Discussion Paper No. 14-110

Overleveraging, Financial Fragility and the Banking-Macro Link: Theory and Empirical Evidence

Stefan Mittnik and Willi Semmler

Discussion Paper No. 14-110

Overleveraging, Financial Fragility and the Banking-Macro Link: Theory and Empirical Evidence

Stefan Mittnik and Willi Semmler

Overleveraging and the Fragility of the Banking-Macro Link: Theory and Empirical Evidence

Stefan Mittnik* and Willi Semmler†

November 20, 2014

Abstract

We investigate consequences of overleveraging and financial–sector stress on real economic activities. When banks become vulnerable, due to high leveraging, and there is a strong feedback between the real and the financial sector, a regime of high financial stress may arise. The vulnerability of the banking system in a high leverage and a high–stress regime can, through macro feedback effects, result in unstable dynamics. To assess this question empirically, we employ a nonlinear, multi–regime vector autoregression approach (MRVAR), to explore the consequences of instabilities arising from regime dependent shocks. We analyze data on industrial production and the IMF Financial Stress Index. In order to assess how output is affected by the individual risk drivers making up the IMF index, we study eight economies—the U.S., Canada, Japan and the UK, and for the four largest euro–zone economies, namely, Germany, France, Italy, and Spain—, using Granger–causality and nonlinear impulse–response analysis. Our results strongly suggest that financial–sector stress, exerts a strong, nonlinear influence on economic activity, but that individual risk drivers affect economic activity rather differently across stress regimes and across countries.

JEL classifications: E2, E6, C13

*Department of Statistics and Center for Quantitative Risk Analysis, Ludwig–Maximilians–Universität München, Akademiestr. 1/I, 80799 Munich, Germany.

†ZEW Research Associate, ZEW, Mannheim, and Department of Economics, New School for Social Research, 79 Fifth Ave., New York, NY 10003, USA, and CEM, Bielefeld.

1 Introduction

Financial–sector instabilities are believed to play a central role in either directly causing or amplifying economic crises (see Reinhart and Rogoff, 2009). In the past, financial and banking crises were typically thought to be triggered by loan losses and bank runs. More recently, however, the focus has shifted toward the role of an overleveraged banking system, and adverse shocks in asset values and overall financial stress (see Gordon (2010)). The financial–accelerator view in Bernanke et al. (1999) links—in a DSGE–type tradition—asset prices to net worth and borrowing cost, so that the rise of asset prices reduces borrowing cost, and vice versa. Whereas in Bernanke et al. (1999) the accelerator–effect ultimately subsides, Brunnermeier (2009) and Brunnermeier and Sannikov (2013), henceforth BS, argue that, due to vicious cycles in the asset market, there could be destabilizing mechanisms at work, causing a downward spiral. A similar view is presented in theoretical models, such as He and Krishnamurthy (2012), Adrian et al. (2010), Stein (2011, 2012), and Mittnik and Semmler (2013).

DSGE–type models have also attempted to empirically capture the relationship between asset prices, financial intermediaries and output. Prevailing modeling approaches, employ stationary, linear models—or linearized versions thereof—where, by construction, departures from the steady state are mean reverting. Although the economy might accelerate, ultimately it will revert back to the steady state. Empirical analyses are, then, often conducted by means of linear vector autoregressions (VARs) as, for example, in Gilchrist et al. (2009) and Christensen and Dib (2008).[1] However, if, due to high leveraging of the banking system, large shocks to asset prices or, more generally, to financial markets, are potentially destabilizing rather than characterized by mean reversion, the question is: To what extent do such financial instabilities impact real economic activity? Furthermore, what are, in turn, the reverse feedback effects toward the banking sector? These questions have been debated in recent theoretical and empirical studies.

Previous theoretical work has been mostly focusing on the destabilizing effects of high leveraging of financial intermediaries, see BS (2013), Stein (2011, 2012) and Brunnermeier (2009). The feedback between the financial and the real sectors were not sufficiently addressed in the early modeling literature. In recent, more empirically oriented literature, such as Adrian et al. (2010), Davig and Hakkio (2010), Hubrich and Tetlow (2011), Roye (2012), Monnin and Jokipii (2010), and Mittnik and Semmler (2013), some

[1] Still, in this tradition, nonlinear models, such as regime change models, have also been recently applied to macrodynamics, see Farmer et al. (2009).

macro feedback effects are explored in multi–country studies. The latter, hereafter MS (2013), using nonlinear, multi–regime vector autoregressions and impulse response analysis, find that the consequences of financial–sector shocks tend to be state–dependent and vary disproportionally with the size and sign of a shock.

Most empirical studies, however, including MS (2013), focus on an aggregate measure of financial stress, such as the financial stress index (FSI) developed by the IMF, and some measure of output. The IMF's stress index is designed to capture aggregate financial stress of numerous countries (see Cardarelli et al., 2011). Although this aggregate measure can provide valuable insight into the interdependence of financial–sector stress and economic activity, it does, however, due to its aggregate nature, not afford a deeper analysis of the role of specific risk drivers and transmitters and, thus, specific policy recommendations. The question of which risk factors are particularly detrimental and may serve as early warning signal for policy makers cannot be answered by an analysis based on a highly aggregate stress index.

To overcome this deficit, we first built a theoretical model of the banking–macro linkage with leveraging and investigate the role of financial stress on output and vice versa and indicate individual risk drivers. Then, we explore empirically the role of both the aggregate FSI and its individual components. By exploring the individual components we expect to gain a better understanding of the implications the individual risk factors have for the real economy. In our empirical analysis, we examine to what extent there are linkages between specific financial–risk indicators and economic activity, measured in terms of industrial production. We conduct our analysis for eight economies: the U.S., Canada, Japan, the UK; and for the four largest euro–zone countries, i.e., Germany, France, Italy, and Spain.

Given that standard linear, dynamic econometric models, such as vector autoregressions (VARs), cannot capture the rich dynamic behavior implied by the theoretical model outlined below, our empirical analysis follows MS (2013) and uses nonlinear, multi–regime VARs (MRVARs). This model class can capture complex dynamics and allows us to assess the implications of individual risk factors and their consequences at different states of the economy. To estimate the interactions between financial stress and economic output, we conduct, for each of the eight countries, bivariate analyses, pairing industrial production with the individual FSI components.

The paper is organized as follows. Section 2 reviews the literature review on modeling real– and financial–sector linkages. In Section 3, building upon BS (2013), we introduce a banking sector becoming vulnerable to overleveraging and show the potential for regime shifts in the presence of banking–macro feedback loops. Section 4 describes the data. Section 5 introduces our empirical modeling strategies and presents the results from causality and MRVAR–based response analyses. Section 6 discusses possible implications from theoretical and policy–making viewpoints. Section 7 concludes. The appendix 1 gives a brief description of the NMPC algorithm that is used to solve the model and provides of the MRVAR–response plots.

2 Relating the Proposed Model to the Recent Literature

Several recent studies explore theoretically how large shocks to asset prices, financial markets and balance sheets of banks may have destabilizing rather than mean–reverting consequences. Examples are Adrian et al. (2010), BS (2013), Stein (2011, 2012), and Mittnik and Semmler (2012, 2013), henceforth MS, to name a few.

The asset price channel as a trigger of instability has been stressed in various studies. In Adrian and Shin (2010), a macroeconomic risk premium drives systemic risk. The approach in BS (2013) focuses more specifically on the banking sector. In their view, it is a shock to asset prices that creates a vicious cycle through the balance sheets of the banks. When prices of bank–held assets fall and, therefore, their equity value and net worth falls, the margin requirements for borrowing on the money market rise, forcing financial intermediaries to take haircuts and to further de-lever to stay liquid. This can ultimately lead to fire sales, depressing asset prices further, decreasing net worth and, thus, triggering an endogenous jump in risk and, possibly, further downward spirals.

In MS (2013), the vulnerability of banks and downward instability essentially depends on improper incentives and the lack of constraints on financial intermediaries, facilitating excessive growth of capital assets through borrowing. On the other hand, generous payouts, with no "skin in the game," affect banks' risk taking, equity formation and leveraging. Higher payouts, for instance, may induce more risk taking and risk transfer, and generate higher (endogenous) aggregate risk and greater risk premia throughout the economy. Initially, banks may have loan losses, arising from defaults of firms, households or sovereigns. Financial stress, triggered by security price movements and higher risk credit spreads may subsequently draw banks into a downward spiral.

Stein (2011, 2012) argues similarly by allowing for bubbles in both asset prices and borrowing. In certain stages, bank–held assets can be overvalued, so that banks enjoy capital gains besides their normal returns and start overleveraging relative to optimal leveraging. This occurs when banks, given their high net worth, face low borrowing cost. Then, banks' operating income is composed of normal returns and stochastic capital gains.[2] Debt tends to rise with the excess return on capital income over and above some normal returns—at least if there are persistent capital gains available, see Stein (2012, Ch. 4). This can hold as long as the central bank keeps interest rates down and credit spreads are low. In fact, empirically, low interest rates and capital gains are frequently highly negatively correlated.[3]

Such situations may appear as a period of tranquility, but may also come with a high degree of fragility. In this case, as Stein (2011, 2012) shows, the present value and net worth of banks will tend to become large, because there is no adequate correction through risk premia.[4] Borrowing is likely to exceed debt capacity, resulting in excess borrowing. Stein (2012) introduces a measure of overleveraging, namely, leveraging above the optimal level. When the borrowing bubble bursts, asset price and net worth will fall, and the risk premia and credit spread suddenly rise, reducing lending, borrowing and financial intermediation, the process reverses.

The model presented below, builds upon both BS and MS, and also refer to Stein's (2012) overleveraging and excess debt approach. We start with a stochastic version; but then, to better understand the macro feedback loops and contrasting our view with BS and Stein, we employ non-stochastic variants. We distinguish between low– and high–stress regimes, which are not only characterized by excess leveraging. The regimes also depend on other co-variates, such as jumps in credit spreads, rise of financial stress and adverse feedback from real economic activity to banks' balance sheets. A regime change will be triggered, when financial stress jumps, due to adverse feedback from real activity to banks' operating income, causing loan losses and a fall in net worth. Thus, the banking–macro feedback loops can be characterized by a regime of low financial stress and stable environment for expansionary periods and booms; but, in a high stress regime, destabilizing forces that trigger contractions and recessions, due to macro feedback loops, can prevail.[5]

[2] Note that the capital gains could be positive or negative, see Stein (2011, 2012).

[3] See Stein (2012, Ch. 5). This could be observed in the U.S. during the real estate boom with low interest rates, low risk premia and low discount rates. Low discount rates, in turn, generate high asset prices and capital gains, Chen and Semmler (2013).

[4] To avoid this misperception, Stein (2011, 2012) suggests to make corrections by incorporating trends in capital gains and interest rates into such a model to better measure debt capacity.

[5] The possibility of such loops for the euro zone has been discussed recently. One of the loops has been

For several reasons, we study these problems in an intertemporal framework. First, an intertemporal model gives better insight into tracking the paths of dynamic variables over a longer horizon. This is in particular important, when studying the sustainability of debt which can only be tracked over a longer horizon. Second, leveraging and the evolution of debt need to be considered in an asset price model, where one can define net worth (see Geanokoplos, 2011; and Stein, 2012). Finally, it is more straightforward to conduct policy analysis in this framework.

A specification of our model is also able to account for destabilizing macro feedback loops, which are however dissipating at an infinite horizon, due to model the transversality conditions imposed. Temporary macroeconomic amplification and destabilizing mechanisms are important in the shorter run. Although this has been known, they are rare in standard DSGE models, which are mostly characterized by mean reversion.

The following amplifying effects could be at work and potentially trigger financial–sector instabilities:

- On the real side, there can be regime–dependent multiplier effects, acting, for example, more strongly in recessions than in expansions (cf. MS, 2012).

