (December 2011), which helped to stabilise the ECB's total assets at higher levels. In order to address market fragmentation in securities markets, the ECB also started purchasing bank bonds within two covered bonds purchase programmes (CBPP and CBPP2), and certain government bonds under the Securities Markets Programme (SMP). Last but not least, in September 2012 the ECB announced the modalities of its Outright Monetary Transactions (OMT) programme, which was likewise geared towards reducing the wide dispersion in government bond yields and, thus, in overall credit conditions across member states. The OMT, however, has not led to an expansion of the ECB balance sheet since there has been no need to activate the programme. Apparently, its announcement—shortly after the well-known “whatever it takes” speech by the ECB's president in which he expressed the Eurosystem's resolve to cope with the sovereign debt crisis (Draghi 2012)—sufficed to bring about much of the desired effects (see Altavilla, Giannone and Lenza 2014).<sup>27</sup>

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<sup>26</sup>In Hoffmann, Kremer and Zaharia (2015), we propose a price-based composite indicator of financial integration in the euro area (FINTEC) that documents a strong price dispersion across euro area countries which took hold of all major market segments during the crisis.

<sup>27</sup>This list of unconventional monetary policy measures by the ECB is not exhaustive. See various

Figure 3.5: Measuring the stance of unconventional monetary policy



Note: Monthly data; Jan. 1999 - Dec. 2013

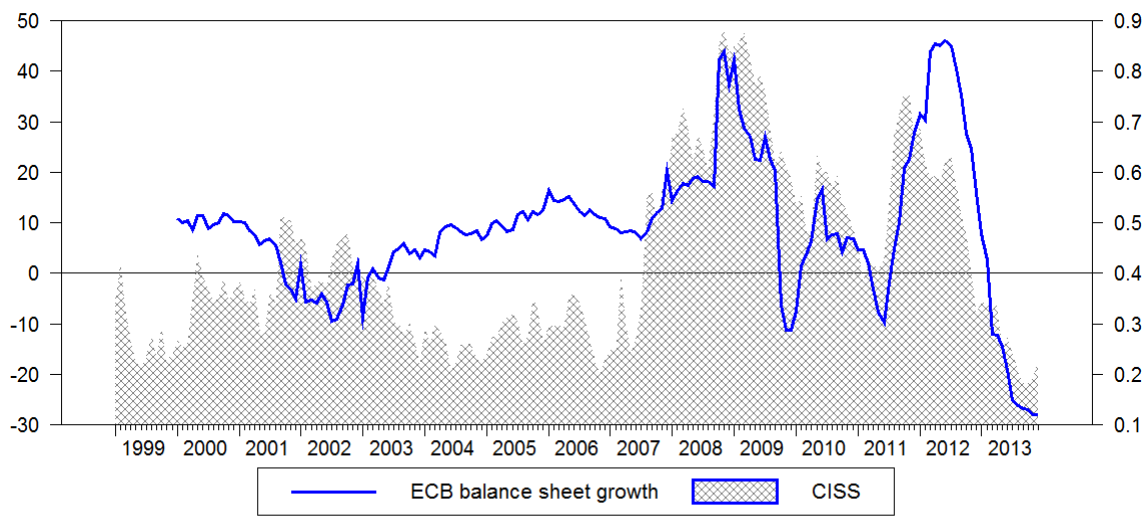
In contrast, most of the other non-standard policy measures had in common that they contributed to an expansion of the ECB balance sheet when being implemented. It may thus make sense to assess the overall stance of the ECB's unconventional monetary policy on the basis of the size of its balance sheet as measured by total assets, an idea also pursued in Gambacorta, Hofmann and Peersman (2014) and Boeckx, Dossche and Peersman (2014). Indeed, throughout the crisis, total asset growth and financial stress as measured by the CISS displayed a close correlation (see Figure 3.6).<sup>28</sup>

This correlation between the CISS and the ECB's balance sheet growth also holds up in the benchmark VAR as already demonstrated in Section 3.4. The exclusion  $F$ -tests established strong evidence in favour of direct causality of the CISS for ECB total assets. In addition, this predictive power of the CISS is robust to the inclusion of my set of control variables. Apart from the CISS, only inflation and own lags emerged as significant direct drivers of changes in the size of the ECB's balance sheet. The structural shock identification further suggests that balance sheet growth also adjusts

issues of the ECB Monthly Bulletin for complete references.

<sup>28</sup>The correlation coefficient between the (square root of the) CISS and annual growth in ECB total assets is about 75% when computed for the sample August 2007 to December 2013. The correlation over the entire sample period drops to 55%.

Figure 3.6: ECB balance sheet growth and the CISS



Note: Annual growth in total assets of the ECB balance sheet (lhs in %); CISS (rhs). Monthly data; Jan. 1999 - Dec. 2013

to contemporaneous news on financial stress, and unpredicted changes in the MRO rate (see the fifth row of the  $A$ -matrix in Equation 3.3). When incorporating indirect effects, we see that innovations in inflation and real GDP growth also impact on ECB total assets (see the panels in the fifth row of Figure 3.1). This is not surprising, since one would expect, at least in the long run, the central bank's balance sheet to grow in tandem with nominal economic activity. According to the FEVD, aggregate supply shocks contribute 9%, aggregate demand shocks 19%, the CISS 33%, and own shocks 30%, to the 24-month-ahead prediction error in the annual growth of the ECB balance sheet (see Table 3.1).

These results may allow the following interpretation. Under normal circumstances, the ECB balance sheet breathes in sync with nominal economic activity. In times of more severe financial stress, however, it is more appropriate to think of the balance sheet in terms of a behavioral policy reaction function with the ECB systematically and directly responding to changing states of financial instability.

The strong direct response of ECB balance sheet growth in conjunction with the

indirect reaction of the MRO rate to variations in financial stress may be viewed as principally consistent with the ECB’s declared intention throughout the crisis to keep separate the motivations behind its standard and non-standard monetary policy measures (“separation principle”). While the interest rate policy shall be determined so as to maintain price stability in the medium term, the non-standard policy measures aim to ensure that dysfunctions in some financial market segments do not disrupt the monetary policy transmission process and, thus, do not counteract the standard monetary policy measures (Constâncio 2011; Bordes and Clerc 2012). Accordingly, the policy rate may generally not be expected to respond to changes in financial stress *per se*, but only to the anticipated consequences of financial instability for the real economy. In contrast, unconventional monetary policy can be expected to directly react to systemic financial stress as long as it signals certain impairments of the monetary transmission process. However, as argued before, a *direct* response of monetary policy rates to observed financial stress may also, in principle, be justified on the grounds of identified material tail risks to the medium-term price stability objective.

The stance of unconventional monetary policy can likewise be gauged by the cumulated structural balance sheet shocks estimated from the benchmark VAR. Figure 3.5 plots this sum of shocks (the grey shaded area around the zero line) together with actual growth in ECB total assets; for better readability the figure only covers the crisis years.<sup>29</sup> This figure may suggest that during the crisis period, ECB balance sheet shocks were mostly expansionary (positive), consistent with the intentions of the implemented non-standard measures. In 2011, however, the stance of non-standard monetary policy turned significantly negative, reflecting to a large extent the lower levels of outstanding LTROs which were not compensated by alternative non-standard measures.

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<sup>29</sup>The idea for this chart is borrowed from Boeckx, Dossche and Peersman (2014) who, furthermore, offer a detailed account of events related to ECB non-standard measures.

The IRFs as plotted in the fifth column of Figure 3.1 provide a yardstick to assess the macroeconomic effects of the ECB’s balance sheet expansion. A positive one-standard deviation shock in the rate of growth of total assets (around 4 percentage points) precedes a mild immediate decline in inflation. The effects on real GDP are zero in the short-term, but become significantly positive after about a year. Over a two-year horizon, balance sheet shocks contribute 11% to the forecast error variance of real GDP growth. The overall impact on the CISS is negative, but not statistically significant at conventional levels. Boeckx, Dossche and Peersman (2014), who estimate a similar VAR model, find a hump-shaped response pattern for the log level of real GDP to a shock in total ECB assets, which becomes strongest (and statistically significant) after somewhat less than a year.<sup>30</sup> Interestingly, they find that the CISS declines instantaneously in response to an expansionary balance sheet shocks.

All in all, the empirical results seem to suggest that the ECB’s unconventional measures only had moderate effects on the real economy. It has to be taken into account, however, that the reduced-form modeling approach of the transmission of unconventional policy may omit essential factors that influence the transmission process and the environment in which specific interventions take place. For instance, Miles and Schanz (2014) argue that the effects of non-standard measures may hinge on the fact that they are implemented in times of dysfunctional markets, stressing the episodic nature of such interventions which may require the adoption of certain non-linear techniques such as regime-switching models. In a similar vein, the estimation of the effects of unconventional policies within a linear VAR framework may suffer from the fact that the true counterfactual—i.e. the state of the world which would have materialised in case a certain non-standard measure would not have been deployed—might be far away from the implied model dynamics under such a scenario due to the uniqueness of the non-standard

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<sup>30</sup>Their VAR is estimated with Bayesian methods for a shorter sample that only covers the crisis and the post-crisis years. They use sign restrictions to identify the structural innovations.

measures, and the economic conditions in which they were implemented (Kapetanios, Mumtaz, Stevens and Theodoridis 2012).

### **3.6 Caveats**

Some general reservations have to be expressed concerning the empirical approach taken in this paper. First, composite financial stress indicators—despite of all their merits—serve to represent a stylised, reduced-form approach to integrate financial instability in empirical macro-financial models. It is desirable that such approaches are complemented by a structural modeling of the main transmission channels through which systemic stress may affect macroeconomic dynamics (see, e.g., Boissay, Collard and Smets 2016). In a similar vein, this paper also takes a highly stylised approach to estimate the effects of non-standard monetary policy measures by exclusively focusing on their impact on the size of the ECB’s balance sheet, and how the balance sheet correlates with a set of macro variables, including financial stress. Such an analysis may be subject to omitted variables biases, among other things, and should therefore be likewise complemented by studies analysing, in greater detail, the conditions in the particular markets in which the interventions occurred, to get an idea about their immediate impacts in the chain of transmission (see, e.g., Beirne et al. 2012, and Eser and Schwaab 2016, on the ECB’s asset purchase programmes). This necessarily requires studying the effects of changes in the composition of the ECB’s balance sheet, rather than its overall size.

Second, for the purpose of this paper, I assume that the dynamic interrelationships between financial stress and the macroeconomy can be meaningfully approximated by a standard linear VAR, thereby ignoring potential non-linearities in the common dynamics of our variables of interest, which may emerge, in particular, during states of financial



instability. For instance, Holló, Kremer and Lo Duca (2012) find evidence for regime-switching in the parameters of a bivariate threshold VAR estimated for the CISS and industrial production growth in the euro area (see also Chapter 2 of this dissertation). When the CISS surpasses its identified threshold or crisis level, the dynamic impact of CISS shocks on output growth is found to be much stronger and statistically significant than in the alternative low-stress regime. In VAR models where the switches between different coefficient and/or variance regimes are governed by latent Markov processes, similar state-dependent effects of financial stress on economic growth and other macroeconomic variables are found, *inter alia*, by Davig and Hakkio (2010) and Hubrich and Tetlow (2015) for the United States, and by Hartmann, Hubrich, Kremer and Tetlow (2015) (which is also Chapter 4 of this dissertation) for the euro area. Kapetanios, Mumtaz, Stevens and Theodoridis (2012) estimate the effects of quantitative easing on the real economy in the UK by gauging the dynamic effects of changes in the term spread on inflation and real GDP within VAR frameworks. They find stronger effects in VARs which allow for coefficient changes—a Markov-switching VAR and a time-varying parameter VAR—compared to a linear VAR. Against this background, the absolute financial stress effects estimated from the full-sample linear VAR presented in this paper may therefore serve as a lower bound of the effects that one can expect to hold during periods of severe financial stress, and as an upper bound in normal times.

### **3.7 Conclusions**

Financial crises are strongly disruptive events which implicate severe losses in economic welfare if not contained by quick, resolute and often unconventional policy measures imposed by public authorities, including central banks. In this paper, variations in the state of financial (in-)stability are measured by the CISS, a specific financial stress in-

dex which focuses on the systemic dimension of financial strains. The empirical analysis confirms a strong and robust role of the CISS as a key driver of macroeconomic developments in the euro area. It also suggests that the ECB reacted in a systematic way to several bouts of financial stress during the recent crisis by implementing standard and non-standard monetary policy measures. Taken together, it seems that these complementary policy measures helped calm financial stress, and thereby limit the real adverse consequences of the crisis.

The empirical evidence available for other countries also finds, in general, a significant explanatory power of financial stress indices for macroeconomic developments. It may therefore represent a robust, though not yet widely known stylised fact in the empirical macro-financial literature. This notwithstanding, the literature is still inconclusive about how best to cope with potential structural instabilities and/or non-linearities in the macro-financial linkages induced by emerging financial frictions and market dysfunctions during crisis times. A systematic comparison of the performance of alternative methods—such as regime-switching or time-varying parameter models—vis-à-vis simple linear frameworks therefore appears to be a valuable topic for future research.

## CHAPTER 4

# MELTING DOWN: SYSTEMIC FINANCIAL INSTABILITY AND THE MACROECONOMY

**Abstract:** We investigate the role of systemic financial instability in an empirical macro-financial model for the euro area, employing a richly specified Markov-Switching Vector Autoregression model to capture the dynamic relationships between a set of core macroeconomic variables and a novel indicator of systemic financial stress. We find that at times of systemic financial instability the macroeconomy functions fundamentally differently from tranquil times. Not only the variances of the shocks, but also the parameters that capture the transmission of shocks change regime, especially around times of high systemic stress in the financial system. In particular, financial shocks are larger and their effects on real activity propagate much more strongly during regimes of high systemic stress than during tranquil times. We find an economically important role of bank lending in the propagation of financial stress to the macroeconomy. We also show that prospects for detecting high systemic stress episodes appear promising, although we argue that more research is required. We conclude that macroprudential policy makers may benefit from taking these non-linearities into account.<sup>§</sup>

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<sup>§</sup>This chapter is based on joint work with Philipp Hartmann (ECB), Kirstin Hubrich and Robert J. Tetlow (both Board of Governors of the Federal Reserve System). We thank Geert Bekaert, Kristoffer Nimark, Harald Uhlig and participants at the Office of Financial Research/Financial Stability Oversight Council conference “The Macroprudential Toolkit”, Deutsche Bundesbank/Institute for Monetary and Financial Stability/SUERF conference “The ESRB at 1”, a meeting of the ESCB Macroprudential Research (MaRs) network, European Economic Association Meetings 2012, Bank of Canada seminar, German Economic Association Conference 2013, Conference “Systemic Risk, Financial Markets and the Post-Crisis Economy” in Nottingham 2013, Central Bank of Mexico Conference 2013, Erasmus University Rotterdam Conference 2013, Stanford University Seminar 2013, ECB 2014 workshop, the Financial Intermediation, Risk and Liquidity Workshop and the Time Series Analysis in Macroeconomics and Finance Workshop at the Barcelona GSE Summer Forum 2014, ESCB Macroprudential Research Network 2014 Conference, the 6th IFABS 2014 conference, the International Association of Applied Econometrics 2014 conference and the NBER Summer Institute 2015 for useful comments.

## 4.1 Introduction

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

The theoretical literature has made progress recently in incorporating within macro models, financial instability and associated non-linearities. One strand of the literature has investigated the origins and mechanisms that can lead to the extraordinary amplification and propagation of shocks through the economy; examples include He and Krishnamurthy (2014) and Archaya et al. (2010) who analyse systemic risk with a focus on financial intermediaries.<sup>2</sup>

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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.

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

<sup>2</sup>See also, e.g., Bianchi (2011), Brunnermeier and Sannikov (2014), Martinez-Miera and Suarez

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

A feature of what we do is make use of the Composite Indicator of Systemic Stress (CISS), recently developed at the European Central Bank by Holló, Kremer and Lo Duca (2012) (see also Chapter 2 of this dissertation) as a measure of the state of systemic financial instability in the euro area. The CISS is particularly well suited for our purposes. It captures the systemic dimension of financial instability, first, by encompassing the main classes of financial markets and intermediaries in a systematic fashion and, second, by capturing time-varying dependence of stress between these major segments of the financial system.<sup>3</sup> Of note is the inclusion within the CISS of financial intermediation, which is likely to be important because of the more bank-centered financial system in the euro area, as compared to the United States where capital markets have a more prominent role.

We embed the CISS—together with a selection of macroeconomic variables—in a richly specified Markov-switching Vector Autoregression (MS-VAR) model. Our specification allows for independent regime shifts in the coefficients of the model, and in the variances of the model shocks. With this framework we explore five central issues.

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(2012), Boissay, Smets and Collard (2015), Adrian and Boyarchenko (2013), Goodhart et al. (2012) and He and Krishnamurthy (2011). The article by de Bandt and Hartmann (2000) reviews the topic of systemic risk, while de Bandt, Hartmann and Peydro (2010) updates the earlier article, but with a focus on banking.

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

First we uncover whether switching, as a driver of episodes of systemic stress, is confined to the variances of shocks, or whether something more fundamental takes place, namely switching in model coefficients and thus the transmission of shocks. The answer to this question is important for policy purposes, among other things, because it speaks to whether or not policy interventions should be directed toward apprehending the source of exogenous shocks, or whether inducing changes in the transmission mechanism need to be considered. Second, we analyze whether any statistically significant non-linearities we find are also economically important. Third, we explore the origins of our results; in particular, we investigate whether certain features of our systemic stress indicator stand out as important for our results, which then casts light on whether particular channels in the financial system are critical for spread of systemic distress. Fourth, we delve into the critical role of bank lending as either the source of, or the propagation mechanism for, fluctuations in output. And fifth, we assess whether our model could prove to be useful for tracking systemic stress episodes in real time.<sup>4</sup>

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

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

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

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

between financial shocks and real activity.

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

## **4.2 The model and data**

Several choices have to be taken at the initial stage of model specification. First, we need a flexible econometric model framework that can accommodate systemic stress episodes and allow for discrete shifts in economic dynamics. Second, we need a measure of systemic financial instability that ably captures the spreading of financial stress across markets and institutions. Third, the variables that fill out the rest of the model have to be representative of macroeconomic dynamics in general and interactions between the macro economy and financial stability in particular. And fourth, the model needs to be identified. We discuss each of these topics, in turn, in the next four subsections.



### 4.2.1 Non-linear multivariate model framework

An important feature of our analysis is the application of an econometric framework that allows to investigate empirically whether the macroeconomy fundamentally changes its functioning when systemic financial stress emerges or disappears. In particular, we ask whether specific non-linearities, in the form of regime switches in the dynamics of and the relationships between key macroeconomic variables, can be empirically identified. For this purpose we apply a richly specified Markov-switching VAR model that can estimate discrete changes in the economic dynamics. Our specific MS-VAR framework distinguishes between two independent sources of regime switching, namely, shifts in the variances of shocks and shifts in the economic structure that transmits those shocks.

There are alternatives to using an MS-VAR model; the two that come immediately to mind are time-varying parameter (TVP) models and threshold models. TVP models, like MS-VAR models, allow for time variation in parameters or shocks, or both, but typically model that variation as drifting coefficients. Our use of the MS-VAR modeling framework reflects our understanding of the nature of systemic financial stress and its effects on macroeconomic dynamics; systemic financial stress, almost by definition, tends to involve discretely non-linear or non-Gaussian effects, either in the financial sector itself, or in their macroeconomic consequences, or both.<sup>5</sup> As such, the MS-VAR framework seems like a natural choice. Threshold models, like MS-VAR models, can allow for discrete shifts in parameters (or in the distributions of shocks), but the researcher is obliged to prespecify a threshold variable. Given the wide range of stories that have been advanced concerning the origins and propagation of financial events, it seems reasonable to us to avoid such prespecification. Our modeling choices notwithstanding, we would not argue that there are no insights to be gleaned from TVP or threshold models

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

in this context, although the particular questions under study might differ in some ways.

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

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

$$y_t' A_0(s_t^c) = \sum_{j=1}^l y_{t-l}' A_j(s_t^c) + z_t' C(s_t^c) + \varepsilon_t' \Xi^{-1}(s_t^v), \quad t = 1, 2, \dots, T. \quad (4.1)$$

where  $y_t$  is an  $n \times 1$  vector of endogenous variables;  $s_t^m$ ,  $m = v, c$  are unobservable (latent) state variables, associated with different regimes for error variances,  $v$ , and for intercepts and slope coefficients,  $c$ .  $l$  is the VAR's lag length.  $z_t$  is a matrix of exogenous variables, which we are setting to a column vector of constants  $1_n$ , i.e. one intercept per equation.  $A_0(s_t^c)$  is an  $n \times n$  matrix of parameters<sup>6</sup> describing contemporaneous relationships between the elements of  $y_t$ ,  $C(s_t^c)$  is an  $1 \times n$  vector of parameters of the exogenous variables and  $A_j(s_t^c)$  is a  $n \times n$  matrix of parameters of the endogenous variables and  $T$  is the sample size.  $\varepsilon_t$  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  $\varepsilon_t$ .  $\varepsilon_t' \Xi^{-1}(s_t^v)$  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:

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

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

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

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<sup>6</sup>Note that we impose identifying restrictions such that  $A_0$  is triangular.

The variance-covariance matrix  $\Sigma(s_t^m)$  of the correlated reduced-form regression errors can be recovered as follows:<sup>7</sup>

$$\Sigma(s_t^m) = (A_0(s_t^c)\Xi^2(s_t^v)A_0'(s_t^c))^{-1}. \quad (4.2)$$

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

## 4.2.2 Systemic stress indicator

To be suitable, a systemic stress indicator must have several attributes. First, as the word *stress* suggests, it needs to capture not just activity or even disruption in the financial sector, but stresses that might be of concern to market participants and policy makers. Second, as the word *systemic* indicates, it should ideally distinguish between stress that is germane to a single or small subset of markets—and thus not of concern to the system as a whole or its regulators—and stress that has the potential to spread through the entire system. It is presumably when stress is widespread that it has implications for the broader macroeconomy. Indeed, a conventional definition of systemic risk is that it is “(...) *the risk that financial instability becomes so widespread that it impairs the functioning of a financial system to the point where economic growth and welfare suffer materially*” (ECB 2010). Third, as the word *indicator* suggests, the candidate measure of systemic stress needs to be timely in the marking of stress episodes, reliably identifying events of potential concern to market participants and policy makers, preferably in real time.

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<sup>7</sup>See Sims, Waggoner and Zha (2008), p. 265.

We will argue that the Composite Indicator of Systemic Stress (CISS) developed by Holló, Kremer and Lo Duca (2012) ably fulfills the roles of a good systemic stress indicator, as just described. Our discussion of the CISS will be brief by necessity; readers interested in more details are invited to consult Holló, Kremer and Lo Duca (2012) or Chapter 2 of this dissertation.

First of all, the scope of the CISS is broad, comprising five aggregate market segments covering the main channels by which the funds of savers are reallocated to borrowers, whether those funds are channeled directly through capital markets or indirectly through financial intermediaries. These segments include: (1) financial intermediaries; (2) money markets; (3) bond markets; (4) equity markets; and (5) foreign exchange markets. Each of the five market segments is populated with three representative stress indicators that are generally recognised as excellent proxies of fundamental risks and market disruptions, such as spreads, volatilities and market return correlations (see Table 2.1 for a precise description of the data). Aggregation of each set of three constituent stress measures—after appropriate transformation to harmonise their scale and variances—results in five segment-specific subindexes of financial stress.

The way the subindexes are aggregated into a composite indicator is the main innovative feature of the CISS. In the same way that portfolio risk is computed from individual asset risks, the subindexes are aggregated by taking into account the time-varying (rank)-correlations between them. This time variation in the correlations means that relatively more weight is applied to components during periods in which stress prevails in several market segments at the same time. Thus, the CISS is designed to capture what might be called the epidemiology of risk, meaning the way in which instability in one market infects other markets, leading to widespread and possibly severe financial instability with systemic implications.

For a plot of the composite indicator, as constructed from euro area data, see Figure 2.6 in Chapter 2. As can be seen, the largest spikes in the indicator coincide with well-known financial stress episodes, such as the 1987 stock market crash, the 1992 crisis of the European exchange rate mechanism, the 1998 Russian debt default and associated Long Term Capital Management crisis, as well as the financial stress around the terrorist attacks on 11 September 2001.<sup>8</sup> More recently, the financial crisis stands out in comparison with previous stress events in terms of both the level reached, in the wake of the September 2008 bankruptcy of Lehman Brothers, and in the duration of high readings.

### 4.2.3 Other variables and data sources

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

The set of endogenous variables is completed by adding the CISS and the growth rate in nominal bank loans to the private sector. The latter choice can be generally motivated by the strong role that bank lending played in the most severe financial crises

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<sup>8</sup>See Hollo, Kremer and Lo Duca (2012) for a more extensive coverage of historical stress events which coincide with peaks in the CISS. The review article by de Bandt and Hartmann (2000) describes methods for measuring systemic risk.

in history; e.g. Schularick and Taylor (2012). It can also be justified by the relatively large share of bank loans in the overall financing of the euro area economy.

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

#### 4.2.4 Structural model identification

The contemporaneous relationships between the endogenous variables—as reflected in the Matrix  $A_0$ —are identified on the basis of a triangular representation analogue to the well-known Cholesky decomposition often used in structural VAR applications.<sup>9</sup>

The conventional ordering in the macro VAR literature places the short-term interest rate last, implicitly assuming that monetary policy may react simultaneously to shocks in the other variables while no other variable is allowed to respond contemporaneously to monetary policy shocks.<sup>10</sup> 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.

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<sup>9</sup>In triangular identification schemes the ordering of the variables determines the contemporaneous causality structure. For instance, the variable ordered first is assumed to be contemporaneously uncorrelated to all other variables.

<sup>10</sup>See e.g. Christiano, Eichenbaum and Evans (1999).

Finally, we order the CISS last such that output, inflation, interest rate and loan shocks can all have contemporaneous effects on financial stress, while systemic financial instability (CISS) shocks are restricted to affect the rest of the economy only with a lag. This ordering reflects the conventional practice in the recent VAR literature of allowing asset price variables to respond instantaneously to shocks in usually more sluggish macro variables such as output and inflation. The variables thus enter the model in the following order: output growth ( $\Delta IP$ ), inflation ( $\Delta P$ ), interest rate ( $R$ ), loans ( $\Delta Ln$ ) and the CISS ( $S$ ). Our main results turn out to be qualitatively robust to different variable orderings, however.<sup>11</sup> In what follows we thus present results only for the above ordering which constitutes the most conservative estimates for the issue we are most interested in, namely the link between systemic financial instability and the real economy.<sup>12</sup>

### 4.3 Systemic stress, regimes and financial crises

#### 4.3.1 Model estimation and evaluation

The five-variable structural MS-VAR model in Equation (4.1) is estimated with Bayesian methods using three lags.<sup>13</sup> We employ a blockwise optimisation algorithm to estimate

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<sup>11</sup>In particular, when placing the CISS first in the order (followed by interest rates, output growth, inflation and loan growth) such that all shocks in financial stress become exogenous to the contemporaneous shocks in the other model variables (assuming, e.g., that output and monetary policy can react simultaneously to surging financial stress), the impulse response functions still convey the same basic messages. The same robustness result holds true when switching the order between bank loan growth and the interest rate (allowing short-term rates to react immediately to lending innovations).

<sup>12</sup>We also carried out several other sensitivity analyses, which again turned out immaterial for our main findings. For instance, we replaced the three-month Euribor by the monthly average EONIA (Euro OverNight Index Average) rate, where the latter substitution takes account of the fact that banks' liquidity and counterparty risk considerations drove a large wedge between both rates during certain episodes of the recent crisis. Results not displayed in the paper are available from the authors upon request.

<sup>13</sup>A model with a lag length of 12 provides similar results in terms of the real effects of a financial stress shock reported later.

the posterior mode. In a first step, parameters are divided into blocks and the resulting initial guesses for the parameters are used in a hill-climbing quasi-Newton routine. At candidate maximum points, we subject the estimator to random perturbations thus generating starting values from which the optimisation process is restarted in order to assure that the estimated posterior mode we obtain is indeed the most likely estimate.<sup>14</sup>

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

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

<sup>15</sup>The Bayesian counterpart to frequentist hypothesis testing is to compare MDDs, or equivalently, to assess Bayes factors, across models.