- Due to credit spreads, interest rates can be regime–dependent (and different from the interest rate implied by the Taylor rule), making them, for example, counter-cyclical. This has been extensively discussed in the literature on the financial accelerator. Also, in certain regimes, there can be constraints on agents' income, credit and liquidity.

- The Fisher debt–deflation effect may become relevant when, in recessionary periods, inflation rates fall or a deflation sets in. This can trigger rising real interest rates, falling demand, due to the Tobin (1979) effect (i.e., demand falls with an expected decline in prices), and increase households' deleveraging.[6]

called the "diabolic loop." Then, there is not just the relationship between banks and the private sector, but there is a triangular relationship between private borrowing, bank leveraging, and sovereign debt (see Brunnermeier and Oehmke, 2012). Banks give not only loans to the private sector, but also hold treasury bonds on their asset side. Banks' vulnerability can arise from a threat of private loan losses, falling asset prices or from a deterioration of the fiscal position of the sovereign. When the banks are threatened by insolvency and a bail out by the public occurs, sovereign debt as well as sovereign insolvency threats rise, making banks even more vulnerable. A resulting cut in private sector loan, in turn, reduces state revenues and increases the risk of insolvency, and so on. Also, private and public borrowing is usually accompanied by an increase in external liabilities, see Stein (2012, Ch. 8).

[6]Eggertsson and Krugman (2012) extensively treat the Fisher debt–deflation effect, but they also stress the effects of deleveraging households on demand.

- The asset–price channel can be amplifying through wealth effects on aggregate demand. This can, for example, amplify an upswing with asset prices rising, but also accelerate a downswing and the severity of a recession in periods of large asset price losses.

- Credit expansions depends on net worth of households, firms, banks and sovereign states. As net worth is rising, the financial sector is willing to expand loan supply, but reduces loans, if net worth falls. With loan losses rising and asset prices falling, banks' vulnerability increases, reducing loan supplies.[7] Further externalities and contagion effects can result in a vicious downward spiral.

Recent literature, see BS (2013) and Brunnermeier and Oehmke (2012), also stresses the importance of such amplifying mechanisms, some of which arise from externalities and contagion effects. Our model refers to the above type of amplification mechanisms. Such dynamic processes can easily be triggered by financial–sector instabilities and amplified by real, nominal and asset–price feedback loops.[8]

3 The Model

Most of the recent dynamic models, such as DSGE models, are working with infinite horizon decisions where such destabilizing feedback loops tend to be smoothed out. We here propose model variants with finite horizon that allow for such destabilizing feedback loops. To solve those models with a finite time decision horizon, we use a new numerical procedure, the NMPC method, see Gruene et al. (2013) and appendix 1. Its solution approaches, with very long horizon, the usual infinite horizon solutions.

3.1 Bank Leveraging without Adverse Macro Feedback Loops

To introduce leveraging and net worth dynamics for financial intermediaries in a finite horizon decision model, we start with a low dimensional stochastic variant, to be modified in sect 3.2. The essentials of the current model can be found in BS (2013: sect. 2), which

[7] See De Grauwe and Macchiarelli (2013) and Gerali et al. (2010).

[8] A related model of the asset price and credit market nexus is presented in Semmler and Bernard (2012).

we are following here, but also in Stein (2011, 2012).[9] Both model variants are stochastic but they do not explicitly model macroeconomic feedback loops.

The BS and the Stein models are similar in the sense that payouts and leveraging are choice variables, and the main state variable is net worth, see $x_{1,t}$, in (3). In order to solve such a stochastic variant through NMPC one needs to add a stochastic shock sequence, see (4), representing another state variable. In BS the capital return is (due to capital gains) stochastic and the interest rate is stochastic as well. Yet BS start with a model where only the capital return is stochastic. They add a stochastic interest rate later by referring to time varying borrowing cost reflecting the cost of screening and monitoring.

Though BS employ a continuous time version, we formulate here the problem as discrete time variant with a discounted instantaneous payout, c_t, and an optimal leveraging, x_t, in (1)-(4).[10] Preferences are given by (1), the dynamics of the aggregate capital stock by (2),[11] net worth by (3), and the stochastic shock process by (4). We model this as finite horizon decision problem, with decision horizon of N, in discrete time, as:

$$V = \max_{c_t, x_t} E_t \sum_{t=0}^{N} \beta^t U(c_t x_{1,t}) \tag{1}$$

s.t.

$$dk_t = (g_t - \delta)k_t dt + \sigma_t k_t dZ_t \tag{2}$$

$$x_{1,t+1} = x_{1,t} + h x_{1,t}[x_t(y + \nu_1 ln x_{2,t} + r) + (1 - x_t)(i - \nu_2 ln x_{2,t}) - a\varphi(x_{1,t}) - c_t] \tag{3}$$

[9]The derivation of the optimal leveraging of the Stein (2012) model can be undertaken analytically, assuming certain restrictions, for example log utility. Here we want to focus on the solution of the dynamic version, with shocks, that displays the mechanism of overleveraging. This allows to be compared with time series data on banks, see Ebisike and Semmler (2014).

[10]In BS (2013) there is also an equation for the evolution of capital stock of the banks as well as for the households which actually then gives rise to two more decision variables an state variables in their context. We neglect those aspects here first, to focus solely on the net worth dynamics. Capital stock will be used in sect. 3.2.

[11]In the solution procedure here we neglect equ. (2). It represents in BS the aggregate capital (with g the growth rate and δ the resource use for managing the assets) of financial specialists and households. A larger fraction of it will be held by financial specialists, since they can borrow. Those details can be neglected here. The aggregate capital will be considered in sect. 3.2.

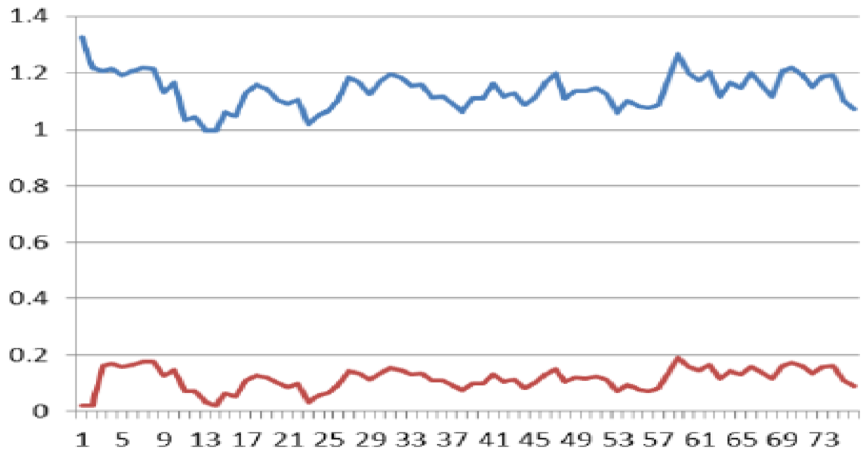

Figure 1: Path of optimal payout, c, red line, and optimal leveraging, $x = (1 + f)$, blue line

$$x_{2,t+1} \quad = \quad \exp(\rho \ln x_{2,t} + z_k) \tag{4}$$

Hereby c and x are the two decision variables, with $c = C/x_1$, and $x = 1 + f$, $f = d/x_1$, with $f = d/x_1$ the leverage ratio, measured as liability over net worth, and d, debt, h =step size, y =capital gains, driven by a stochastic shock, $\nu_1 logx_{2,t}$. Furthermore, r, is the return on capital, i, the interest rate, also driven by a stochastic shock, $\nu_2 lngx_{2,t}$[12], and $a\varphi(x_{1,t})$ is a convex adjustment cost, ρ, a persistence parameter, with $\rho = 0.9$, and z_k is an i.i.d. random variable with zero mean and a variance, $\sigma = 0.03$. We solve this through a stochastic version of NMPC, see Gruene et al (2013) and appendix 1.

Figure 1 presents the path of the payout, c_t, red line, and leveraging $x_t = 1 + f_t$, blue line. As can be observed the stochastic capital gains and interest rates generate a volatility of both, payout and leveraging. Note that we solve here only for optimal leveraging.[13] The payouts tend to move with leveraging. Both BS as well Stein assume that in each period the debt is redeemed and, without cost, frictionless re-obtained on the market.

In figure 2 the black line is the path of net worth, upper line, and the red line is the process of stochastic shocks, with the expected value of one, lower line. One can observe in figure 2 that the volatility of net worth is considerably lower than for the stochastic

[12]Stein (2012) posits that the interest rate shocks are highly negatively correlated with capital gains' shocks, we have thus a negative sign in equ (3). We here also assume that the interest rate shocks have smaller variance than the capital gains' shocks.

[13]Stein (2011, 2012) computes then also actual leveraging and can thus define excess leveraging.

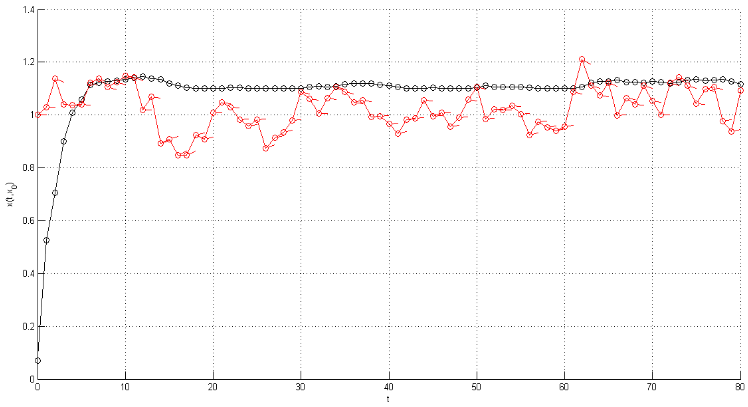

Figure 2: Paths of net worth, modeled by (3), black line, and shock process, modeled by (4), red line, with initial net worth below stochastic steady state

shocks.

We want to note that in BS there is only implicitly a macro feedback loop stylized, namely an externality, i.e. endogenous volatility, that is triggered below the steady state which makes the steady state unstable downward and not mean reverting as in Bernanke et al. (1999). In BS the feedback loop arises from large shocks, the fire sale of assets, fall of asset prices and fall in net worth, generating a downward spiral.[14] Though in the above model (1)-(4) instability is not modeled yet, the above figure 1 depicts the volatility of x_t, the optimal leveraging, and the payouts, c_t.[15]

Through our numerical computations we can also directly observe the leveraging as defined in BS (2003: 23) as the ratio of assets to net worth: The upper graph of figure 1, the blue line, represents this ratio. As BS properly state, through leveraging, the capital share of banks in total capital – the share of financial experts in their terms– is greater than the net worth of banks, due to the extensive leveraging of them, even at the stochastic steady state. This is also what creates the source for endogenous risk. What is missing in BS – but also in Stein – is the specification of macro feedback loops generating further amplifications. Feedback loops as discussed in sect. 2 will be studied next.

[14]In Stein the vulnerabilities and possibly adverse feedback loops are triggered by overleveraging, capital losses and rising borrowing cost.

[15]In Stein (2011, 2012) the actual leverage over and above the optimal leverage is caused by a shock sequence of high capital gains and a shock sequence of low interest rates, both giving rise to excess leveraging. In this sense, Stein models explores only the vulnerability of the overleveraged sector, but does not model particular feedback loops, as MS (2013) do, which maybe amplifying, see sect. 3.2. Yet, the Stein model can neatly make the distinction between optimal debt, actual debt and excess debt.

3.2 Bank Leveraging with Adverse Macro Feedback Loops

To do this we will modify the model of sect. 3.1 and introduce also more explicitly the capital stock dynamics. In BS the capital stock is shared by households and banks (financial experts), but remains relatively passive. We also introduce more specifically the evolution of leveraging by defining debt now as state variables, as macro economists have proposed when studying the financial-macro link. We also consider the effect of leveraging in the households' welfare.[16] We study two regimes– a regime of low debt and low financial stress and a regime with high leveraging and high stress.

3.2.1 Low Leveraging and Low Financial Stress

The low stress regime is characterized by low interest rates on borrowing, low leveraging and no credit spreads. This can be seen as equivalent to the case of the central bank pursuing a low – or near zero – interest rate policy which keeps the economy in a low financial stress regime. The detailed measure of financial stress will be discussed in sect. 4. Our model variant for the low stress regime reads as follows:

$$V\left(k,d\right)=\max_{c_t,g_t,}E_t\int_0^N e^{-rt}(U(c_t)-\chi(\mu_t-\mu^*)^2)dt \tag{5}$$

s.t.

$$dk_t=(g_t-\delta)k_t dt+\sigma_t k_t dZ_t \tag{6}$$

$$db_t=(rb_t-(y_t-c_t-i_t-\varphi(g_t k_t)))dt \tag{7}$$

In (5) there are preferences over log utility, now penalized by some excess leveraging.[17] Hereby we have $\mu_t=b_t/k_t$, $\mu^*=steady$ state leveraging. The decision variables in (5) are payouts (for consumption), c_t and growth rate of capital stock, g.[18] The horizon T

[16] See Blanchard (1983) and Roch and Uhlig (2013).

[17] See Roch and Uhlig 2012). They allow for a one-time cost of default, such that $\chi(\mu_t-\mu^*)^2$ occurs only ones. We stretch this default cost out over time, making it depending on the excess leveraging. A similar approach as ours has been proposed by Blanchard (1983).

[18] Actually in the numerics we can take $\tilde{c}=c/k$, and then multiply it by k in the preferences, so that the first two choice variables can be confined to reasonable constraints between 0 and 1.

does not have to be very large, or go to infinity.[19]

As above in equ. (2) equ. (6) represents the evolution of capital stock. It increases due to investment but declines due to the resource use to manage the assets, δ.[20] Note that BS (2013) have normally distributed shocks and volatility dependent asset prices and returns. We here present and solve a non-stochastic version, but with nonlinearities.

Equ. (7) represents the dynamics of banking leveraging.[21] with $y = Af(k)$ the return on capital, with $A > 0$.[22] The interest payment on debt, rb_t, increases debt but the surplus $(y_t - c_t - i_t - \varphi(g_t k_t))$ – the excess of income over spending – decreases debt. Hereby we have defined $i = g_t k_t$. Note that payouts and investment are separate decision variables. Moreover, $\varphi(g_t k_t)$ is the adjustment cost for investment, which is presumed to be quadratic.

Note that the model has two decision variables and two state variables. We could have formulated the second state equation in terms of net worth and leveraging, the latter as a decision variable as in BS. We prefer leveraging here as a state variable where then debt can only sluggishly be redeemed and issued again. We can also bring in the distinction between the discount rate and interest rate, the latter impacted by leveraging.[23] One can also allow the income y to be split up into $y =$ normal return on capital + capital gains, as in Stein (2012). Then the excess return on capital income over the interest rate, fueled through capital gains, can be used to service the debt, see Stein (2012, chs 4-5).

We can solve our above model (5)-(7) by using again NMPC.[24] Assuming here $r = 0.04, \delta = 0.03$ and quadratic adjustment cost of investment, we obtain the following solutions using NMPC.

For a regime of low financial stress, in figure 3 the vertical axis shows the leveraging, the horizontal is the capital stock. The paths are shown for different initial conditions. Given low interest rates and low stress, all three initial conditions lead to convergence. The upper two initial conditions represent the starting point for low operating income flow,

[19]For details of such a model with short decision horizon, approximating well models with longer time horizons but needing much less information, see Gruene et al (2013). Those type of models are called Nonlinear Model Predictive Control, see Gruene and Pannek (2011), there however without discounting.

[20]This rate could be made time dependent, or its change triggered by a shock, for example due to loan losses.

[21]This can be justified by a two type of agents' model as in BS (2013).

[22]In earlier versions, BS have used the return on capital as linear in capital, but we take here $y = Af(k) = Ak^{\alpha}$.

[23]For example in a two types of agents model, see BS (2013) and also Eggertsson and Krugman (2012).

[24]See the sketch of the algorithm in appendix 1.

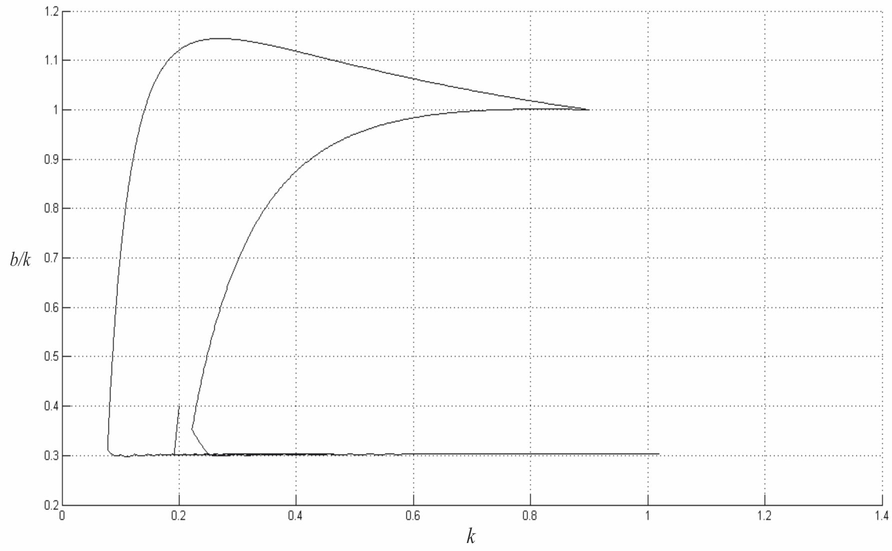

Figure 3: dynamic paths of assets and leveraging for low and constant interest rate, for three initial conditions; two initial conditions $k(0) = 0.9$, $b(0) = 0.9$ (large), the left trajectory with $A = 0.1$, the right with $A = 0.2$, and one other initial condition $k(0) = 0.2, b(0) = 0.08$ (small); all trajectories converging to steady state $\mu^* = 0.3$, with $r = 0.04$.

$A = 0.1$, left trajectory, and the higher operating income $A = 0.2$, right trajectory. The third initial condition is chosen rather low, $k(0) = 0.2, b(0) = 0.08$ which also converges to the steady state.

The NMPC numerics guarantees that the transversality condition holds – the trajectories are not explosive but converge toward a steady state where the left hand side of equ. (7) is zero.[25] We can have here global stability if the central bank can manage to keep the interest rate and credit spread down. In such a regime of low financial stress debt sustainability is prevailing.[26]

This may, however, generate a tranquil period where there are large capital gains, entailing an asset price boom, where risk premia are low and asset prices rise. Yet, when an overleveraging occurs and the asset price bubble bursts and capital gains become negative, then net worth may quickly deteriorate. As the debt ratio rises and the capital gains

[25] This is consistent with the case put forward by Bohn (2007) that the debt is mean reverting when the reaction coefficient (the response of the surplus with respect to debt) in his debt dynamics is greater than the interest rate. In his case however the interest rate is a constant, or only slightly varying through the growth rate of marginal utilities, if he takes the latter to determine the discount rate.

[26] This however might not hold if asset prices and capital gains will rise, and subsequently credit spreads will jump up, see the next scenario.

fall, and interest rates and credit spreads are likely to rise – the latter being negatively correlated with the capital gains – net worth of the assets can also quickly vanish.[27] This may give rise to a new regime.

3.2.2 High Leveraging and High Financial Stress

We next allow the financial stress and credit spread to be endogenous. We here employ economic mechanisms that entail endogenous feedback loops of the financial stress to macroeconomic activity, generating non-linearities, possibly giving rise to greater instability. This is likely to occur if the central bank is not attempting – or not being able – to pursue a monetary policy to reduce financial market stress and to bring down credit spreads. Let our model now be defined as follows

$$V(k,d) = \max_{c_t, g_t,} E \int_0^T e^{-rt}(U(c_t) - \chi(\mu_t - \mu^*)^2)dt \tag{8}$$

s.t.

$$dk_t = (g_t - \delta)k_t dt + \sigma_t k_t dZ_t \tag{9}$$

$$db_t = r(s_t|\gamma, c^*)b_t - (y_t - c_t - i_t - \varphi(g_t k_t)))dt \tag{10}$$

The difference to the model of low stress regime is here now that we assume that there is a state dependent credit spread. The built up of financial stress is a nonlinear function of the leverage ratio. Since we want to have the function to be bounded we can define it by a function such as given by:[28]

$$r(s_t|\gamma, c^*) = [1 + \exp(-\gamma(s_t - c^*))]^{-1}, \ \gamma > 0, \ c^* > 0 \tag{11}$$

This function makes the credit cost depending on a state variable, s_t, a threshold variable, c^*, and a slope parameter, γ. The above represents the logistic function often used in

[27] For details of such a scenario and an exact measure of overleveraging, as compared to optimal leveraging, see Stein (2012).

[28] Note, however, we take this to represent financial stress. Empirically we will introduce a host of factors generating financial stress. Note also that in the numerics we approximate the function used here by an arctan function which is numerically more convenient, which has however the same shape. For further details on the logistic function, see Schleer and Semmler (2013).

STAR models.[29]. It is also roughly the function that has been empirically observed in De Grauwe and Ji (2012),[30] but one can also derive from Roch and Uhlig (2012).[31] In our numerical solution procedure we will approximate this function above by a closely related function.[32].

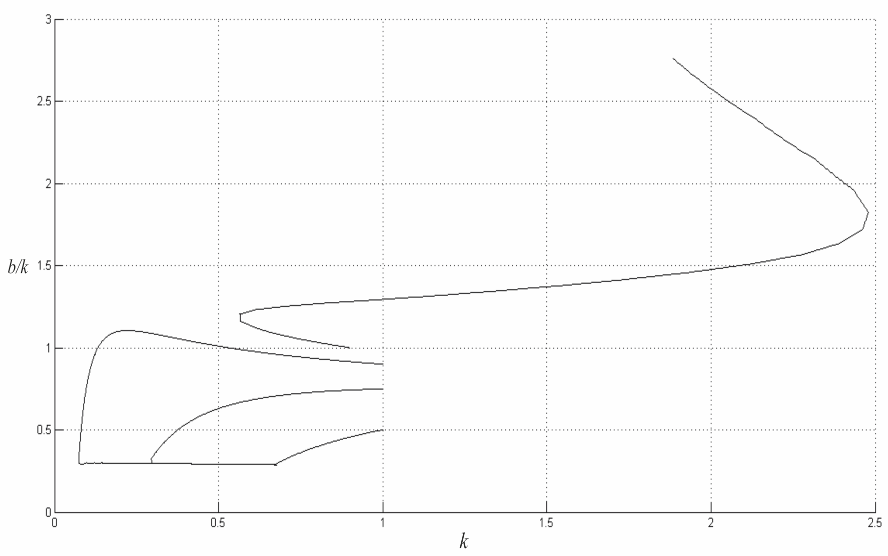

Figure 4: Debt dynamics for nonlinear financial stress effects; lower three trajectories for low stress case with borrowing cost below a threshold, for three initial conditions, convergence to some steady state, even in high stress regime but for low credit costs; yet triggering of unstable dynamics, upper trajectory; for initial conditions $k(0) = 1$, $b(0) = 0.9$ with high credit cost

In figure 4 we present two cases. In the first case there is state dependent risk premia and credit spread but the leveraging (expressed by initial conditions) is low. Credit risk and financial stress do not build up and there are no adverse macro feedback effects. The lower three trajectories represent this case, with initially low stress and with borrowing cost below some threshold. For these three initial conditions we can observe a convergence

[29]For example used in the VSTAR model of Schleer and Semmler (2013)

[30]Presenting there EU debt and bond yield data, see also Corsetti et al (2012).