The standard modified harmonic mean (MHM) method for computing MDDs of Gelfand and Dey (1994) has been found to be unreliable when the posterior distributions are very non-Gaussian as is likely to be the case here. To overcome numerical problems that arise in this context, and to better approximate the posterior density function, we are using an elliptical distribution as a weighting function to calculate MDDs (Waggoner and Zha 2012, Appendix B).<sup>16</sup>

We employ two sets of priors for estimating our model, one for the VAR parameters, the other for the transition matrix. Following Sims, Waggoner and Zha (2008) we use standard Minnesota priors for the VAR parameters; for the transition matrix, we use the Dirichlet prior.<sup>17</sup>

### 4.3.2 Determining and interpreting regimes

#### Model selection

Before turning to the results, a few words on notation are useful in order to interpret the table to follow. In table headings and elsewhere, a  $v$  indicates the Markov chain associated with switching in shock variances, while a  $c$  refers to the chain governing model coefficients. A number preceding either  $v$  or  $c$  indicates the number of regimes allowed in the Markov chain governing shock variances or coefficients, as applicable. So, for example,  $3v2c$  indicates a specification that allows for three regimes in the variances of shocks and two regimes in coefficients.

Table 4.1 presents the log MDDs for several combinations of the two types of regimes.

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

<sup>17</sup>For more details on the priors, see Appendix B.

Table 4.1: Goodness-of-fit statistics, selected model regime specifications

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

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

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

According to Jeffreys (1961), differences in log MDDs of 10 or more can be taken as strong evidence that one model is more likely than the other. As can be seen, the results provide strong evidence against a constant-coefficient ( $1v1c$ ) model. The difference between the constant-coefficient model, column [1], and any of the models with regime switching is at least 98 in terms of log MDDs, and in most cases much above 100. Restricting the number of coefficient regimes to one, and allowing for two or three regimes in shock variances, as in columns [2] and [3], shows that the models with several regimes in shock variances outperform the constant coefficient model: the  $3v1c$  specification is the preferred one among the three specifications that allow only switching in variances. Consider, however, starting with two regimes in shock variances—that is, the  $2v1c$  specification—whether the addition of a third variance state ( $3v1c$ ) or a second coefficient state ( $2v2c$ ) improves the model fit. Columns [3] and [4] suggest that there is no strong reason to prefer one of these models over the other. Lastly, the specification with three variance regimes and two coefficient regimes— $3v2c$ , column [5]—is shown to outperform the other, simpler models.<sup>18</sup> Indeed, on the basis of log MDD comparison,

<sup>18</sup>Marginal data densities penalise non-parsimony of models. Kass and Raftery (1995) show that the Schwarz criterion (or BIC) gives a rough approximation to the logarithm of the Bayes factor.

a model allowing even more states in shock variances, the  $4v2c$  model in column [6], is favored.<sup>19</sup> However, these more elaborate models might not be very different from each other. The RCM evaluates the ability of the different models to sharply distinguish one regime from another. Lower readings of the RCM indicate sharper regime classification. Regarding the distinction between the  $2v2c$ , the  $3v2c$  and the  $4v2c$ , the RCM effectively penalises the addition of variance regimes that do not lead to a sharper regime distinction for the coefficient regimes than the more parsimonious specifications. According to the RCM the  $3v2c$  specification is preferred. Finally, our review of the economic properties of the  $3v2c$  specification of the model suggests to us that this specification is at least as good as the alternative candidates, based on the criterion of economic plausibility.<sup>20</sup> On this basis, we select the  $3v2c$  specification as our preferred model.

### **Economic characterisation of regimes**

We now turn to an economic characterisation of the different regimes identified in our preferred model specification. Table 4.2 shows the estimated standard deviations of the structural shocks across the three identified variance regimes, normalised such that the volatilities of the first regime are unity. For reasons that will only become clear a bit later on, we will call our three variance regimes ,“low” ( $vL$ ), “medium” ( $vM$ ), and “high” ( $vH$ ) regimes; similarly, we will refer to the two regimes for VAR-equation coefficients as  $cL$  and  $cH$ . Several noteworthy conclusions arise from the table. First, switching in shock variances is consequential, at least statistically, as can be seen by the substantial differences in the (normalised) standard deviations from regime to regime. Second, there exists no uniform pattern in the ranking of standard deviations across all variables in

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<sup>19</sup>Models with additional coefficient regimes could not be estimated given the high number of parameters.

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

Table 4.2: Relative standard deviations of structural shocks by regime

	$\Delta IP$	$\Delta P$	$R$	$\Delta Ln$	$S$
Low-variance regime ( $vL$ )	1.00	1.00	1.00	1.00	1.00
Medium-variance regime ( $vM$ )	0.91	1.53	0.29	0.74	0.62
High-variance regime ( $vH$ )	0.85	1.99	0.65	0.56	2.98

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

that the standard deviations of shocks do not rise or fall uniformly from regime to regime. Third, for the shock of principal interest for this paper, namely the CISS ( $S$ ) shock, the variance of the shock in  $vH$  state clearly stands out. Finally, while the  $S$  shock and also the inflation shock, ( $\Delta P$ ), rises substantially, in  $vH$  relative to  $vL$ , the pattern is the opposite for shocks to loans, ( $\Delta Ln$ ), and the interest rate ( $R$ ), while there is little difference across states in the variances of shocks to industrial production, ( $\Delta IP$ ). Precisely what to make of the lack of uniformity in shock variances across regimes is not entirely clear from these particular statistics, but it does suggest that shocks to financial stress play a more important role in driving dynamics in  $vH$  than do shocks to loan growth and real activity, operating independently of financial stress. In short, the suggestion is that in the  $vH$  regime, it is stress shocks that dominate.

Table 4.3, which shows descriptive statistics for endogenous variables conditional on each of the six possible combinations of our independent variance and coefficient regimes, sheds some light on the economic characterisation of regimes from the viewpoint of financial stability.<sup>21</sup> For ease of comparison, the regimes are ordered such that regimes with  $v = vL$  and  $c$  varying from  $cL$  to  $cH$  are presented in the first two rows of the table, while regimes with  $v = vM$  and  $v = vH$  are displayed in the subsequent four rows with the respective coefficient regimes. Several interesting observations arise with regard to the interpretation of these data. First, and most obviously, as one moves

<sup>21</sup>These summary statistics compute the moments, conditional on regime, for each variable over all months in which a given regime dominates. The dominant regime is the one with the highest smoothed regime probability in the respective month. As we show below in the analysis of the smoothed probabilities in Section 3.2.3, regime dominance is rarely ambiguous in our model.

Table 4.3: Descriptive statistics, by regime

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

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

down the rows of Table 4.3 from row [1] to [3] and [5], or from row [2] to [4] and [6], the regime-dependent means of the CISS rise.<sup>22</sup> It would appear, therefore, that at least a portion of elevated levels of stress, when applicable, stem from stress shocks themselves. Second, as demonstrated by lines [5] and [6], the  $vHcL$  regime and the  $vHcH$  regime are periods of extremely high levels of financial stress—at least twice as high as in other states—but are relatively rare, as judged by their sample shares of 5 and 7 percent, respectively. Third, while growth in loans,  $\Delta Ln$ , and growth in real activity,  $\Delta IP$ , rise as one goes from  $vL$  to  $vH$  when  $c = cL$ , they both fall sharply and monotonically with  $v$  when  $c = cH$ . Evidently, periods of financial stress also feature reduced lending activity and deterioration in real economic performance. And clearly, shifts from regime  $cL$  to  $cH$  are economically consequential, although in precisely what way depends a great deal on the prevailing variance regime as we will explore in more detail in section 4.3.2.

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

<sup>22</sup>There is an element of arbitrariness in designating a variance regime as “high” or something else. In the present case, our assignment of labels reflects how the regimes coincide with the level, on average, of financial stress as measured by the CISS, shown in the table. So, for example, the  $vL$  regimes shown in rows [1] and [2] of the table have the lowest levels of  $S$ , as noted in the column second from the right, and the  $vM$  states in rows [3] and [4] have larger average levels of  $S$  than their counterparts in  $vL$  states, and so on.

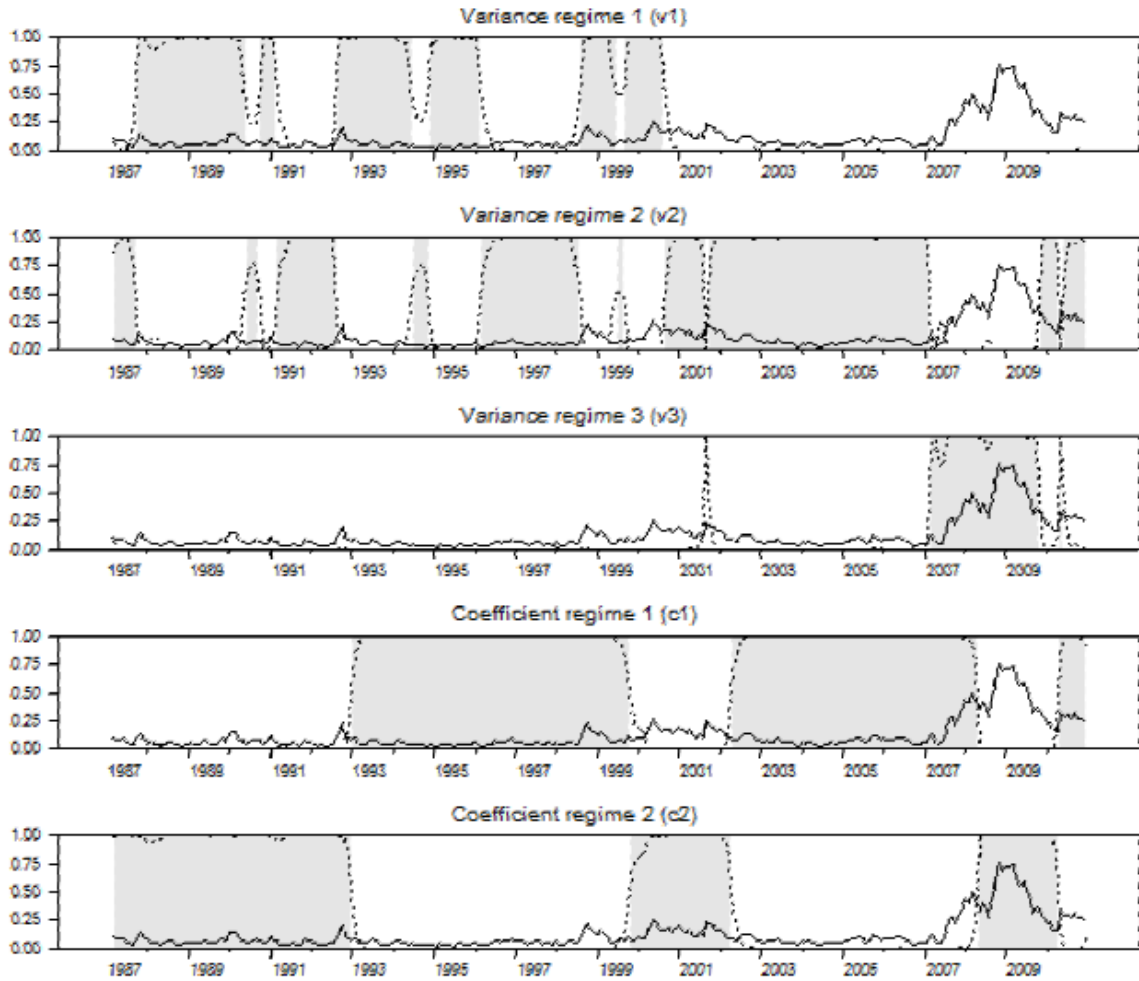
Similar logic follows for  $cL$  and  $cH$  where for any state for  $v$  it can be seen that the average level of  $S$  is higher in what we call  $cH$  than it is in  $cL$ .

column from the left in Table 4.3, as well as in one of the notes to the table. The  $vLcL$ ,  $vLcH$  and  $vMcL$  regimes are associated with periods of relatively low levels of financial stress. Inasmuch as these three regimes collectively prevail in about 70 percent of the sample period and they are periods where the economy behaved in a manner that could be regarded as “normal,” we will refer to as *tranquil times*. Even so, these normal periods do include episodes of occasional, short-lived spikes in financial stress. One way to think about this collection of regimes is that they feature either shocks of modest magnitude (the  $vLcL$  and  $vLcH$  regimes) or weak propagation of shocks as will be demonstrated below is the case when  $c = cL$  ( $vMcL$ ), or both ( $vLcL$ ). The  $vMcH$  regime, shown on line [4] of the table, might be labelled *elevated stress* in part because, as we show below, it occurs during the first two years of the bursting of the dot-com bubble—during which, according to the CISS, financial stress persisted at an elevated, though not extremely high level—and it occurs over the roughly half a year immediately after the failure of Lehman Brothers in August 2008 (see Figure 2.6).

Tables 4.2 and 4.3 showed that, in general, no uniform ranking exists in terms of regime-dependent shock volatilities or conditional means; nevertheless, all of the series exhibit their “worst” readings in terms of conditional means in the  $vHcH$  regime, shown in row [6] of Table 4.3. That is, these were the periods where stress levels were at their highest, and were also associated with negative growth in industrial production and the lowest levels in each of loan growth, inflation and interest rates. Consequently, we label this regime the *systemic crisis* regime. Lastly, as shown in row [5], the  $vHcL$  regime, which involves a substantial degree of shock-driven volatility, but as we demonstrate below, little propagation of those shocks, is labelled the *systemic fragility* regime.