[31]In DSGE models the rise of risk premia and its persistence on a high level is often modeled through large shocks with some strong persistent, see also Gilchrist et al (2011).

[32]Since in our numerically we cannot directly read in the financial stress, s_t, we approximate (11) by an arctan function such as $r(b_t/k_t) = \beta arctan(b_t/k_t)$ with the state variable $s = b/k$. We hereby have set $\beta = 0.1$. In this function the credit cost rises in a non-linear way with leveraging, first slowly, then more rapidly but is finally bounded. Yet, the latter function behave the same way as the above logistic function, except it is a bit flatter at its upper and lower branches. Also, the arctan function is not bounded by 1 and 0 but can move in reasonable bounds as needed to approximate actual credit cost.

to the steady state.

In the second case the initial leveraging is higher. The function (11), representing the steeply rising credit spread, making the credit cost rising with higher financial stress. Note also if in this case we were to look at the asset side of the economy, asset prices are likely to fall or do not grow any more and capital gains could become negative and the income y would need to be adjusted to a lower level[33] and surpluses would shrink, the debt service rise with higher interest rates and debt sustainability becomes threatened.[34]

Next we consider a slightly modified variant of the above case. As in sect. 2 discussed, adverse macro feed back effects arising from financial stress can affect banking vulnerability. There are not only endogenous risk premia, rise of interest rates and prices of assets declining but the macro feedback loops are likely to trigger decline in aggregate demand and output[35] and thus banks' operating income and market valuation – with the consequence of a further reduction of credit supplies by banks. So the real side starts to have effects on the financial sector and the reverse.

Though optimal payouts and and investment might be targeted, actual operating income of banks, are likely to decline due to the macro feedback loops. So overall we may experience that actual gross operating income in (13) adjusts downward:

$$db_t = r(s_t|\gamma, c^*)b_t - ({y^a}_t - c_t - i_t - \varphi(g_t k_t)))dt \tag{12}$$

$$y^a_t = (1 - r(s_t|\gamma, c^*))(y_t) \tag{13}$$

Note that in equ. (13) we have defined actual operating income to be driven by aggregate activity in the regime of financial stress $(1 - r(s_t|\gamma, c^*))(i^{opt} + c^{opt})$, where actual payouts and investment, responding to financial stress, $(1 - r(s_t|\gamma, c^*))$, are determining actual income. So the optimally chosen decision in each time period of the state variables are

[33]Stein (2012) suggests then to make corrections by suggesting to take the trends/drifts in capital gains that would better measure some optimal debt. The borrowing exceeding that debt would amount to excess borrowing.

[34]For a scenario like this see Stein (2012) where this is exemplified with macroeconomic data for Spain and Ireland.

[35]See Blanchard and Leigh (2013) and Corsetti et al (2012). They show of how empirically for example sovereign debt and banking risk also increases private borrowing cost and thus make aggregate demand falling. They employ, as we do here, the spillover effects of risk spreads to aggregate demand, but one can also think of another channel through which macro economic contractions are triggered. A reduction of loan supplies by banks will set in when asset prices and net worth of banks fall, i.e. they will reduce their loan supply to households and firms, see Gerali et al (2010) and De Grauwe and Machiarelli (2013).

actually not realized, but the actual outcome depends on the degree of financial stress and the macro feedbacks triggered by this.

The outcome of both the financial stress and the macro feedbacks are captured in the upper two trajectories of figure 5. Actually what is modeled here is what has been called the feedback of financial market stress on aggregate demand and output.[36] This version of the model is also numerically solved using by NMPC. We illustrate the outcome for two versions. In both versions we are in a regime of high financial stress.

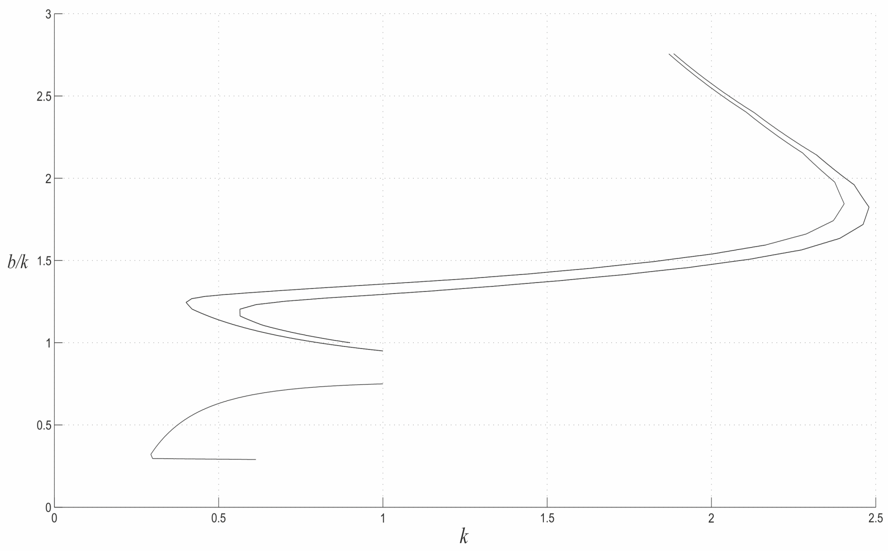

Figure 5: Debt dynamics with macro feedbacks to bank's income (upper two trajectories); right trajectory, with weak feedback effects, and solely credit spreads, for initial conditions, $k(0) = 0.9, b(0) = 0.9$, left trajectory includes stronger macro feedback loops to banks operating income, for initial conditions $k(0) = 1, b(0) = 0.9$; lower trajectory $k(0) = 1, b(0) = 0.5$ representing stabilization of debt with low leveraging and financial stress

First, we are setting the macro feedback loops on aggregate demand to be weak. We get the right trajectory of the upper two figures. The left trajectory of figure 5 represents the path with lower initial leveraging but stronger macro feed back effects. Whereas the same initial conditions in the previous graph, figure 4, generated a stable debt dynamics, the debt dynamics becomes now unstable in the case of stronger macro feedback loops, see left trajectory of the upper two trajectories in figure 5. On the other hand leveraging

[36] This is what a recent IMF study defines as follows: "The risk channel amplifies the transmission of shocks to aggregate demand, unless monetary policy manages to offset the spillover from sovereign default risk to private funding costs". Corsetti et al (2012).

and credit spread below a certain threshold becomes sustainable, see lower trajectory of figure 5.

As to the upper unstable trajectories, the economic intuition is that stronger macroeconomic feedback loops[37], with negative impact on demand, may arise due to the following:

- There is the wealth effect reducing aggregate demand – when the capital appreciation falls, or becomes negative, aggregate demand would fall and with lower collateral value banks would reduce loans or increase funding cost
- The share of households that are income and credit constrained, in the sense of Gali et al. (2007), and households that are higher leveraged and are under financial stress,[38] are significantly rising in a contraction period of the business cycle, and thus demand falls[39]
- As the financial market forces trigger banking and financial stress,[40] the central bank may have no instruments available – or is not willing – to force the interest rate down further and/or to reduce risk premia and credit spreads, which may adversely affect demand and output
- A fraction of private households start strongly deleveraging[41] that reduces income and liquidity of other households and firms. This might be accompanied by a Fisher debt deflation process, causing higher real debt and declining demand because of expected price fall (Tobin effect)[42]
- Finally, there could occur even a worse feedback: a weak financial sector, holding risky sovereign or other debt, may come under severe stress, because debt may go into default and banks reduce lending to the real economy, or worse, may even default.[43]

[37]A systematic study of macroeconomic feedback effect, know from the history of macroeconomics, partly stabilizing partly destabilizing, are extensively discussed in Charpe et al (2013).

[38]The share of those households matter, since there is empirical evidence that the drop in demand will be larger for households with larger debt, that are forced to deleverage more, see Eggertsson and Krugman (2012).

[39]See also Mittnik and Semmler (2012, 2013)

[40]This documented by the ZEW financial condition index as presented in Schleer and Semmler (2013).

[41]See Eggertsson and Krugman (2012)

[42]A detailed discussion of further macroeconomic feedback effects of this type can be found in Charpe et al (2013).

[43]See Brunnermeier and Oehmke (2012) and Bolton et al (2011), the latter present data on the sovereign debt holdings of banks.

We expect thus, starting with a leverage ratio roughly above normal that the above macro feedback mechanisms lead to higher financial market stress, higher risk premia, higher credit spreads, less credit supply and lower demand and output, leading to a contraction in the utilization of the capital stock, and falling capital stock, with increasing stress to the banking system.[44]

Given those above sketched adverse macro feedback loops, it can be explained why there might be a regime switch from a low to a high stress regime where the vulnerability of financial intermediaries increase and a faster deterioration of demand and output can occur which has then again feedback effects from the real to the financial side. This is happening the more, the more central banks fail to undertake an unconventional intervention into asset markets. Overall, in this latter case there is only a smaller stability region left. The corridor of stability has shrunk and even small shocks may matter, see BS (2013) and Dimand (2005).

4 Measures of Real Activity and Financial Stress

To study the question of how financial stress and real economic activity empirically interact, appropriate proxies for the phenomena under investigation need to be specified. As our empirical analysis is based on data sampled at a monthly frequency, the growth rate of industrial production (IP) is a reasonable measure for real activity. It should be kept in mind, however, that the relative sizes of the industrial sector differ across the countries, which could induce heterogeneity in our empirical finding.

We use the components of the advanced financial stress index the IMF constructs on a monthly basis for advanced economies as measures of financial–sector risk.[45] The advantage of the FSI constructed by the IMF is that is consistently defined across all the countries here under investigation. The index is comprised of seven country–specific risk indicators, which can be grouped into three segments, relating to banking, securities markets, and foreign–exchange markets:

Banking related:

- TED spread: 3–month LIBOR or commercial paper rate minus the government short-term rate.

[44] This could equivalently create a downward spiral in net worth, if the model is written in terms of net worth, as BS (2012) and Stein (2012).

[45] The samples cover the period 1981 through mid 2012. The construction of the FSI is detailed in Caradelli et al. (2011).

- Inverted term spread: Government short-term rate minus government long-term rate.

- Banking–sector beta: The standard capital asset pricing model (CAPM) beta, computed over a 12-month rolling window. A beta–value above one indicates that banking stocks are more volatile than the overall stock market, suggesting that the banking sector is excessively risky. To link the beta measure to banking–related financial stress, the IMF lets the banking beta only enter when returns on bank stocks are lower than the overall market return.[46]

Securities markets:

- Corporate debt spreads: Corporate bond yield minus long–term government bond yield.

- Stock market returns: Computed as the month–to–month change in the stock index multiplied by minus one, so that a decline in equity prices corresponds to increased securities-market-related stress.

- Stock market volatility: Measured as the 6-month (backward looking) moving average of the squared month–on–month stock–index returns.

Foreign–exchange markets:

- Foreign exchange market volatility: Measured as the 6-month (backward looking) moving average of the squared month–to–month growth rate of the exchange rate.

All series are de-meaned and standardized, so that values around zero reflect, on average, a neutral financial–market condition across the subindices, while positive values indicate financial stress. A value of one indicates a one-standard deviation from average conditions.

The aggregate FSI is simply the (standardized) sum of the seven components and, hence, has the same interpretation as the individual stress indicators. Figure 6, as an example, shows the time series of the stress indicators together with the (scaled) IP levels for the US.

[46] Otherwise it is set to zero, so that the truncated paths, after de-meaning and standardization, arise.

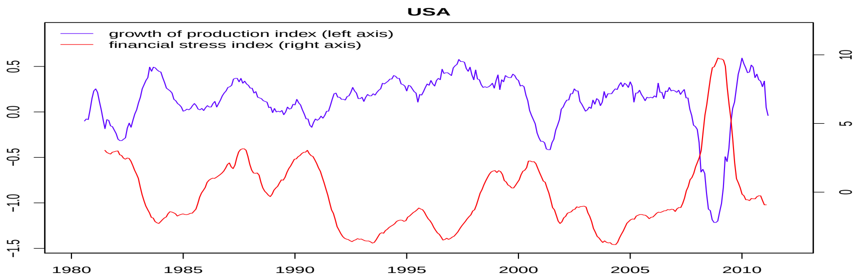

Figure 6: FSI and IP for the US

5 Empirical Analysis

Our strategy for empirical analysis is as follows. Though overall we are interested in the aggregate financial sector-macro link, we will also focus on the individual risk drivers of the FSI. For the latter we first, to generally assess whether or not variations in the individual FSI components have an influence on an economy's IP growth, we conduct bivariate tests for Granger causation with respect to component and the aggregate FSI. Next, considering the nonlinear dynamic effects of the aggregate FSI on IP reported in MS (2013), we turn to nonlinear analyses. First, we conduct bivariate tests for *nonlinear* Granger causality to assess the possible presence of dynamic dependencies beyond linear relations. We, then, fit nonlinear MRVARs and examine whether causal relationships within low–stress and high–stress regimes are different across regimes. Finally, based on estimated MRVARs, we investigate how IP growth responds to shocks to individual risk drivers. Specifically, we examine to what extent responses vary in situations of low and high financial stress and whether responses are sign–symmetric, i.e., whether responses to positive and negative shocks are symmetric.

Table 1: p-values from Granger–causality tests, testing the null hypothesis that IP growth is not Granger–caused by the stress indicator

	TED	Term Spr.	Beta	Corp. Spr.	Stock Ret.	Stock Vola	FX Vola
USA	0.001	0.047	0.918	0.000	0.000	0.007	0.190
CAN	0.003	0.000	0.743	0.000	0.000	0.811	0.003
JPN	0.913	0.142	0.992	0.478	0.008	0.000	0.000
GBR	0.875	0.016	0.149	0.000	0.074	0.183	0.137
DEU	0.000	0.016	0.843	0.000	0.003	0.251	0.610
FRA	0.806	0.439	0.311	0.104	0.018	0.278	0.137
ITA	0.453	0.092	0.062	0.811	0.006	0.731	0.674
ESP	0.567	0.396	0.953	0.044	0.031	0.729	0.763

5.1 Testing for Causality

5.1.1 Linear Granger Causality

We conduct bivariate tests for Granger causality with respect to component and the aggregate FSI. We regress IP growth on a constant, lagged IP growth and lagged values of the respective stress indicators, using a common lag length of four. Table 1 reports the p-values of these tests.

Treating p–values below 0.10 as mild and those below 0.05 as strong empirical evidence, the Granger–causality tests reveal some specific patterns. For one, stock–market returns are a good leading indicator of economic activity. For all eight countries, the hypothesis of no Granger–causality is rejected. Overall, the rejection is rather strong: for five of the eight countries, we have significance at the 99%–level, for two countries (France and Spain) at the 95%–level, and the weakest rejection, with a p–value of 0.074, is for the UK.

Corporate debt spreads, another securities markets indicator, significantly Granger–cause real activity, except in Japan, France and Italy. The third securities–markets indicator, stock–market volatility, plays only for the U.S. and Japan a significant role.

Among the banking–stress drivers, beta turns out to be insignificant in all eight cases. The TED spread and term spread are both significant in the U.S., Canada, and Germany; in addition, the term spreads Granger–cause in the UK and in Italy. FX volatility appears to affect IP growth in Canada and Japan.

Finally, except for Spain, the aggregate FSI Granger–causes IP growth in all countries at highly significant levels.

5.1.2 Testing for Nonlinear Granger Causality

Granger–causality is defined in terms of linear predictability. The empirical evidence in MS (2013), however, reveals that the aggregate FSI impacts IP in a nonlinear fashion. To assess the presence of such nonlinearities, we test to what extent a nonlinear specification of the stress components may indicate Granger–causality. As a crude check, in addition to regressing IP growth on its own lags and lagged stress–indicator values, we also include a variant of the stress–indicator as regressor that assumes the value of the stress measure when it exceeds the sample median and is zero otherwise. I.e., for each country we estimate

$$ip_t = \alpha + \sum_{i=1}^{p} \beta_i ip_{t-i} + \sum_{i=1}^{p} \gamma_i si_{t-i} + \sum_{i=1}^{p} \delta_i \mathbf{1}_{\{si_{t-i} > si_{thresh}\}} si_{t-i} + u_t, \tag{14}$$

where si_{t-i} represents a generic stress indicator; and $\mathbf{1}_{\{si_{t-i} > si_{thresh}\}}$ is an indicator variable that is one, if si_{t-i} exceeds a predefined threshold, and zero otherwise. We simply define the sample median as threshold.[47] Thus, the coefficient associated with regressor si_{t-i} is $\gamma_i + \delta_i$, if si_{t-i} is above the threshold, and simply γ_i, if it does not exceed the median. In line with the standard approach to Granger–causality, we test the joint significance of δ_i, $i = 1, \ldots, p$.

The results, shown in Table 2, demonstrate that already this crude check delivers an indication for the presence of nonlinear dynamics. Whereas linear tests do not find that the banking beta causes growth, it turns out that the European economies, with the exception of Spain, are affected by large beta values. IP growth rates in Japan and the UK, which do not appear to be linearly affected by TED spreads, seem, however, to respond to high TED–spread levels. For the term spreads, the third variable in the banking group, we do not find that large values have an impact that goes beyond that of a linear specification.

With respect to the securities–markets indicator group, corporate spreads are found to also have a nonlinear impact on U.S. and UK growth. For Italy, where there is no evidence for linear causality, we strongly reject that large spreads do not Granger–cause growth. With the exception of the U.S. and Japan, we do not find that above–median stock–return losses have an impact on IP. Beyond linear effects, growth in Japan is also driven by above–median stock–market and FX volatility.

[47] The sole exception is the banking beta, which, by construction, is only recorded when bank stocks underperform the market. This eliminates more than half of the sample. We, therefore, set the threshold to 25%–quantile of the remaining observations.

Table 2: p-values from Granger–causality tests, testing the null hypothesis that excessively high stress–indicator values do not Granger–cause IP growth beyond a linear specification.

	TED	Term Spr.	Beta	Corp. Spr.	Stock Ret.	Stock Vola	FX Vola
USA	0.823	0.920	0.333	0.042	0.073	0.947	0.333
CAN	0.096	0.789	0.331	0.245	0.566	0.896	0.648
JPN	0.002	0.545	0.464	0.271	0.002	0.036	0.022
GBR	0.011	0.612	0.022	0.023	0.317	0.744	0.318
DEU	0.014	0.861	0.042	0.112	0.723	0.473	0.959
FRA	0.767	0.546	0.003	0.588	0.227	0.583	0.661
ITA	0.755	0.476	0.076	0.001	0.174	0.563	0.661
ESP	0.130	0.175	0.939	0.128	0.883	0.930	0.520

5.2 Regime–dependent Effects of Financial Risk on Economic Activity

5.2.1 The MRVAR Approach

The tests for Granger–causality reported in the previous section gives insights into the questions *whether* above–median levels of a stress indicator affect on real activities differently from below–median ones. They do, however, not provide information about *how* they affect growth. Impulse–response functions derived from estimated linear VAR models are commonly used in linear settings. In the presence of nonlinearities, this is a valid strategy, when studying local behavior due to infinitesimal disturbances. In generally, it will not provide meaningful insights into responses to large shocks, nor does it allow for state–dependence or size–dependence in the response behavior. Also, as MS (2013) point out, the presence of so–called "corridor stability," discussed in the earlier literature on Keynesian macro dynamics (cf. Dimand, 2005; Bruno and Dimand, 2009) and also referred to in the context of financial–market regulation (cf. Schinasi, 2005), cannot be analyzed using conventional, linear VAR specification.

Given these deficits, MS (2013) employ a more general modeling framework that can accommodate varying dynamic patterns. Specifically, they use multi–regime vector autoregressions (MRVAR)s in form of threshold vector autoregressions in the vein of Tong (1978, 1983) and (Tsay, 1998), to allow for regime–dependent phenomena.[48] The threshold–based MRVAR approach is a simple and parsimonious strategy for nonparametric function es-

[48]For an application of the MRVAR approach to assessing the fiscal multiplier see Mittnik and Semmler (2012).

timation and for modeling multi-equilibria settings (Hansen, 2000).

The MRVAR specification we use is given by

$$y_t = c_i + \sum_{j=1}^{p_i} A_{ij} y_{t-j} + \varepsilon_{it}, \quad \varepsilon_{it} \sim (0, \Sigma_i), \quad \text{if } \tau_{i-1} < r_{t-d} \leq \tau_i, \quad \text{for } i = 1, \ldots, M, \tag{15}$$

where r_{t-d}, $d > 0$, is the value of the threshold variable observed at time $t-d$; and regimes are defined by the threshold levels $-\infty = \tau_0 < \tau_1 < \cdots < \tau_M = \infty$. In the following, we restrict ourselves to two–regime VARs, with the financial–stress indicator defining the threshold variable.[49]

5.2.2 Response Analysis

Granger causality suggests the presence of influence, but does not reveal the specific nature of the impact. For this reason, we derive response functions of IP due to shocks in the individual risk components. Response analysis for linear VAR models is a well–known tool in empirical macroeconomics; and point estimates and asymptotic distributions of shock response can be derived analytically from the estimated VAR parameters (cf. Mittnik and Zadrozny, 1993). For nonlinear settings, Koop et al. (1996) propose the use of simulation–based generalized impulse responses (GIRs), which depend on the overall state, z_t, the type of shock, v_t, and the response horizon, h, so that $GIR_h(z_t, v_t) = \mathrm{E}\left(y_{t+h} \mid z_t, u_t + v_t\right) - \mathrm{E}\left(y_{t+h} \mid z_t, u_t\right)$, where the overall state, z_t, reflects the relevant information set.

For each of the risk components[50] and all eight countries, we derive generalized, cumulative responses from estimated MRVARs with regimes being defined by above– and below–median stress values. By choosing the median as the threshold level, we divide the samples evenly into high– and low–stress phases. This differs from the regime–dependent testing for Granger causality discussed in the previous section. There, the estimated MRVARs served as a descriptive tool for detecting possible nonlinearities. As a consequence, we were interested in obtaining regimes that yield the best piecewise linear fit for the data—and, thus, probably most distinct regimes—, in order to obtain high diagnostic power. When conducting response analysis with the application of policy intervention in mind, we

[49] For details on MRVAR specification and estimation and a discussion of the advantages of specification (15) over Markov–switching VARs see MS (2013).

[50] In view of its truncated nature and the fact that about half of the observations are zero (before demeaning, we omit the banking beta from the analysis, since the interpretation of a positive and negative shock becomes dubious.

may choose thresholds in such a way that we can best assess the expected impact of policy measures for a given state of the economy—the current state, for example. Moreover, by dividing the regimes evenly, the estimated responses have similar sampling uncertainty, so that the differences in significance across the regimes are not due to differences in sample sizes.[51]

We derive responses for both high– and low–risk states, with the states being defined by the average state for the below–median (above–median) stress states. Moreover, we investigate to what extent IP reacts asymmetrically to positive and negative stress shocks in the two states. This provides us with four cumulative response functions for each indicator/country pair. The 36–month, cumulative IP response functions, together with the 90% confidence bands, for all eight countries, grouped by stress indicator, are graphed in Figures 7 to 12.