**Regime probabilities** Time series of the (smoothed) probabilities are presented in Figure 4.1. In general, the regime probabilities are either very close to one or very close

Figure 4.1: CISS and probabilities for variance and coefficient regimes



**Note:** Dominant regimes shaded.

to zero, indicating that the model classifies regimes rather sharply. The five panels in the figure show the periods that contribute to estimates of the parameters of the variance and coefficient regimes. As can be seen, the estimation of the two coefficient regimes is supported by data spanning several elongated periods. It follows that these periods are comfortably sufficient for estimating the parameters of the coefficient regimes.<sup>23</sup>

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

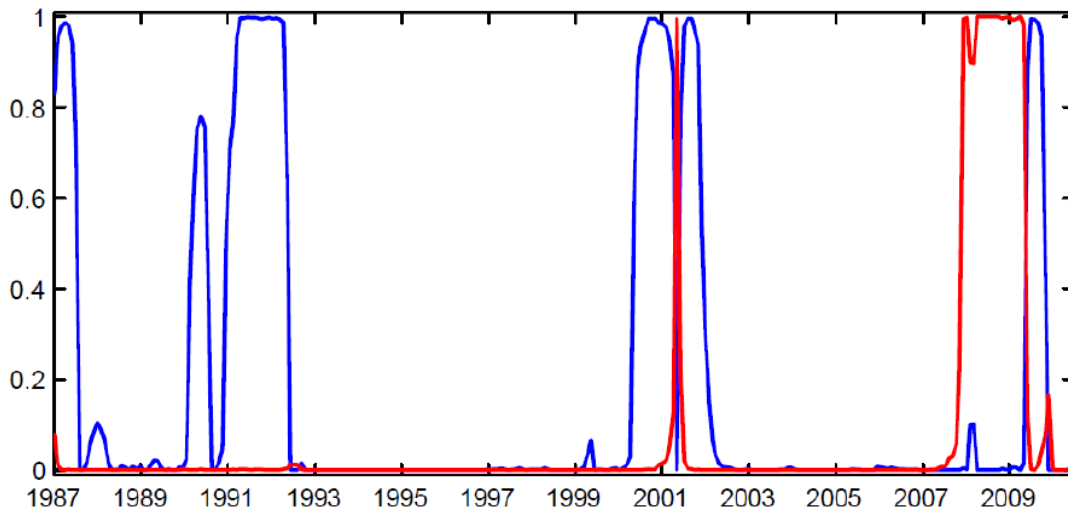
In the next subsection we demonstrate that the coefficient regime  $cH$  features much stronger transmission of financial stress to the broader economy than does coefficient regime  $cL$ . Building on this assertion, Figure 4.2 shows the probability of two regimes in which the propagation of shocks is strong and shocks are either medium (the *elevated stress regime*  $vMcH$ ) or large (*systemic crisis regime*  $vHcH$ ). These regimes pick up, as we already noted, periods in which absolute the level of the CISS, ( $S$ ), is rather high. These two regimes are also periods in economic history that are associated with demonstrable financial turmoil, as can be seen by comparing panels of Figure 4.1 with the events shown in Figure 2.6. Episodes captured by these regimes include the aftermath of the 1987 stock market crash; the Gulf war in 1990; the run-up to the crisis in the European Exchange Rate Mechanism (ERM) in the early 1990s; the bursting of the dot-com bubble in the early 2000s; the US terrorist attacks in September 2001; the global financial crisis of 2008 and the associated meltdown of the euro area economy; and finally a time period in 2009 when the financial crisis was moderating until the euro area sovereign debt crisis emerged in early 2010.<sup>24</sup> As line [6] of Table 4.3 notes, there were only two periods that are associated with  $vH$  regimes: a short episode immediately following the US terrorist attacks in September 2001, and the culmination of the global financial crisis, including the large decline in output growth, the “meltdown” as it were, of the euro area economy. Interestingly, the initial stages of the recent global financial crisis are associated with a *systemic fragility* regime,  $vHcL$ . While not itself a state of high systemic stress, this regime might be considered a precursor to such states; it shares the large shocks of the systemic crisis regime but lacks the strong propagation of those shocks. Thus, according to the model, the initial stages of the subprime crisis had not yet reached the point of being *systemic stress* and thus did not immediately bring about

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<sup>24</sup>We note that the level of the CISS index itself was not elevated in 1991-92, a period when the Eurosystem came under stress following German reunification. And yet Figure 4.2 indicates that this was a period of systemic stress. This observation demonstrates the fact that the (unobservable) regimes representing systemic stress are functions of all the variables in the system, and cannot be inferred solely by the values of the systemic stress index.



Figure 4.2: Smoothed state probabilities for two high-stress transmission regimes



Note: The blue series shows the regime probability for the medium-stress variance/high-stress coefficients regime. The red series shows the regime probability for the high-stress variance/high-stress coefficients regime.

large-scale output losses. The full, systemic crisis emerged—according to our model—a few months prior to the bankruptcy of Lehman Brothers.

### Transmission of financial shocks

We now explore the properties of the various regimes through comparisons of their regime-specific impulse response functions (IRFs).<sup>25</sup> While the three shock-variance regimes differ in the magnitude of one-standard-deviation shocks, but their propagation will differ only to the extent that the coefficient regime differs. Because the main purpose of our paper is to study state dependencies in the transmission of systemic financial instability to the real sector, we focus on the IRFs describing the dynamic effects of structural shocks to the CISS. Figure 4.3 plots the impulse responses to shocks in the CISS ( $S$ ) for two starkly different regimes, the  $vHcH$  regime (solid red lines) and the  $vLcL$  regime (blue dashed lines). To aid in the interpretation, the figure also includes

<sup>25</sup>Note that the impulse responses presented here are computed at the posterior mode.

the IRFs for a constant-coefficient Gaussian VAR model (the  $1v1c$  specification).<sup>26</sup>

The differences in IRFs between systemic crisis and tranquil times are striking. In the  $vLcL$  regime, industrial production growth (as well as all other variables) displays hardly any response at all to a CISS shock. It thus appears that financial stress shocks are effectively irrelevant in tranquil periods, an observation that accords well with the fact that the CISS aims to measure systemic stress and not general financing conditions. By contrast, in the  $vHcH$  regime, a positive shock in financial stress leads to a quick, severe and protracted contraction in economic activity. On this evidence, we conclude that the  $cL$  coefficient regime implies weak financial-real linkages—which is to say, weak propagation of financial stress shocks—while the  $cH$  coefficient regime implies very strong ones. These findings ratify our designation of the  $vHcH$  regime, featuring the largest CISS shocks and the strongest financial-real linkages, as a regime of systemic crisis.<sup>27</sup>

The lower-right panel of Figure 4.3 shows a relatively strong, gradual and persistent effect of a CISS shock on loan growth in the systemic crisis regime. This suggests that bank lending may also play a role in amplifying the transmission of financial stress to the real economy in times of financial turbulence. The gradual decline in loan growth in response to an adverse CISS shock may reflect firms' ability to draw down existing credit lines at the early stages of a financial crisis, mitigating the overall constraints on bank loan supply in the short term.<sup>28</sup> At the same time, this fact is also in line with a lagged reaction of lending following the strong and immediate decline in output growth.

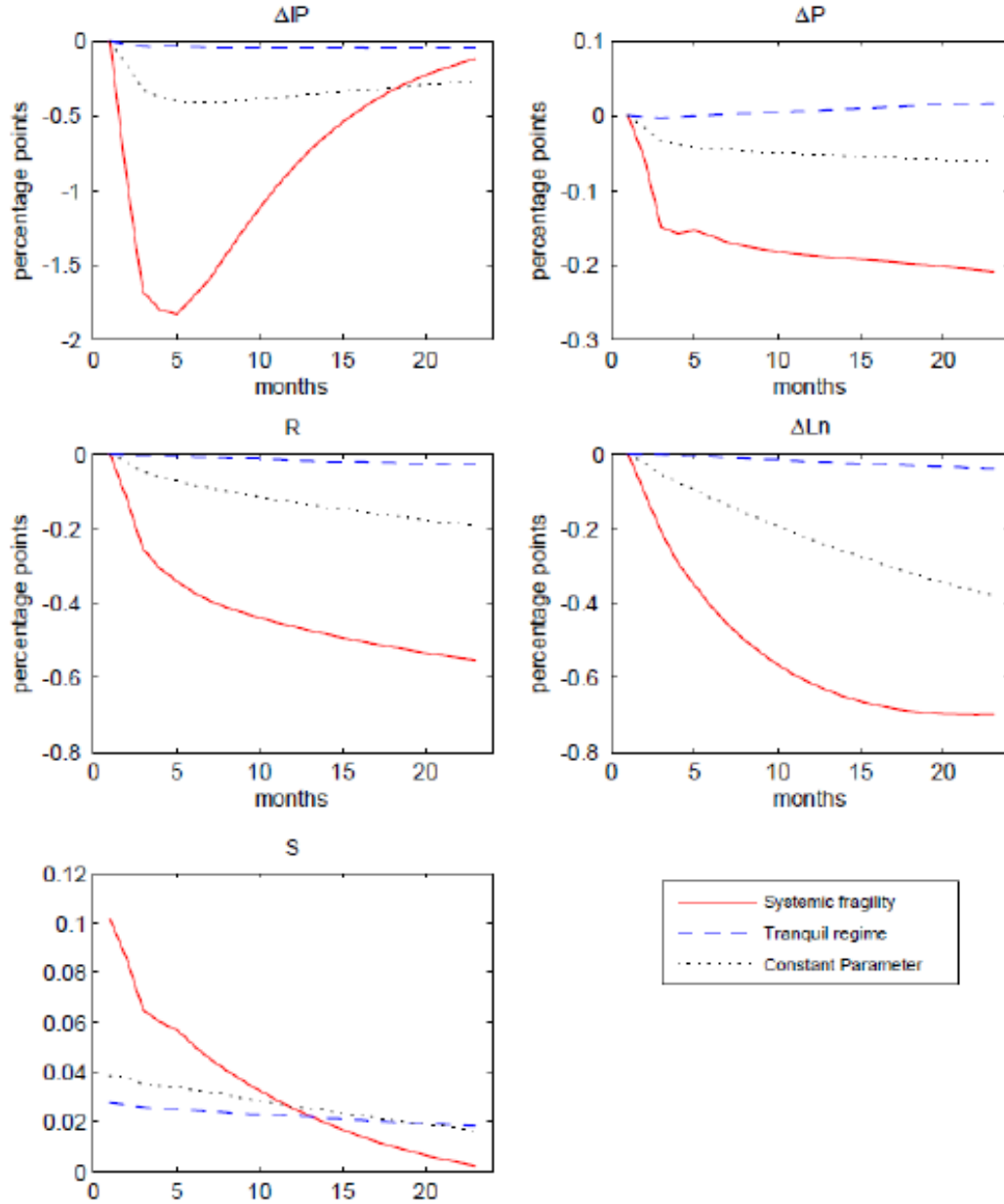
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<sup>26</sup>The IRFs are calculated for a positive one-standard-deviation shock to the CISS for the two most different regimes, the systemic crisis regime ( $vHcH$ ) and in the tranquil regime ( $vLcL$ ). Up to a scaling factor, similar conclusions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

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

<sup>28</sup>See Ivashina and Scharfstein (2010) for evidence on the relevance of this point for the case of the United States.

Figure 4.3: Regime-dependent impulse responses to financial stress shocks



The impulse response functions (IRFs) are for one-standard-deviation shocks; responses in output growth ( $\Delta IP$ ) inflation ( $\Delta P$ ), interest rate ( $R$ ), loan growth ( $\Delta Ln$ ) and systemic financial stress ( $S$ ). IRFs shown for a linear VAR, the constant parameter model, and for the systemic crisis regime (vHcH) and a tranquil regime (vLcH) from our preferred model with two coefficient and three variance regimes (3v2c).

Figure 4.3 also illustrates that the IRFs estimated for a constant-parameter Gaussian VAR model (the black dotted lines) would clearly underestimate the effects of financial stress shocks on economic activity in certain states of the world, as well as on the other macro aggregates. We conclude that policy guidance from our non-linear VAR may be more realistic under circumstances of elevated financial stress.

### 4.3.3 Counterfactual analyses

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

#### The role of systemic stress

To explore the fundamental change in economic dynamics during crisis episodes, we consider a counterfactual scenario in which tranquil times are assumed to have persisted from October 2008 to February 2009, instead of incurring the switch to systemic crisis that our baseline specification says took place.<sup>29</sup> Figure 4.4 demonstrates that in this scenario the level of systemic stress would have been substantially lower, by almost 0.2, and that impact of this switch on output growth was substantial. The figure shows that growth in industrial production would have declined at only 6 percent annual rate, instead of “melting down” at a rate of 21 percent per annum; loan growth and

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<sup>29</sup>This counterfactual employs the estimated coefficients and the parameters of the shock variances of the counterfactual regime to compute the counterfactual path of the variables during the counterfactual period. See also Sims and Zha (2006) for a similar counterfactual experiment in a different context.

inflation would have remained more or less stable at the rates observed at the outset of the exercise, instead of being 2.5 percentage points and 3 percentage points lower, respectively. Monetary policy would have been less accommodative with short-term interest rates dropping by only 1 percentage point instead of the 3 percentage points that was observed. Additional counterfactual experiments comparing the effects of a different path of financial stress in systemic crisis versus tranquil times are presented in Appendix C. They show that an increase in systemic financial stress has little effect in tranquil times, but substantial effects in episodes of systemic crisis.

### **The role of lending**

In this Section we investigate the role of bank lending for the macroeconomy. In particular, we are interested whether lending has an impact for the real economy beyond that which originates from financial stress. To this end, we conduct a counterfactual experiment that assesses the real effects of a reduction in the growth in bank lending to zero percent—as opposed to growth of about 6 percent in the baseline—between October 2001 and March 2002. Our model characterises the counterfactual period as one of elevated stress,  $vMcH$ .<sup>30</sup> In order to isolate the effects of loan growth independent of the effect operating through fluctuations in financial stress we hold the path for financial stress constant at its average level over this period. The situation is one such that credit growth during the burst of the dot-com bubble would have declined as much as it actually did during the 2008-09 financial crisis.<sup>31</sup> We find that if loan growth had been flat

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

<sup>31</sup>This simulation (as well as another counterfactual shown in an appendix) involves computing the sequence of shocks to the relevant variable that is necessary to produce the counterfactual path for that variable, with all other variables being allowed to follow whatever path is implied by the sequence of shocks, except where otherwise indicated. For a discussion of how counterfactual experiments work in a linear framework, see Waggoner and Zha (1999). The experiments are designed to be “small” in the sense that the sequence of shocks is within an empirically plausible set.