Altogether, the plots indicate substantial evidence for state–dependence and sign–asymmetry in IP responses to financial stress. In particular, we observe state or regime dependence of financial stress shocks on IP for the spread variables, i.e., TED spreads, term spreads and corporate bond spreads. For TED spreads, see Figure 7, we find that a positive stress shock in a high–stress regime has mostly a stronger impact on IP than in a low–stress regime; and a stress reduction negative shock has, as a rule, a stronger impact in high– as compared to low–stress regimes. This holds especially for the U.S., Canada, Germany, and, to some extent, for Italy. For other countries, such as Japan, the UK, France, and Spain, the hypothesis holds only partially or the responses lack significance.

Stronger results are obtained for term spreads (Figure 8). As banks are typically short–term borrowers and long–term lenders, it comes as no surprise that the (inverted) term spread is a central variable for the stability of the banking sector. For most of the countries (except Italy) a positive stress shock in an already high–stress state, arising from term–structure shocks, reduce IP more than in a regime of low stress, with the reverse holding for stress reductions. Stress reduction has a greater effect in high stress regimes, except for Spain, where the results have the right sign in the low stress regime, but are not significant.[52]

As to corporate bond spreads (Figure 9), we find that the signs of the responses are mostly as expected and the size of the effects of shocks are different in high–stress as compared to

[51] The different threshold specifications may explain the occasional differences in the significance we find from causality tests and response analysis.

[52] See the discussion in MS (2013) for why the Spanish economy may behave differently, due to a delayed enforcement of IFRS accounting standards, compared to the EU countries.

the low–stress regime. This is not fully the case for Canada and Italy and is less verifiable for Japan, Spain, and France. For the latter countries the difference in the results might come from the fact that the financial market is more "bank-based" than "market-based", as Bijlsma and Zwart (2013) argue.

We obtain less strong results for the other proposed risk drivers. As to the role of (negative) stock returns as stress factors (Figure 10), with the exception of the U.S. we see low significance in the responses. This may come from the fact that, overall, stock returns are an overly noisy risk measure and only potent in combination with sector–specific stress (like the real estate market, see Stein 2011), or jointly with other financial stress variables.

Similarly, less clear results can also be seen for stock–price volatility (Figure 11), which has the predicted impacts only in the high– and low–stress regimes in the U.S. and Japan. More "bank–based" financial systems and less deeply developed financial markets seem to be less vulnerable to stock market volatility.

Finally, responses to shock in FX volatility (Figure 12) have the predicted outcome mostly for stand–alone countries, meaning for countries that have their own currency. The responses in countries that are members of the euro–currency zone are mostly insignificant.

6 Implications of our Results

In our theoretical considerations in Sect. 3, we have stressed model variants that imply different vulnerability to financial stress shocks. Also, the role of particular risk drivers that can induce regime changes from low to high stress regimes were discussed and that stress shocks may have less of an impact in low stress than high stress regimes.

Essential in the theory of BS (2013) are the banks' balance sheets and the endogenous generation of risk through fire sales of assets and asset–price volatility as causes for financial instability and a downward spiral. Though our empirical results are broadly in line with the BS (2013), the empirical results presented here, however, especially the response analyses, indicate that asset–price volatility itself, which plays a prominent role in the BS (2013) model, is not a strong driver of risk and regime changes.[53]

In Stein (2011, 2012), it is the asset price and borrowing boom—excessive, non-optimal capital gains and overleveraging—that moves one out of a low risk into a high risk regime.

[53]Though it it fair to assume that BS (2012) presumably wanted to explain more the rare and large event of the period 2007/08 with their theory rather than the effects above– or below–median average states.

Excessive capital gains, and its negative correlation with interest rates, results in excessive leveraging, which are the risk drivers for the high vulnerability regime. Stein is, however, more concerned with a banking sector that is exposed to sector–specific overleveraging (like real estate and agricultural sectors) through loan supplies. On the other hand, overleveraging (over and above the optimal level), in the banking sector is not directly measured, and it may not be a sufficient indicator for vulnerability and financial stress. We also do not have a direct measure of overleveraging in the FSI. One might take the credit spreads, as we found relevant as risk drivers in our empirical study, representing overleveraging and financial stress.[54]

In MS (2013), the role of state dependent risk premia and credit spreads are stressed as risk drivers and indicators of financial risk, having amplification effects to the real side of the economy. Our results reported here, the particular strong state dependence of responses to spread variables, such as TED spreads, term spreads and corporate bond spreads, is broadly consistent with MS (2013) and supportive of the model proposed in sect. 3. — though MS (2013) focus mostly on the aggregate stress measure. The disaggregated results for individual risk drivers presented here, such as TED spreads, term spreads and corporate bond spreads, provide quite informative insight into the role of specific risk drivers and risk transmitters, and, thus, may aid policy efforts.

With respect to the current debate on monetary–policy effectiveness, our results may also offer more insight. The currently held view by monetary policy makers that zero or near zero interest rate policies might not have been sufficient to counteract the large financial market meltdown in the U.S., in the years 2007/08 and the ongoing debt crisis in the Euro-zone is supported by our model of sect. 3.2 and our response analysis. Stress reducing policies—nowadays referred to as "unconventional monetary policies"—, where central banks buy "bad assets" in order to bring down risk premia and credit spreads in situations of high financial stress, seem to be justified by our model of sect. 3 and our response analysis of sect. 5. Though one has to keep in mind that our response analysis is confined to bivariate reduced–form modeling and 36–month horizons.

Solely zero or near zero interest rate policies have been criticized of not being very effective in stimulating persistent output and employment growth, see Gavin et al. (2013) and the literature cited there. This in fact is true, in particular if it overlooks that it is not the near zero interest rate that determines the effective funding cost for firms and households,

[54] His model, however, presumes a considerable delay in financial stress build up, which seems to be predicted already in tranquil periods with low interest rates and in periods with negligible risk premia.

but rather the risk–premia–augmented credit spreads – TED spreads and corporate bond spreads – that are relevant for borrowing, lending and spending decisions as well as for debt sustainability as we have shown in sect. 3.2. As to the individual risk drivers, as table 2 has also shown, in EU countries the bank beta is also an important risk driver. Stock market returns, on the other hand, seem to be a relevant risk driver only in the US and Japan, and share price volatility only in Japan.

7 Conclusions

Theoretically and empirically, we have investigated the potential role of overleveraging and financial– and real–sector interactions in causing economic instabilities. Our theoretical model, building upon Brunnermeier and Sannikov (2013), Stein (2011, 2012), and Mittnik and Semmler (2013), allows both overleveraging and adverse asset–price movements—and their impact on risk premia and credit spreads—to induce shifts to high– or low– risk regimes, financial–sector instabilities and downward spirals. Such phenomena are more prevalent as strong, adverse real–sector feedback mechanisms exist. In contrast to infinite horizon models, the solution method we have used, the NMPC method of Gruene et al. (2013), allows us to allow for short– and medium–term amplifying and destabilizing forces, forces which are typically smoothed out in conventional dynamic models.

In an empirical multi–country study, we have assessed conjectures of our theoretical model by investigating how different types of financial–sector stress variables affect real economic activity. The stress variables used, are given by the individual components of the (country–specific) financial stress indices constructed by the IMF. We have employed Granger–causality tests and response analysis based on nonlinear, multi–regime vector autoregressions to evaluate model–implied conjectures about banking–macro linkages. Our empirical results from eight economies—namely, the U.S., Canada, Japan and the UK, and for the four largest euro zone economies, i.e., Germany, France, Italy, and Spain, suggest that financial–sector stress exerts a strong, nonlinear influence on economic activity and that the nature of the influence is more complex than can be typically captured by conventional linear modeling techniques. As was to be expected, with eight countries and six risk factors under investigation, the various risk drivers affect economic activity differently across countries. However, there is strong empirical evidence that credit–spread variables, such as the TED spread, corporate bond spreads and banks' beta, have a strong impact, whereas stock returns and stock market volatility seem to be less potent risk drivers.

References

[1] Adrian, T., A. Moench, and H. S. Shin (2010), “Macro Risk Premium and Intermediary Balance Sheet Quantities,” Federal Reserve Bank of New York, Staff Report No. 428

[2] Bernanke, B., M. Gertler, and S. Gilchrist (1999), “The Financial Accelerator in a Quantitative Business Cycle Framework,” in J. Taylor and M. Woodford (eds), Handbook of Macroeconomics, Amsterdam, North-Holland.

[3] Bijlsma, M. J., and G. T. J. Zwart (2013),“The Financial Market in Europe, the United States and Japan,” Bruegel Working Paper, 20013/02.

[4] Blanchard, O. (1983), "Debt and the Current Account Deficit in Brazil," In Financial Policies and the World Capital Market: The Problem of Latin American Countries, by Rudiger Dornbusch, and Maurice Obstfeld, eds. Pedro Aspe Armella, 187 - 198. University of Chicago Press.

[5] Bohn H. (2007), “Are Stationarity and Cointegration Restrictions Really Necessary for the Intertemporal Budget Constraint?”, Journal of Monetary Economics (54(7): 1837-1847.

[6] Bruno, R. and R.W. Dimand (2009), “The Corridor of Stability in Tobin’s Keynesian Model of Recession and Depression,” International Journal of Applied Economics & Econometrics, XVII, 17–25.

[7] Brunnermeier, M. (2009), “Deciphering the Liquidity and Credit Crunch 2007–2008,” Journal of Economic Perspectives, 23, 77–100.

[8] Brunnermeier, M. K. and M. Oehmke (2012), “Bubbles, Financial Crises and Systemic Risk,” NBER Working Paper 18398, September.

[9] Brunnermeier, M. and Y. Sannikov (2013), “A Macroeconomic Model with a Financial Sector,” forthcoming in: American Economic Review

[10] Cardarelli, R., S. Elekdag, and S. Lall (2011), “Financial Stress and Economic Contractions,” Journal of Financial Stability, 7, 78–97.

[11] Chen, P. and W. Semmler (2013), “Financial Stress, Regime Switching and Macrodynamics: Theory and Empirics for the U.S., EU and Non-EU Countries,” Working

Paper, Economics, The Open Access, Open Assessment E Journal, No. 2013-24, March 15, 2013.

[12] Christensen, I. and A. Dib (2008), “The Financial Accelerator in an Estimated New Keynesian Model,” Review of Economic Dynamics, 11, 155–178.

[13] Corsetti, G., A. Meier, et al. (2012), "What Determines Government Spending Multipliers?" IMF Working Papers 12/150. IMF, International Monetary Fund.

[14] Davig, T. and C. Hakkio (2010), “What is the Effect of Financial Stress on Economic Activity?” Economic Review, Federal Reserve Bank of Kansas City, Second Quarter, 35–62.

[15] De Grauwe, P. and C. Macchiarelli (2013): “Animal Spirits and Credit Cycles,” CESIFO working paper, no 4480, November.

[16] Dimand, R. W. (2005), “Fisher, Keynes, and the Corridor of Stability,” American Journal of Economics and Sociology, 64, 185–199.

[17] Eggertsson, G. B. and P. Krugman (2011), “Debt, Deleveraging, and the Liquidity Trap:A Fisher-Minsky-Koo approach, Manuscript, Princeton.

[18] Farmer, R., D.F. Waggoner, and T. Zha (2009), “ Understanding Markov-Switching Rational Expectations Models”, Journal of Economic Theory, 144: 1849-1867.

[19] Geanakoplos, J. (2010) “Solving the Present Crisis and Managing the Leverage Cycle”, forthcoming, Federal Reserve Bank of New York Economic Policy Review.

[20] Gerali, A. et al. (2010), “Credit and Banking in a DSGE Model of the Euro Area.” Journal of Money, Credit and Banking, 42(1), 107–141.