Figure 4.4: Counterfactual simulation: tranquil times (vLcL) instead of systemic crisis regime (cHcH), Oct. 2008 to Feb. 2009

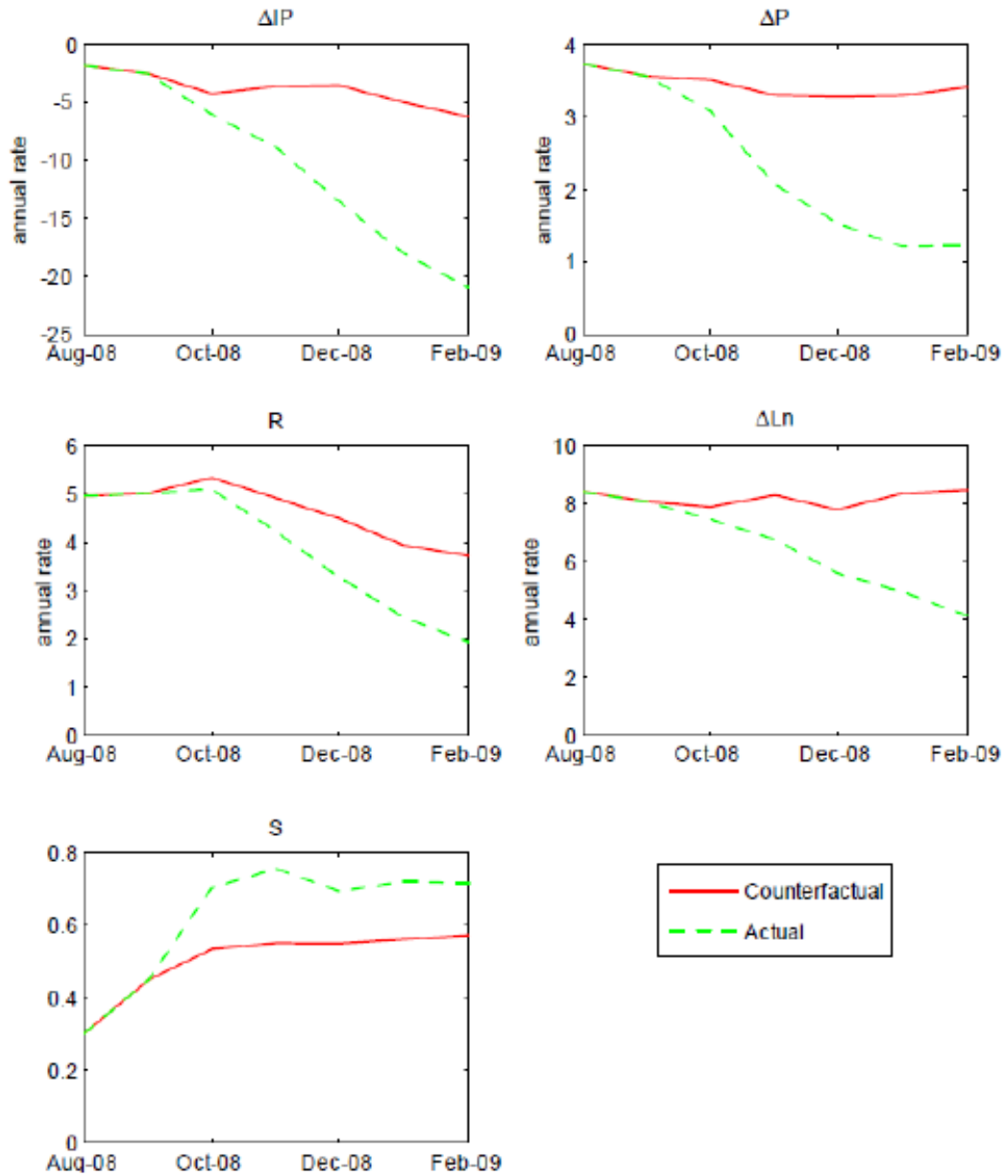
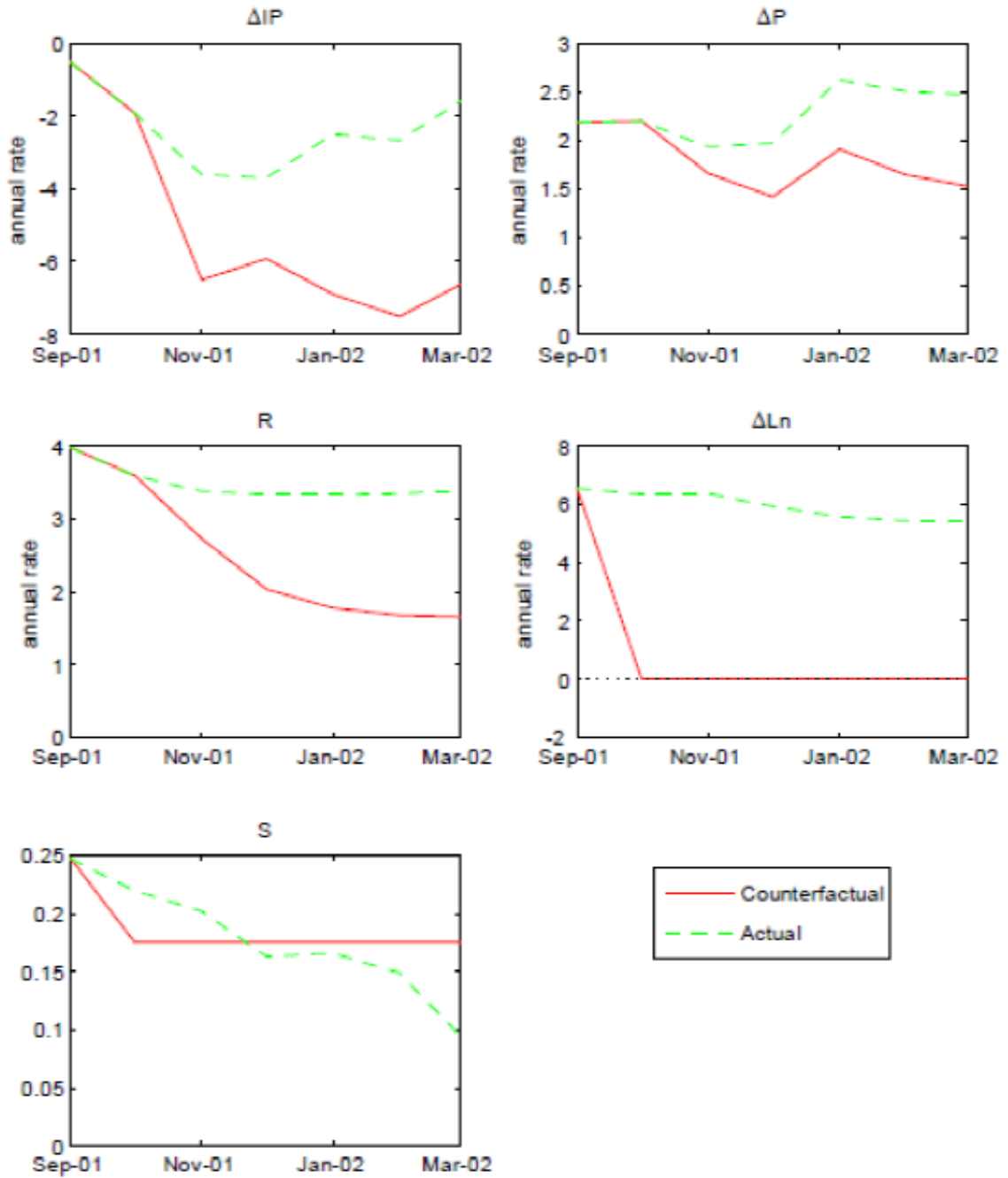


Figure 4.5: Counterfactual simulation: zero loan growth with stable CISS over counterfactual period, Oct. 2001 to Mar. 2002



during the counterfactual period, output growth would have been about 5 percentage points lower, as displayed in Figure 4.5. Inflation and the interest rate would have also been substantially lower, specifically by about 2 percentage points, compared to history. The lower interest rate would have probably reflected a monetary policy reaction to the output losses and the contraction in loan growth. These results suggest that bank loans may play a material role for the macroeconomic dynamics during regimes of systemic stress that imply a strong shock propagation, bearing in mind that the estimated effects of lower loan growth are derived under the assumption that financial stress remains unchanged over the counterfactual period.<sup>32</sup> To further illustrate the implications of disturbances to bank lending, we also present the impulse responses to lending shocks for two regimes with different coefficient regimes but the same variance regime, where the size of the lending shock is comparable across regimes.

These impulse responses, shown in Figure 4.6, demonstrate that in response to an exogenous shock to bank lending, output growth is not declining in time of systemic fragility (vHcL), where large shocks affect the economy, but there is no strong shock propagation. However, in systemic crisis episodes (vHcH) output growth is declining since in those periods credit supply constraints may become binding. Since this is an identified shock and output growth is initially being held constant, this shock is properly interpreted as a loan supply shock. Moreover, the negative, though small, reaction in financial stress can be explained by a loosening of monetary policy in response to the loan reduction, which more than offsets the increase in financial stress.<sup>33</sup>

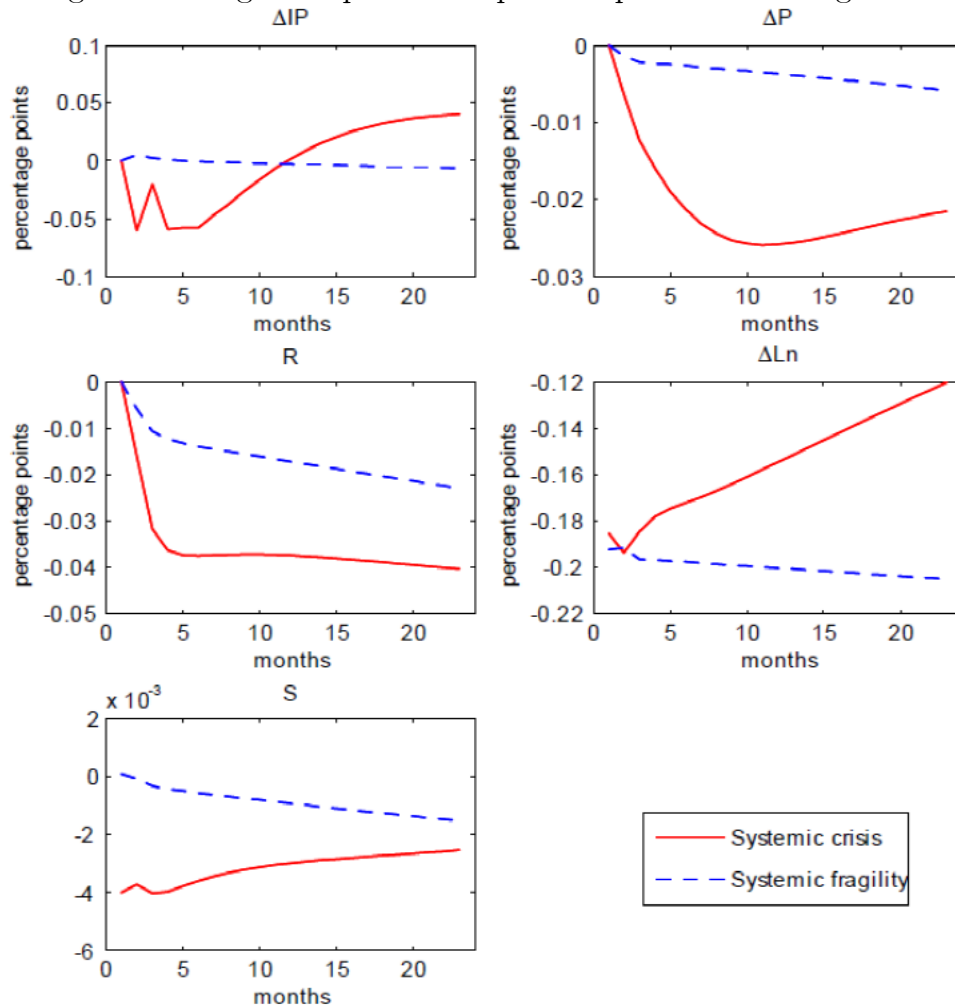
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<sup>32</sup>Note that if unrestricted, financial stress would go down. This might be explained by a looser monetary policy stance in response to the loan reduction, which alleviates the increase in financial stress that might have otherwise been generated.

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



Figure 4.6: Regime-dependent impulse responses to lending shocks



IRFs for a one-standard-deviation shock to bank lending growth from our 3v2c model. IRFs shown for the systemic crisis regime (vHcH) and the systemic fragility regime (vHeL).

#### 4.3.4 Macprudential Surveillance and Real-time Probabilities

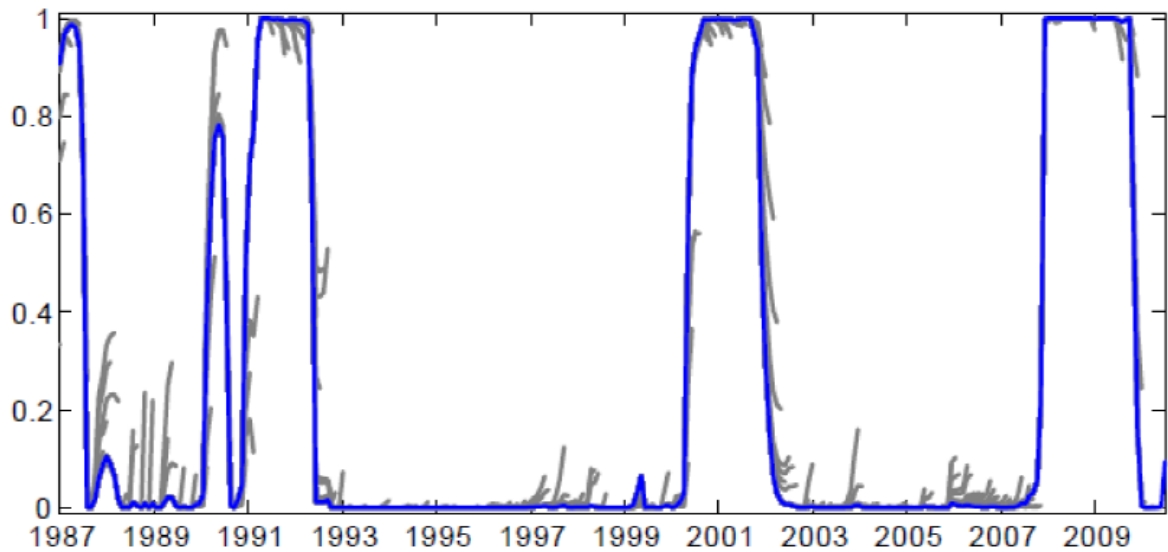
A necessary condition for this model to be useful as a macroprudential surveillance tool would be to demonstrate the reliability of the model for real-time nowcasting of switches in regime. As a modest step in this direction, we estimate the state probabilities in pseudo real time based on a monthly expanding data window, holding the VAR model coefficients fixed at their full-sample estimates. These probabilities may provide advance

real-time information (“early warnings”) as to whether the economy is likely to have entered a state of increased vulnerability to systemic shocks.

The results are shown in Figure 4.7. While the blue colored lines represent the full sample estimates of the smoothed state probabilities of the  $vMcH$  and  $vHcH$  regimes, the gray lines are the estimates based on the recursively expanding samples. If the model is successful, it should provide relatively few false signals of a change in regime, meaning that the gray lines should be small and not terribly frequent. Indeed, as can be seen, the recursively estimated regime probabilities appear to provide quite robust information. The model only rarely indicates a regime switch (indicated by a real-time regime probability that is larger than 0.5, i.e. 50%) that would not be confirmed by the full-sample estimate *ex post*. As one may expect, at the beginning of the sample period—when information from the data is scarce—the pseudo-real-time probabilities of being in a high systemic stress regime sometimes rise, but they never reach a value close to 0.5. At the same time, when the full-sample estimates signal the presence of a high systemic stress regime, the real-time probabilities tend to do so as well. In other words, there are only a few cases in which the pseudo-real-time probabilities from our Markov-switching VAR falsely predict a switch to a high-stress regime, or falsely predict a return to tranquil times.

This exercise, however, can only provide indirect and thus tentative evidence on the model’s ability to serve as an effective real-time tool for macroprudential analysis. A more thorough assessment would require real-time estimates also of model coefficients and the use of vintage data, for instance.

Figure 4.7: Real-time regime probabilities



This figure plots estimates of real-time smoothed regime probabilities for a regime which combines the elevated stress regime (vMcH) and the systemic crisis regime (vHcH), both featuring high shock transmission.

#### 4.4 Alternative Measures of Financial Stress

We have, in this paper, tried to establish the usefulness of the CISS as an efficacious tool for measuring systemic financial distress. The CISS is not, however, the only measure that has been proposed for purposes of this nature. In this section, we take two steps towards investigating the role of the particular construction of the CISS for our results. In particular, in one subsection, we explore the replacement of the CISS by two plausible alternative measures that have been suggested and used in the literature; in another subsection, we isolate two features of the construction of the CISS.

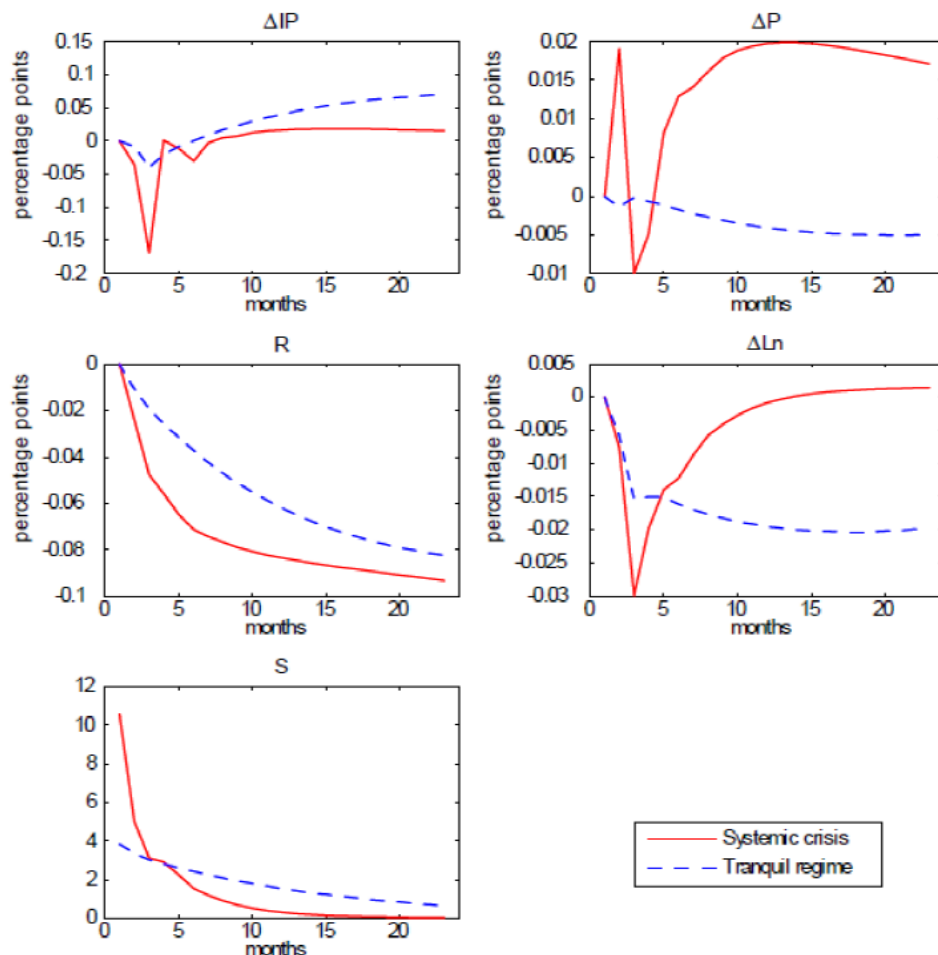
### 4.4.1 Stock market volatility and corporate bond spreads

It is often argued that the VIX or realised stock price volatility are useful indicators of risk aversion and financial stress more generally; see e.g. Coudert and Gex (2008) and Bekaert and Hoerova (2014). As one assessment of the value added of the CISS, in this section we re-estimate our preferred model replacing the CISS with a measure of realised stock market volatility. In this instance, we measure realised volatility as the square root of average daily squared log price returns on the broad EMU equity price index, as maintained by Thomson Financial Datastream.

Figure 4.8 displays the impulse responses to a one-standard-deviation shock in realised stock market volatility. Comparing the responses of output growth to this shock with their counterparts from the model using the standard CISS (see Figure 4.3), we find that with the model that uses stock market volatility, the output responses are much smaller and much less persistent. Thus if one were to adopt the prior belief that financial stress is an important driver of output fluctuations in times of systemic stress, relying exclusively on stock market volatility as a measure of systemic stress might be regarded as unsatisfactory. This interpretation may appear plausible because stock market volatility does not capture other, less transitory markers of financial stress, such as increased risk premiums. In point of fact, the level of stock market volatility displays notably less persistence than does the CISS, especially during the recent crisis; this observation might explain, at least in part, the lower estimated persistence of the real effects of a shock to stock price volatility as compared with a financial stress shock measured by the CISS.

A different strand of the literature argues that corporate bond spreads, in particular for bonds of non-financial corporations, contain substantial predictive content for the business cycle and other macroeconomic aggregates. Corporate bond spreads arguably capture changes in market perceptions of the quality of borrowers' balance sheets and

Figure 4.8: Impulse responses to shocks in realised stock market volatility



IRFs for a one-standard-deviation shock to realised stock market volatility, as an alternative measure of financial stress, from our 3v2c model. IRFs shown for the systemic crisis regime (vHcH) and a tranquil regime (vLcH).

thus their default risk; these measures tend to lead the business cycle, as documented by Gertler and Lown (1999) and Gilchrist and Zakrajšek (2012). Corporate bond spreads also move when the price of risk changes, and spreads can capture general disruptions in the financial system either through declines in the value of such bonds as collateral or via decreases in second market trading and thus in liquidity premiums. To explore the adequacy of the corporate bond spreads as a measure of systemic financial stress—or almost equivalently, to explore how much the documented success of the CISS is because it contains corporate bond spreads—we re-estimate our base case model, substituting

in place of the CISS the spread between German non-financial corporate bonds and the average yield of all German government bonds, as published by the Bundesbank.

The regime identification based on this model variant appears plausible in general. While the estimated regime probabilities suggest that the global financial crisis started in September 2008, they also indicate a relatively quick termination of the worst state of systemic stress, in the beginning of 2009. This is in contrast with our base case model with the CISS which dates the end of the global financial crisis in October 2009, after the release of the U.S. bank stress test results in May of that year. In broad terms, the two models identify approximately the same date ranges as being periods of systemic stress. However, the impulse responses to the financial shock identified in this model are economically implausible. We conclude that the corporate bond spread is a useful indicator of systemic stress and that it probably is a major contributor to the applicacy of the CISS.

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

#### **4.4.2 Exploring the composition and construction of the CISS**

Two important elements characterise the construction of the CISS as a measure of systemic stress: first, that the CISS encompasses five different, broad-based financial market segments; and second, that the time-variation in the dependence between these financial market segments is taken into account in its construction. With respect to the former

feature, the role of financial intermediaries is of special importance for a bank-centered financial system as in the euro area. To investigate the importance of these features, we carry out two different experiments. Our first experiment explores the importance of the banking sector within the construction of the CISS, by rerunning our preferred  $3v2c$  model, along with some of the associated model assessment exercises, using a version of the CISS that excludes the banking sector.<sup>34</sup> Some of the recent theoretical literature has emphasised the role of disruption in financial intermediation as an important mechanism driving large output fluctuations; see, for example, He and Krishnamurthy (2014) and Boissay, Collard and Smets (2016). To succinctly summarise our results, we find that excluding financial intermediaries from the CISS leads to estimated durations of states that are too short lived to be regarded as plausible, and to model properties that are difficult to explain. In particular, we find implausibly small and not very persistent responses in output growth to financial stress shocks in periods of systemic crises.

Our second experiment examines the systemic dimension of the CISS. The base case construction of the CISS encompasses the notion of cross-market correlations of systemic stress on an aggregate level by allowing time variation in the weights of the index's five components.<sup>35</sup> We explore the importance of this feature of the CISS by replacing the time-varying correlations between the different subindexes with a simple (time-invariant) equally-weighted average. Then we once again re-estimate our preferred model and analyze its properties.<sup>36</sup> Our results show that not all regimes are identified with this

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

<sup>35</sup>Allen, Bali and Tang (2012) similarly argue that their macromasure of systemic risk complements microlevel systemic risk measures.

<sup>36</sup>The relevance of the systemic dimension of financial stress has been emphasized in the literature on systemic risk. The comovement of the financial firm's assets with the aggregate financial sector in a crisis has been argued to be an important component of systemic stress. Acharya et al. (2010) have proposed an economic and statistical approach to measure the systemic risk of financial firms. Correlation-based measures of connectedness, including systemic risk, are discussed, for instance, in Diebold and Yilmaz (2014) who propose another way of measuring the connectedness of financial firms.

modified CISS. And this version of the model exhibits impulse response functions with economically implausible features. We take these results as demonstrative of the importance of taking the systemic aspect of financial stress into account by incorporating time-varying cross-correlation between different financial markets.

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

## 4.5 Concluding remarks

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

We found evidence that the Euro area economy is subject to occasional switches into what we called periods of high systemic stress. We further found that switching behavior manifested itself in both the variances of model shocks and in the structural characteristics of the model; that is, in the parameters that propagate those shocks throughout the economy. Our results show that this switching behavior is economically



important. In particular, the effects of financial stress stress shocks on output are much larger, more persistent, and more consequential for the real economy in regimes of high systemic stress than during tranquil times, and bank lending plays an independent role for the determination of real activity during episodes of high systemic stress, with exogenous identified shocks to loan growth having important consequences for the rest of the economy, whereas in tranquil times they do not. It follows from this that a single-regime, constant-variance characterization of the economy will miss these features and is therefore likely to provide misleading answers to questions of this nature.

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

## CHAPTER 5

### POLICY CONCLUSIONS

Which policy conclusions can we draw from the findings of the three studies presented in this dissertation? To recap, all three papers are mainly about an indicator that measures the current state of financial (in)stability in the euro area, and about how this indicator can be used to assess empirically the real effects associated with financial stress, and how thus measured financial stability interacts with the ECB's conventional and unconventional monetary policy making. Since these issues mainly concern stability conditions in the financial system and the economy as a whole, I distinguish between the two policy areas mainly tasked with monitoring and safeguarding financial stability from a macroeconomic or, better, systemic risk perspective, namely monetary and macro-prudential policy.

To set the stage for a discussion of the, by nature, relatively narrow policy implications of my research, I start with putting it into a broader policy context derived from the relevant general lessons of the Great Recession. As an organising principle of my remarks, I refer to three main lessons of the crisis distilled from a central bank perspective (see Liang 2014 and Smets 2015).

**1. Price stability is not sufficient for financial stability.**—The crisis exposed the obvious deficiency of the ruling pre-crisis monetary policy paradigm that the primary focus on price (and economic) stability is not sufficient to ensure financial stability, and that financial instability can have much larger negative feedback effects on macroeconomic stability than what was widely considered possible. To be sure, the interdependency between the two objectives of price stability and financial stability has always been acknowledged by the profession, including the conditional nature of this interdependency in the sense that both objectives can at times be in harmony, and in

other times may confront central banks with a conflict of interest or trade-off. Such different constellations of the macroeconomic environment reflect the extent to which the financial and the business cycles are aligned or out of sync, respectively. The pre-crisis consensus view (“Jackson Hole consensus”) arrived at the conclusion that the preconditions are too weak for monetary policy to lean against the financial cycle with a view to contain financial stability risks. The consensus view was particularly sceptical as to the ability of central banks to identify bubble-like phenomena *ex ante* at any sufficient level of certainty. In addition, as a means to address the financial cycle, adjusting interest rates in a counter-cyclical fashion was considered as too blunt a tool. For example, because conventional monetary policy has a broad impact on the economy and financial markets, attempts to use it to “pop” an asset price bubble would likely entail many unintended side effects. Weighing the associated costs and benefits of “leaning against the wind” made the consensus view to believe that it is preferable to respond to financial stability concerns only to the extent that they affect the outlook for inflation and economic activity. From this it also follows that “cleaning up” after the bubble was viewed as preferable to “shooting in the dark” where rather uncertain effects on the bubble dynamics meet quite predictable costs in terms of the effects of an overly restrictive monetary policy. The consensus view surely received support from the experiences with the burst of the late 1990s dot-com bubble. The excessive growth in the valuation and issuance of high-tech stocks was not fueled by increased debt and leverage in the financial and non-financial sectors, a fact which contributed to containing the contractionary macro effects when the bubble burst along with the massive stimulus from monetary policy easing in particular by the Fed (see Adrian and Liang 2014).

Against this background, the Great Recession changed the consensus view in two main dimensions: First, the meltdown of the world economy upgraded the perception of the possible costs of financial instability, tilting the intertemporal trade-off between

the costs and benefits from central banks leaning against the financial cycle towards the latter. This holds true even if financial stability were not added as a separate, coequal objective to the central bank mandate, but would instead still be evaluated exclusively in terms of the expected net effect from short- to long-term risks of macroeconomic instability. Second, there is general agreement that in order to ensure macroeconomic and financial stability under principally all circumstances, a macro-prudential policy toolkit has to be introduced as a second source of counter-cyclical policies consistent with the famous Tinbergen-Mundell separation or policy assignment principle (Smets 2015). Macro-prudential policies are supposed to aim primarily at financial stability by containing the build-up of financial imbalances and by improving the resilience of the financial system to adverse shocks, and monetary policy continues to be mainly directed towards macroeconomic stability.