[21] Gilchrist, S., A. Ortiz, and S. Zagrajsek (2009), “Credit Risk and the Macroeconomy: Evidence from an Estimated DSGE Model,” manuscript, Department of Economics, Boston University.

[22] Gruene, L. and J. Pannek (2011), “Nonlinear Model Predictive Control,” Springer, New York, Heidelberg.

[23] Grüne, L. and Semmler, W. (2004). Using Dynamic Programming with Adaptive Grid Scheme for Optimal Control Problems in Economics, Journal of Economic Dynamics and Control. no 28: 2427–2456.

[24] Gruene, L., W. Semmler and M. Stieler (2013), "Using Nonlinear Model Predictive Control for Dynamic Decision Problems in Economics," SSRN, ssrn.com/sol3/Delivery.cfm?abstractid=2242339.

[25] Hansen, B. E. (2000), "Sample Splitting and Threshold Estimation," Econometrica 68, 575–603.

[26] He, Z. and A. Krishnamurthy (2012), "Intermediary Asset Pricing," forthcoming in: American Economic Review.

[27] Hubrich, K. and R.J. Tetlow (2011), "Financial Stress and Economic Dynamics: The Transmission of Crises," unpublished working paper, European Central Bank.

[28] Koop, G., M. Pesaran and S. Potter (1996), "Impulse Responses in Nonlinear Multivariate Models," Journal of Econometrics, 74, 119–147.

[29] Mittnik, S. and W. Semmler (2012), "Regime Dependence of the Fiscal Multiplier," Journal of Economic Behavior & Organization, 83, 502–522.

[30] Mittnik, S. and W. Semmler (2013), "The Real Consequences of Financial Stress," Journal of Economic Dynamics and Control, 37, 1479–1499.

[31] Mittnik, S. and P. Zadrozny (1993), "Asymptotic Distributions of Impulse Responses, Step Responses, and Variance Decompositions of Estimated Linear Dynamic Models," Econometrica, 61, 857–887.

[32] Monnin, P. and T. Jokipii (2010), "The Impact of Banking Instability on the Real Economy," Working Paper 2010-5, Swiss National Bank.

[33] Reinhart, C. and K. S. Rogoff (2009), This Time Is Different: Eight Centuries of Financial Folly, Princeton: Princeton University Press.

[34] Roch, F. and H. Uhlig (2012), "The Dynamics of Sovereign Debt Crises and Bailouts", working paper, University of Chicago, CentER, NBER, CERP.

[35] van Roye, B. (2012), "Financial Stress and Economic Activity in Germany," unpublished working paper, Kiel Institute for World Economy.

[36] Schinasi, G. J. (2005), "Preserving Financial Stability," International Monetary Fund, Economic Issues, 36.

[37] Schleer, F. and W. Semmler (2013), “Financial Sector and Output Dynamics in the Euro Area: Non-linearities Reconsidered”, ZEW, Discussion Paper No. 13-068, Mannheim.

[38] Semmler, W. and L. Bernard (2012), “Boom-Bust Cycles; Leveraging, Complex Securities and Asset Prices,” Journal of Economic Behavior and Organization, vol 81, No: 2: 442-465.

[39] Tobin, J. (1975), “Keynesian Models of Recession and Depression.” American Economic Review 65(2): 195-202.

[40] Stein, J. L. (2011), “The Diversity of Debt Crises in Europe.” CESIFO Working Paper No. 3348, Category 6: Fiscal Policy; Macroeconomics and Growth, February 2011.

[41] Stein, J. L. (2012), “Stochastic Optimal Control and the US Financial Crisis,” Heidelberg/New York, Springer Publishing House.

[42] Tong, H. (1978), “On a Threshold Model,” in: Pattern Recognition and Signal Processing, edited by C. H. Chen, Amsterdam: Kluwer.

[43] Tong, H. (1983), Threshold Models in Non-linear Time Series Analysis, New York: Springer–Verlag.

[44] Tsay, R. S. (1998), “Testing and Modelling Multivariate Threshold Models,” Journal of the American Statistical Association, 93, 1188–12