However, while there is broad agreement about these two basic insights, a wide spectrum of different opinions exists as to how precisely financial stability considerations should be taken into account in the redesign of monetary policy strategies. The menu of proposed options ranges from rather mild amendments to the previous approach (the “modified Jackson Hole consensus”) to a rather radical shift in the monetary policy paradigm which postulates that all macro policies (monetary, fiscal and macro-prudential policies) have to be closely coordinated in order to achieve the joint objectives of price/macroeconomic stability and financial stability.<sup>1</sup>

The different approaches mainly contrast in their assessment as to whether the policy objectives, the policy instruments, and the transmission mechanisms of monetary

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<sup>1</sup>Smets (2015) distinguishes between three new views of monetary policy making, labelled as the “modified Jackson Hole Consensus”, “leaning against the wind vindicated”, and “financial stability is price stability”. The first view is supported by Bernanke (2015), Collard et al. (2014) and Ajello, Laubach, Lopez-Salido and Nakata (2015). The third view, that financial and price stability are too closely intertwined to be separated, is held by Brunnermeier and Sannikov (2014). The middle ground is covered by and Christiano, Ilut, Motto and Rostagno (2010), Adrian and Shin (2009), Gilchrist and Zakrajsek (2011), Woodford (2012) and Stein (2014).

and macroprudential policy can easily be separated or not. For instance, the degree of spillover effects across the different policy functions decides about the extent to which policy objectives can be separated and the extent to which achievement of the different objectives requires policy coordination. The assessment also critically hinges upon the size of a trade-off that features in all relevant models which try to integrate financial stability consideration into otherwise more or less standard macro frameworks: when deciding whether to conduct an expansionary monetary policy in order to reap any potential gains from short-run macroeconomic stabilisation (typically involving the conventional short-run Philipp-curve trade-off), a central bank faces the trade-off that the very same expansionary policy may spur financial imbalances which in the long-run can lead to financial instability and associated output losses and deflationary effects. Vice versa, if a central bank wants to contain long-term risks to financial stability by raising interest rates today, thereby leaning against the financial cycle, it may have to tolerate a short-term undershooting in its output and/or inflation objectives. This intertemporal trade-off depends, firstly, on the quantitative importance of the underlying financial frictions which ultimately produces the trade-off (since financial stability risks would not exist in a frictionless financial system). It also depends, secondly, on the assumed ability of monetary policy to control the financial cycle, and about the simultaneous impact of cyclical financial conditions on current macroeconomic dynamics and on the build-up of financial vulnerabilities. In any case, for leaning against the wind to come out as the optimal monetary policy, any model has to produce asymmetric (and thus non-linear) effects of the financial boom-bust cycle. For instance, the anticipated gain from mitigating the tail risk of adverse macroeconomic outcomes caused by the possible burst of an identified asset price bubble has to exceed the expected losses from subpar output and inflation performance produced by implementing a tighter monetary policy stance than what would have been optimal in the absence of the bubble.

Now, how do the findings of my empirical research fit into this discussion about how to optimally conduct monetary policy after the Great Recession?

First of all, all three of my papers demonstrate—for the case of the euro area and the Great Recession—that a systemic crisis inflicts large output losses on the affected economy. In addition, the results from the Threshold-VAR and the Markov-Switching VAR of Chapters 2 and 4, respectively, seem to also suggest the existence of the above-mentioned asymmetric relationship between the costs and the benefits associated with the unravelling and the build-up of financial imbalances. Both regime-switching models produce much larger output effects of a given shock in the CISS during crisis times than during normal times. Hence, a sharp and quick increase in the CISS as the result of several large shocks, pushing the economy into a systemic crisis state, would be associated with relatively large losses in economic activity; in contrast, the gradual return of the CISS to its pre-crisis level would generate relatively weak output gains since the normalisation would likely take place during a non-crisis regime period featuring a weaker transmission of financial shocks to the real sector.

Furthermore, if we interpret the short-term interest rate equations of the linear VAR used in Chapter 3 and the Markov-Switching VAR of Chapter 4 as reduced-form estimates of the ECB's monetary policy reaction function, we can discuss some properties of the ECB's actual monetary policy making in the years before and during the Great Recession. Let me start with a discussion of the results from the linear VAR. The CISS is found to impact on the ECB's interest rate policy only indirectly, mainly through its predictive power for future economic activity. How can this role of the CISS be interpreted theoretically? I think one realistic interpretation sees the CISS as what it actually is, namely an indicator of financial (in)stability conditions which also provides information about future macroeconomic risks first and foremost in crisis times. The

indirect explanatory power of the CISS for the ECB policy rate does not require that the ECB reacted to the CISS *per se*—since the CISS did not exist before 2010—but probably rather to the common information component included in the CISS’s ingredients which are mostly well-known financial indicators. This interpretation would assign to the CISS the role of a non-standard business cycle leading indicator, and it is consistent, as I claimed before, with the ECB’s declared *separation principle*.

An alternative interpretation receives support from the strong direct impact of the CISS on short-term interest rates in the systemic crisis regime identified by the MS-VAR model. This interpretation suggests that the ECB reacted to large shocks in the CISS as a means of *crisis management*. During the peak times of the crisis, the ECB lowered interest rates rather quickly in response to the observed stresses in the financial system, and perhaps beyond what would have been called for by the then available information about the medium-outlook for price stability. In that sense, anticipating severe but highly uncertain tail risks to price stability associated with unfamiliar levels of financial stress, the ECB might have bought insurance against this tail risk by easing its policy. This view presupposes that the CISS did not only proxy the information from omitted variables like survey- or market-based inflation expectations. While this in principle would make sense since our VARs do not contain any forward-looking indicators apart from the CISS, the tests for spurious causality in Chapter 3 suggest that the explanatory power of the CISS is a robust feature. As a side effect, low interest rates also contributed to restore health in the banking sector due its generally positive impact on bank profitability. The CISS therefore could have also picked up the ECB’s desire to introduce elements of *crisis resolution* into its standard monetary policy stance.

However, all the theoretical discussions above about the need for a revised monetary policy strategy that takes into account financial stability considerations was about the

role of *crisis prevention* in the policy strategy. While there is no obvious way to associate the CISS's role in the VAR dynamics with any potential historical efforts of the ECB to counter financial excesses, one could conceive of future possible uses of the CISS for such purposes, perhaps as part of an enhanced second pillar of the ECB's monetary policy strategy that explicitly aims at quantifying tail risk for financial stability. For instance, the CISS as a coincident crisis indicator can be used to construct the dependent variable of an early warning model, one that tries to predict crisis events at least one or two years ahead based on conventional vulnerability indicators such as bank leverage or credit growth or other measures of excess credit (see Lo Duca and Peltonen 2013 for a similar application). If the best predictors of systemic stress would indicate a material probability of a systemic event to happen say two years hence, monetary policy may consider counteracting this risk by raising interest rates in the near term. Relatedly, an alternative approach could try to endogenise the regime probabilities in the Markov-switching VAR model of Chapter 4, perhaps using lagged bank leverage or asset valuation indicators as potential triggers of regime shifts towards crisis states.

It has to be considered, though, that reduced-form regression estimates of a monetary policy reaction function must be very cautiously interpreted. For instance, the estimated impact of the CISS on policy interest rates probably averages over historical policy actions which were guided by rather different motives, reacting to the particular policy challenges posed by the specific economic environment at the time. A solution to this problem requires a structural model that links the different policy objectives with the policy instrument(s) and the macroeconomy in a theoretically consistent way, a point long made in the literature (see, e.g., Woodford 1994).

**2. Traditional tools of monetary policy are inadequate for effective crisis management.**—The conventional pre-crisis toolkit of monetary policy proved insuffi-



cient to manage the manifold challenges posed during the various stages of the systemic crisis. This deficiency has been reflected in the vast array of non-standard or unconventional monetary policy measures designed and implemented in a mostly *ad hoc* fashion during the recent crisis by basically all major central banks around the globe (for an overview see Rogers, Scotti and Wright 2014).

In Chapter 3, I estimate a VAR model that includes the growth rate of the ECB balance sheet as a catch-all measure of the various unconventional measures undertaken by the ECB in the course of the Great Recession and the ensuing sovereign crisis in the Eurozone. The fact that this variable is strongly directly influenced by the CISS, and by not much else, is consistent with the view that the ECB's crisis management focused on the implementation of non-standard policy measures with the aim to alleviate various stress phenomena which plagued the euro area financial system during the different stages of the crisis. As I mentioned in the previous section, the fact that also short-term interest rates responded directly to the CISS in the systemic crisis regime identified by the MS-VAR model, may be interpreted as an exceptional move ("escape clause") to fend off tail risks of financial stability and a worst state of the economy.

Hence, in the context of monetary policy crisis management, the CISS may be a useful indicator to monitor the overall current state of financial instability in real time. In addition, it might also be informative to watch the CISS during a gradual period of crisis resolution, as it not only indicates the current level of systemic stress, but one might also infer the fragility of the financial system during such a period by the sensitivity of the CISS to smaller adverse shocks which may interrupt the recovery occasionally. On the other hand, financial stress indices like the CISS might also be used to assess the impact of one-off policy measures which mainly work through their effects on market expectations, confidence and risk aversion. A prime example of such

a case is the ECB's announcement of the OMT—which never had to be activated thus far—and its anticipating London speech by President Draghi. It is widely acknowledged that the OMT announcement contributed to a massive reduction of risk premia and market volatility (see Altavilla, Giannone and Lenza 2014 for the OMT's impact on sovereign bond yields in the euro area) as reflected in the strong decline of the CISS after the events. The stress-reducing effects of the OMT announcement are also captured by the ECB balance sheet equation of my VAR, which establishes a strong positive conditional correlation between balance sheet growth and the CISS. However, in this particular case, this positive correlation cannot be interpreted in the sense of a non-standard monetary policy reaction function. The announcement of the possibility to purchase sovereign bonds of crisis-stricken countries fostered a rapid deceleration of the growth rate in ECB total assets. Due to much reduced uncertainty and fear in financial markets, banks started repaying liquidity borrowed in the ECB's 3-year LTROs at a gradually higher speed which dampened the growth rate of ECB total assets (see Figure 3.5). The simultaneous declines in the CISS and ECB balance sheet growth after the OMT announcement therefore does not reflect a causal relationship between the two but rather the impact of the policy announcement as the omitted third variable driving both series.

**3. Pre-crisis financial regulatory and supervisory framework insufficient to maintain financial stability.**—As already mentioned in the context of the first lesson, the crisis accelerated the introduction of a new policy domain called macro-prudential policy. This was based on the realisation that ensuring the soundness and safety of individual financial institutions is not enough to guarantee the stability of the financial system as a whole. Due to the apparent neglect of systemic risks in the financial regulatory and supervisory framework, the pre-crisis framework not only failed to ensure financial stability, but it even promoted the gradual build-up of financial imbal-

ances at the macro and micro level by providing incentives for widespread endogenous and strongly correlated risk-taking. The design of the new regulatory framework is very much inspired by the idea to contain systemic risks in the various segments of the financial system. To this end, the new framework also brought about institutional innovations which conferred new macro-prudential policy powers to either newly established or existing authorities (e.g., the European Systemic Risk Board and the ECB/Single Supervisory Mechanism).

A major task of macro-prudential policy consists of the continuous monitoring of the financial system in order to track the current levels of strains in the system and, even more important, to identify systemic risks early on. For these purposes, macro-prudential authorities around the globe have been active in building up an appropriate data and analytical infrastructure, among which so-called financial stability indicators play an important role.

Financial stress indexes like the CISS have become an integral part of financial stability indicator toolboxes, complementing standard single indicators traditionally used for the monitoring of current stress levels in individual market segments. As I documented in the introductory Chapter 1 (see Footnote 6), the CISS has meanwhile become a well-established macro-prudential surveillance indicator applied by the ECB and other central banks, an indicator that summarises the coincident state of financial stability in the financial system as a whole.

In addition, as I outlined before, the CISS can also help improve empirical early warning models which aim to anticipate risks of widespread financial strains sufficiently in advance for macro-prudential, but also monetary policy authorities to consider countervailing measures (Lo Duca and Peltonen 2013). For instance, in conventional early warning models the dependent variable exists of binary dummy variables which only

distinguish between crisis and non-crisis events. The CISS, in contrast, can differentiate between financial crisis events of different intensity since it can assume values anywhere between zero and one; hence, the CISS may be used to identify financial crisis events in a more granular and systematic fashion. As an example of a multi-layered early warning system that is based on a financial stress index similar to the CISS, see Oet, Bianco, Gramlich and Ong (2013). Their model, which is implemented at the Federal Reserve Bank of Cleveland, illustrates how conventional macro variables capturing aggregate financial vulnerabilities and proprietary and public micro-supervisory data capturing institutional vulnerabilities, can be combined into an encompassing early warning system that aims to detect risks of a systemic banking crisis in the US.

In sum, despite some scepticism on the side of some academics about the usefulness of composite indicators of financial conditions (see Leeper and Nason 2014). I strongly believe that the findings presented in this dissertation make a good case for taking financial stress indices like the CISS seriously. They offer the basis of a promising, broad and rich research agenda which is very likely to produce tangible results feeding into the practice of monetary and macro-prudential policy making.

APPENDIX A  
**DESCRIPTION OF CONTROL VARIABLES**

This appendix describes the control variables used in the block exogeneity tests reported in Table 3.4.

**Commodity price index:** Annual change of the log HWWI commodity price index; Hamburg Institute of International Economics (HWWI) index for the euro area based on prices in euros; weights for individual commodities are based on their share in total euro area raw material imports between 1999 and 2001 (in 2000 prices); monthly data. Source: Haver Analytics.

**Consensus inflation forecast:** Mean forecast of the one-year ahead percentage change of the euro area HICP, computed as the pro rata average of the mean forecast of the percentage year-on-year change of the index for the current year and the subsequent year; in percent per annum; monthly data. Sources: Own calculations and Consensus Forecasts by Consensus Economics.

**Unemployment rate:** Average euro area harmonised unemployment rate, seasonally adjusted; in percent; monthly data. Source: Haver Analytics.

**Consensus real GDP forecast:** Mean forecast of the one-year ahead percentage change of the euro area real GDP, computed as the pro rata average of the mean forecast of the percentage change of the index for the current year and the subsequent year on the respective previous calendar year; in percent per annum; monthly data. Sources: Own calculations and Consensus Forecasts by Consensus Economics.

**Business climate index:** European Commission business climate indicator for the euro area in standard deviation points, seasonally adjusted; monthly data. Source: Haver

Analytics.

**Policy uncertainty index:** The News-based Policy Uncertainty Index quantifies newspaper coverage of policy-related economic uncertainty. The index is based on news articles from two papers from each of the five largest European economies (Germany, the United Kingdom, France, Italy, and Spain). The papers include El Pais, El Mundo, Corriere della Sera, La Repubblica, Le Monde, Le Figaro, the Financial Times, The Times of London, Handelsblatt and FAZ. The primary measure for this index is the number of news articles containing the terms “uncertain” or “uncertainty,” “economic” or “economy,” as well as policy relevant terms (scaled by the smoothed number of articles containing “today”). Policy relevant terms include: “policy,” “tax,” “spending,” “regulation,” “central bank,” “budget,” and “deficit.” All news searches are done in the native language of the paper in question. Each paper-specific series is normalised to standard deviation 1 prior to 2011 and then summed. The series is normalised to mean 100 prior to 2011; monthly data. Source: PolicyUncertainty.com/Haver Analytics.

**Bank loans:** Annual change of the log of euro area MFI loans to the private non-financial sector; monthly data. Source: ECB.

**Effective euro exchange rate:** The nominal euro effective exchange rate is defined as a geometric weighted average of the bilateral exchange rates of the euro against the currencies of the EER-12 group of partner countries which includes Australia, Canada, Denmark, Hong Kong, Japan, Norway, Singapore, South Korea, Sweden, Switzerland, the United Kingdom and the United States. The bilateral exchange rates used in the calculation are the official ECB daily reference rates. Weights are based on trade in manufactured goods with the trading partners in the period 1999-2001 and are calculated to account for third-market effects; monthly data. Source: Haver Analytics.

**10-year government bond yield:** Average yield to maturity of government bonds with maturity of ten years (or the closest available maturity) of euro area member states, weighted by the relative amounts of relevant bonds outstanding; in percent per annum; monthly average of daily data. Source: ECB.

**Term spread:** Difference between the euro area average 10-year government bond yield and the three-month Euribor; in percent per annum; monthly average of daily data. Source: ECB.

**BBB corporate bond spread:** Yield spread between BBB-rated bonds of non-financial corporations and AAA-rated government bonds with five to seven years of maturity based on Bank of America Merrill Lynch bond indices for the euro area; in percent per annum; monthly average of daily data. Source: Datastream.

**High yield corporate bond spread:** Yield spread between non-investment grade bonds of non-financial corporations of all maturities and AAA-rated government bonds with three to five years of maturity based on Bank of America Merrill Lynch bond indices for the euro area; in percent per annum; monthly average of daily data. Source: Datastream.

**Option-implied stock volatility:** Measured by the main EURO STOXX 50 Volatility Index (VSTOXX). The VSTOXX does not measure implied volatilities of at-the-money EURO STOXX 50 options, but the square root of the implied variance across all options of a given time to expiry. The main index is designed as a rolling index at a fixed 30 days to expiry that is achieved through linear interpolation of the two nearest available sub-indices; in percent per annum; monthly average of daily data. Source: Datastream.

## APPENDIX B

### PRIORS FOR THE MS-BVAR ESTIMATION

This appendix describes the priors applied in the estimation of the Markov-switching BVAR model presented in Chapter 4. Two sets of priors are relevant for our model, one on the reduced-form parameters of the VAR conditional on a state,  $s$ , and the other on the transition matrix. The priors on the reduced-form VAR are the standard Minnesota prior on the lag decay dampening the influence of long lags. In other words, this prior shrinks the model towards a random walk.  $\mu_1$  controls the overall tightness and the prior of  $A_0$ .  $\mu_2$  controls the tightness of the random walk prior on the lagged coefficients. The prior for constant terms is zero and the prior standard deviation is  $\mu_3$ . The priors that further play a role are  $\mu_4$  that controls the tightness of the prior that dampens the erratic sampling effects on lag coefficients (lag decay).  $\mu_5$  and  $\mu_6$  are the priors that express beliefs about unit roots and cointegration.

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 in Equation (1) can be written as

$$y'_t A_0(s_t^c) = x'_t A_+(s_t^c) + \varepsilon'_t \Xi^{-1}(s_t^v), \quad t = 1, 2, \dots, T. \quad (\text{B.1})$$

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

$$A_+(s_t) = D(s_t) + \hat{S} A_0(s_t) \quad \text{where} \quad \hat{S} = \begin{bmatrix} I_n & 0_{(m-n) \times n} \end{bmatrix} \quad (\text{B.2})$$

which means that a mean-zero prior can be placed on  $D$  which centers the prior on the usual reduced-form random-walk model that forms the baseline prior for most Bayesian



VAR models; see Sims and Zha (1998) for details on this particular prior set-up. The relationship contained in (B.2) means that a prior on  $D$  tightens or loosens the prior on a random walk for the reduced-form parameter matrix  $B$ .

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

$$p(P) = \prod_{k \in H} \left[ \frac{\Gamma(\sum_{i \in H} \alpha_{ik})}{\prod_{i \in H} \Gamma(\alpha_{ik})} \right] \times \prod_{i \in H} p_{ik}^{\alpha_{ik}-1} \quad (\text{B.3})$$

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

For our baseline specification, we use priors that are well-suited for a monthly model. In particular, we specify  $\mu_k$   $k = \{1, 2, \dots, 6\} = \{0.57, 0.13, 0.1, 1.2, 10, 10\}$ . With the values of  $\mu_k$  we employ what Sims and Zha (1998) and Sims, Waggoner and Zha (2008) suggest for monthly data. The Dirichlet priors we use are looser than what would be usually used for monthly data. They imply an 87 and 83 percent prior probability for the variances and coefficients, respectively, that the economy will, in the next period, continue in the same state as it is in the current period. These probabilities imply a shorter duration of regimes than the priors used in Sims, Waggoner and Zha (2008) use for the macroeconomic application based on quarterly data, consistent with the notion that in our study jumps in financial markets play an important role in driving the regime shifts. We found that the data move the posterior away from the prior in the

sense that coefficient regimes turn out to be more persistent than the variance regimes. Interestingly, our results are relatively robust to some variation in the Dirichlet prior. For instance, if we impose a 74 and 85 percent probability, implying a more persistent coefficient regime than variance regime, we get similar impulse responses and regime durations of variance and coefficient regimes from the resulting model than from our model.

## APPENDIX C

### COUNTERFACTUALS ON THE ROLE OF SYSTEMIC FINANCIAL STRESS IN THE MS-BVAR MODEL

This appendix presents the results on two additional counterfactual experiments conducted on the basis of the Markov-switching BVAR model presented in Chapter 4. The first simulation sets the CISS by an amount of 0.25 above its historical level, starting in March 1995 (see the bottom-left panel of Figure C.1). According to the estimated regime probabilities, this period is one of tranquil times (*vLcL*). The effect on output growth (as shown in the upper-left panel of Figure C.1) would be very small given the magnitude of the change in the level of systemic stress; output growth drops by at most 0.5 percentage points below its historical path. In contrast, a similar increase in the level of the CISS implemented as from October 2008—i.e., during the systemic crisis regime—leads to a massive decline in output growth by about 7 percentage points, relative to its historical path (see Figure C.2). Moreover, inflation and loan growth decline by 0.5 percentage points, which is 1 percentage point below their actual path. The short-term interest rate also falls more strongly by about 1 percentage point vis-à-vis its actual path, probably reflecting a systematic easing of conventional monetary policy in response to the deteriorating financial and macroeconomic environment.

Figure C.1: Counterfactual simulation: tranquil times (vLcL) with CISS increased by 0.25 as of Mar. 1995

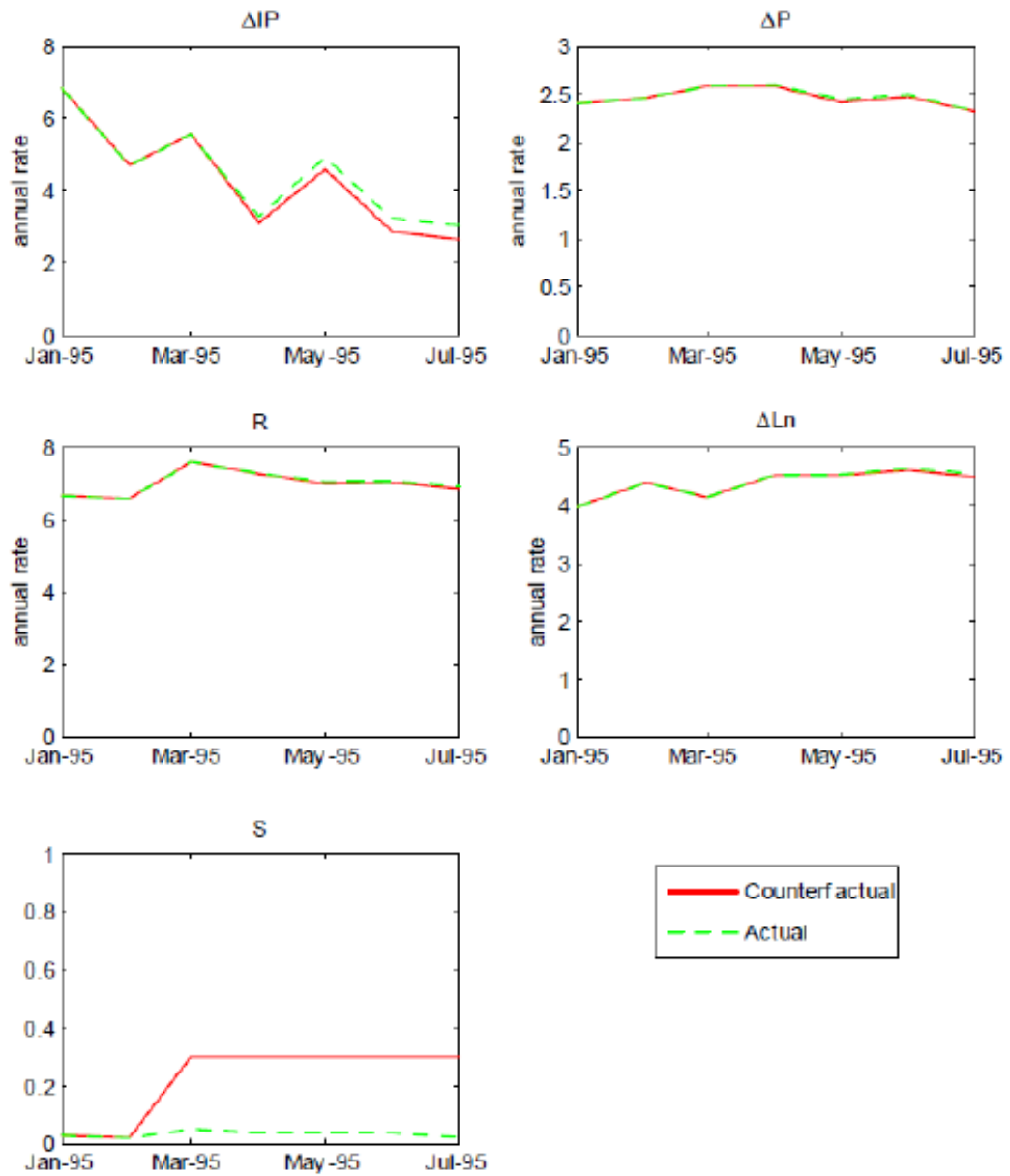
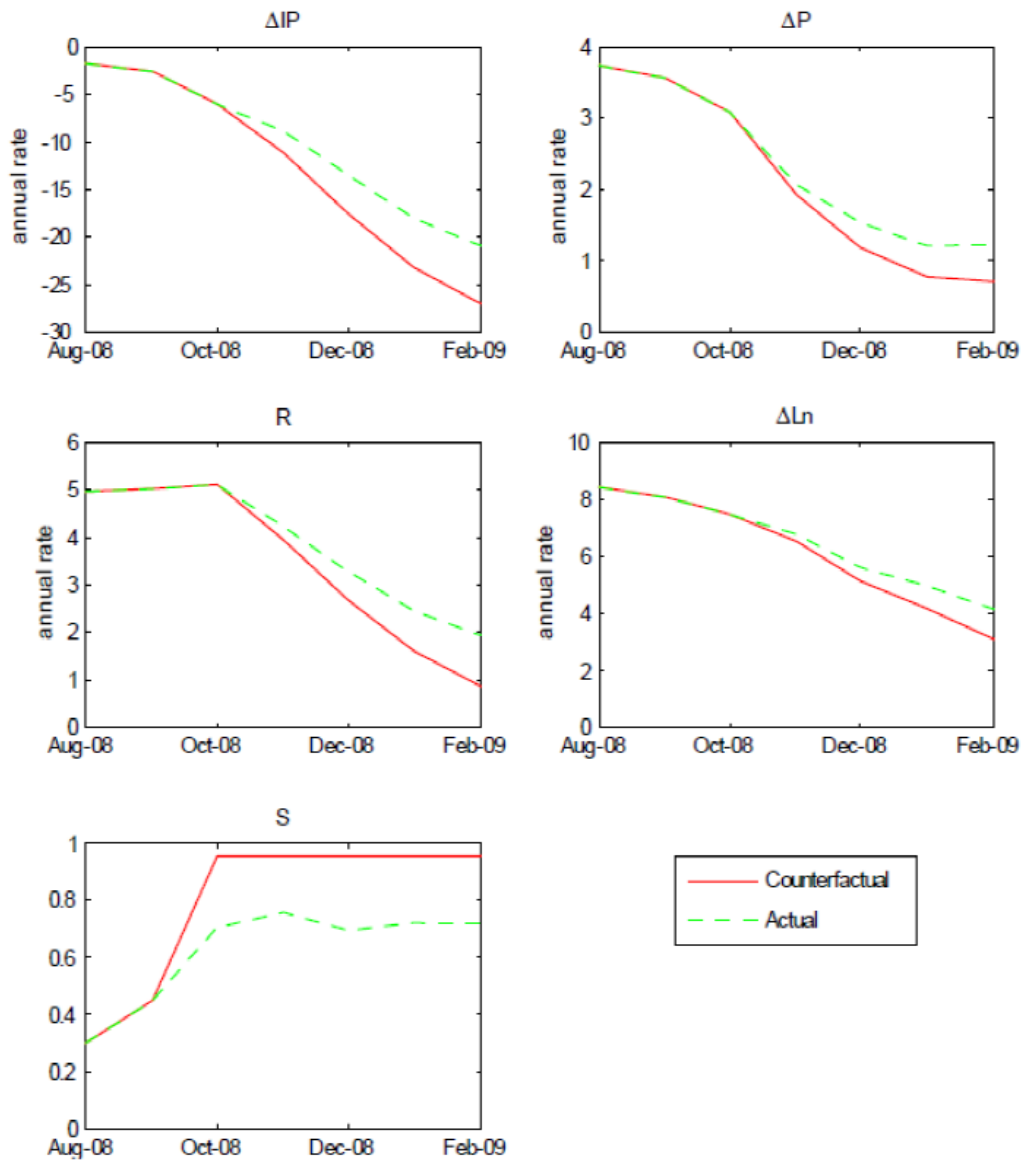


Figure C.2: Counterfactual simulation: systemic crisis period (vHcH) with CISS increased by 0.25 as of Oct. 2008



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