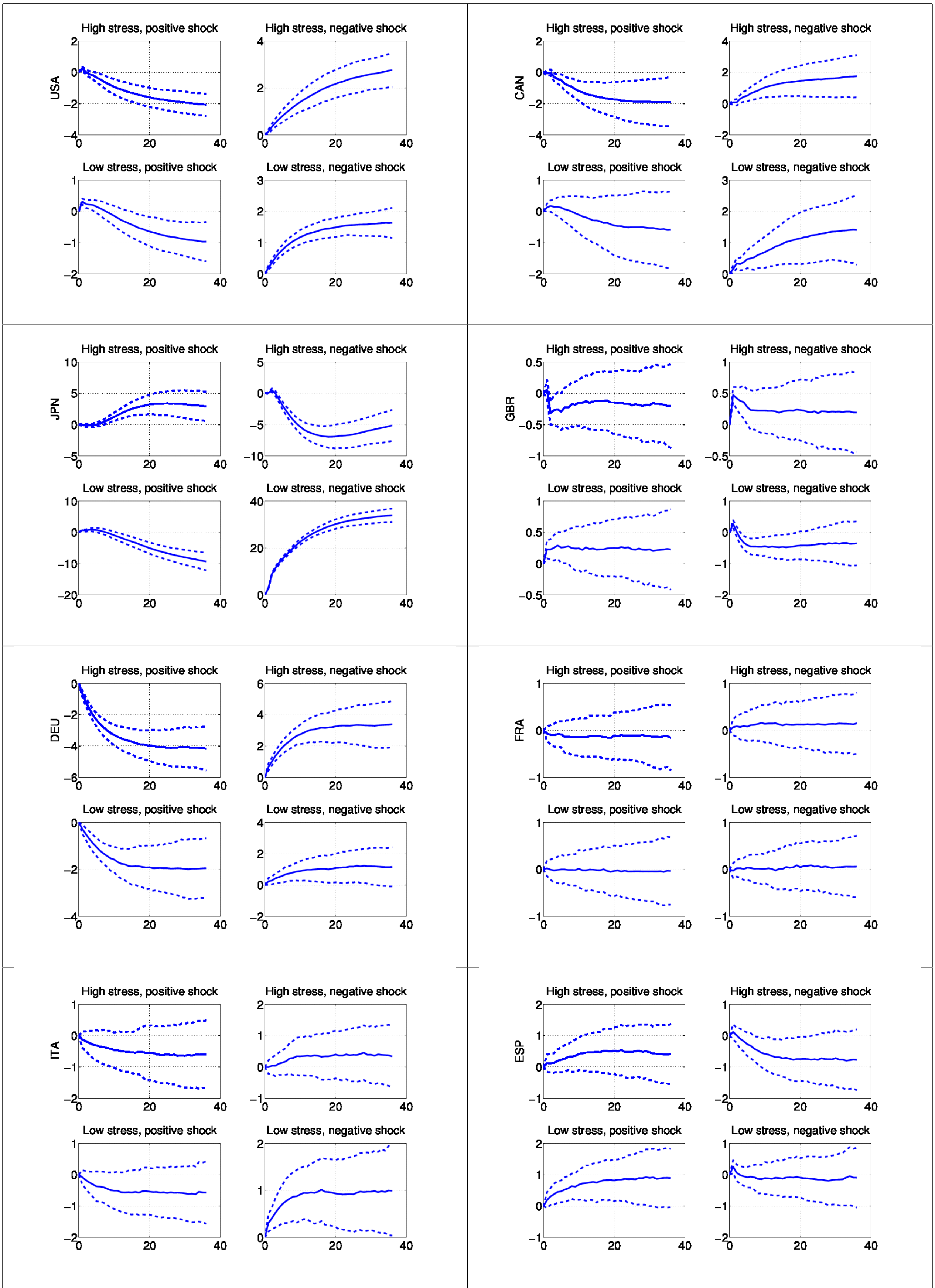

Figure 7: Cumulative MRVAR responses to shock in TED spreads

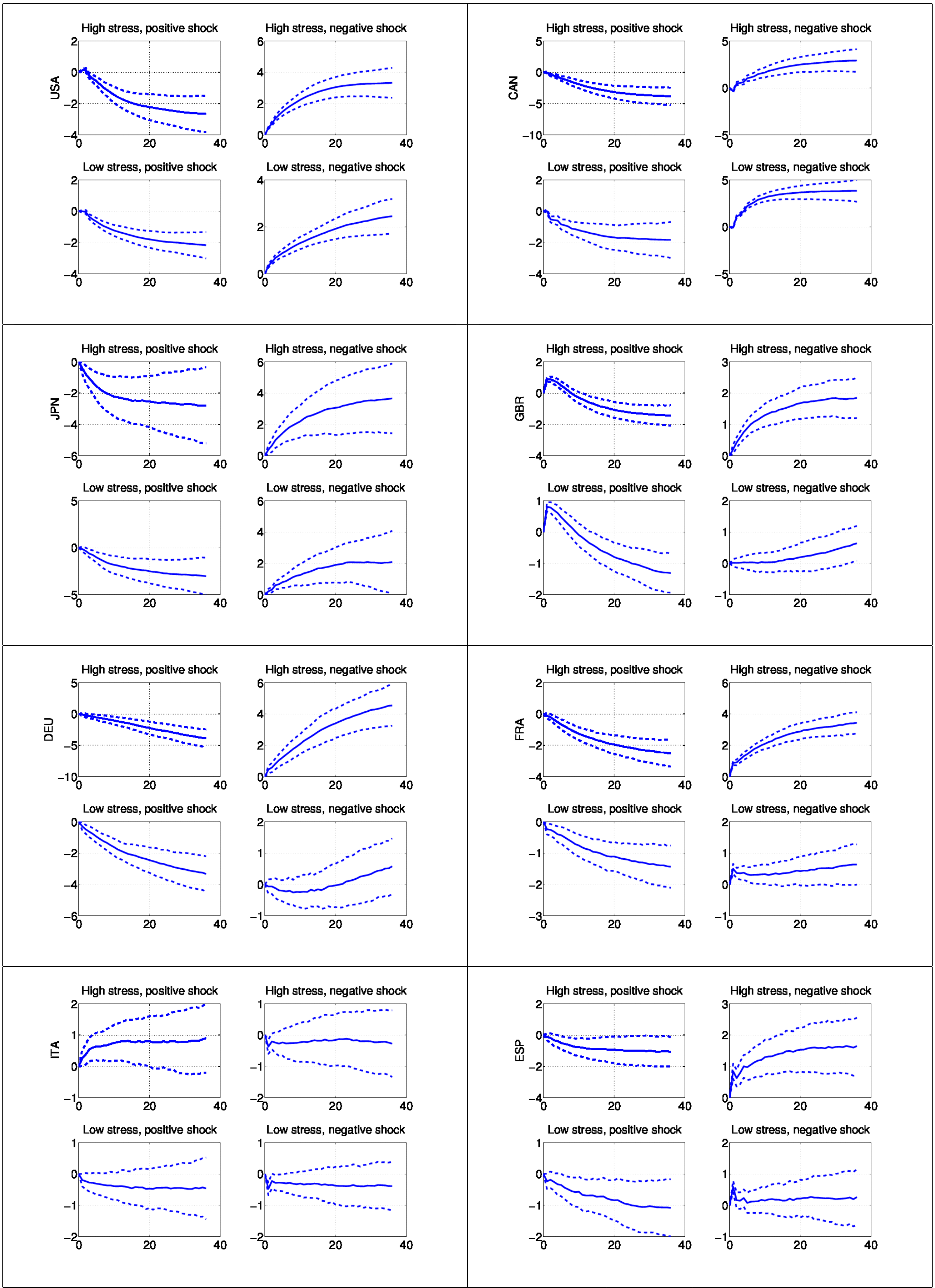

Figure 8: Cumulative MRVAR responses to shock in (negative) term spreads

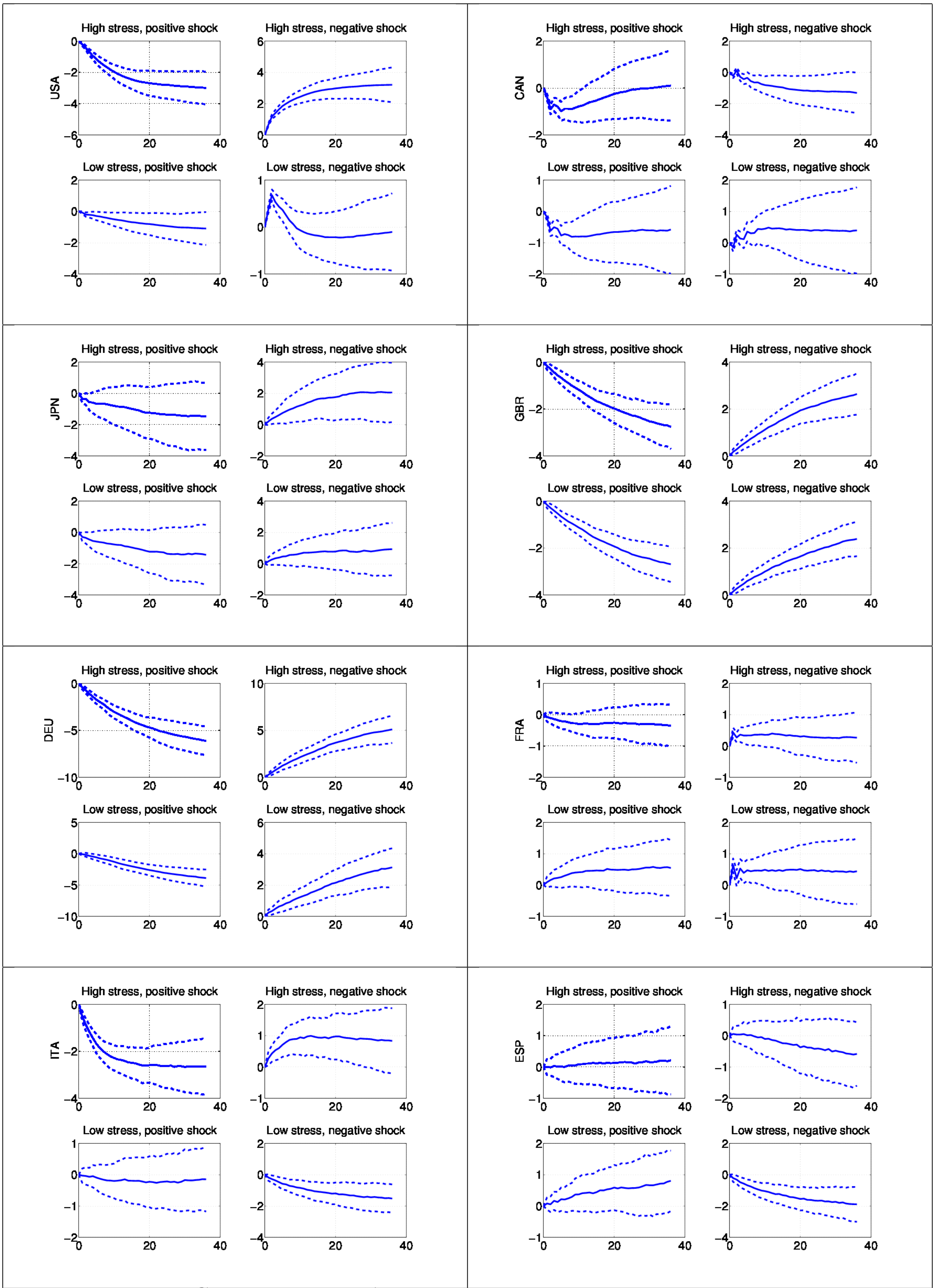

Figure 9: Cumulative MRVAR responses to shock in corporate spreads

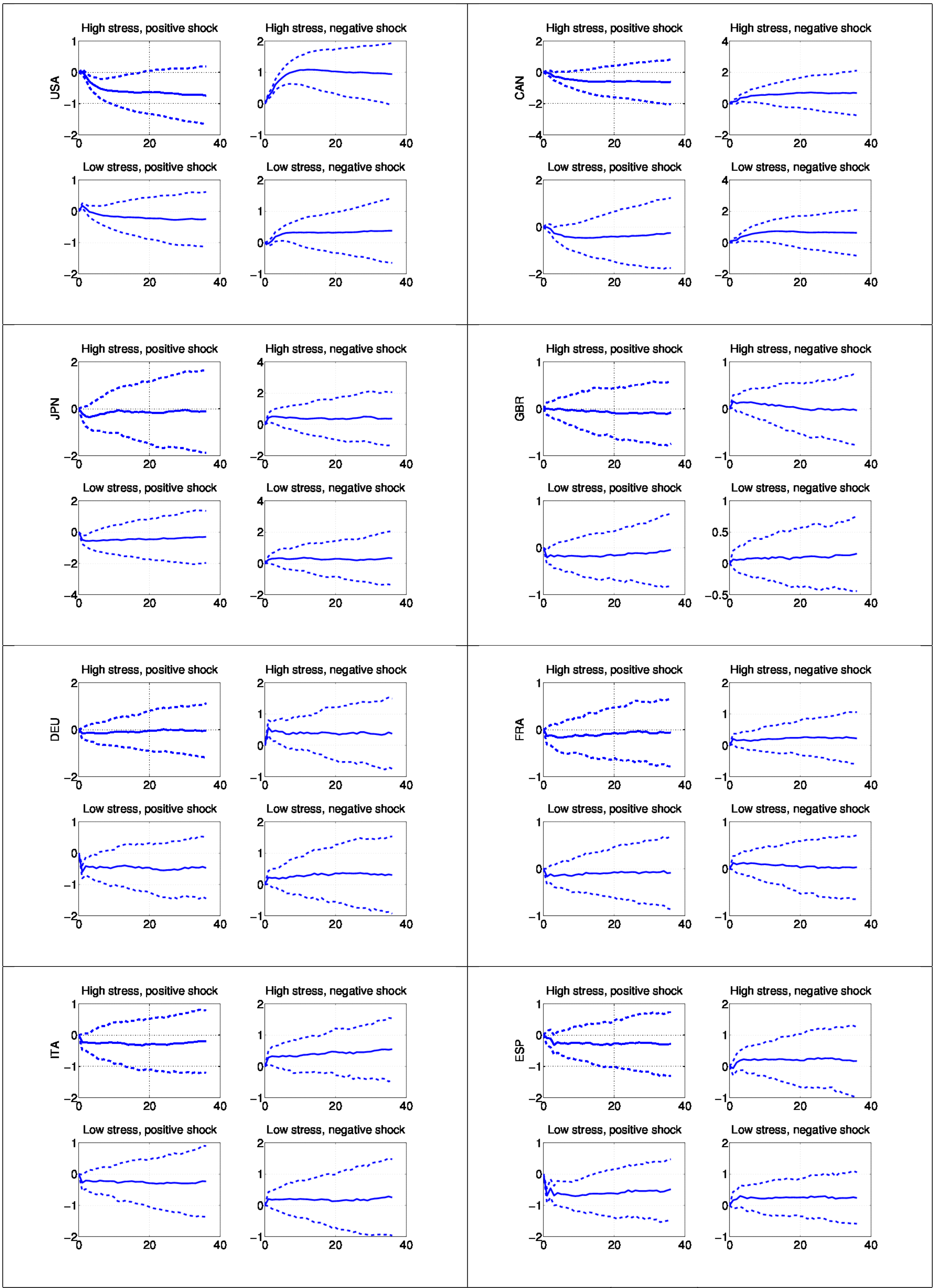

Figure 10: Cumulative MRVAR responses to shock in (negative) stock returns

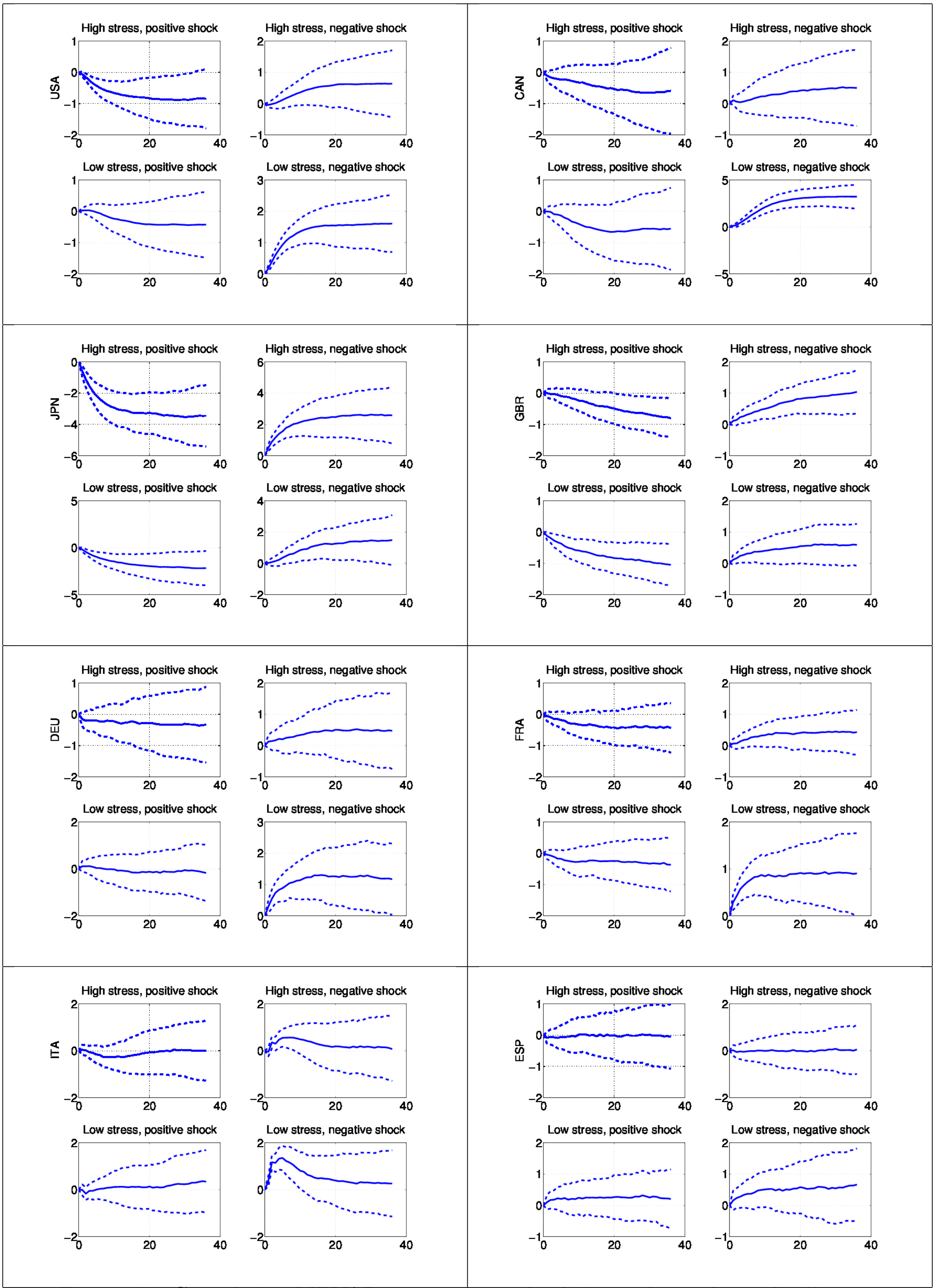

Figure 11: Cumulative MRVAR responses to shock in stock–market volatility

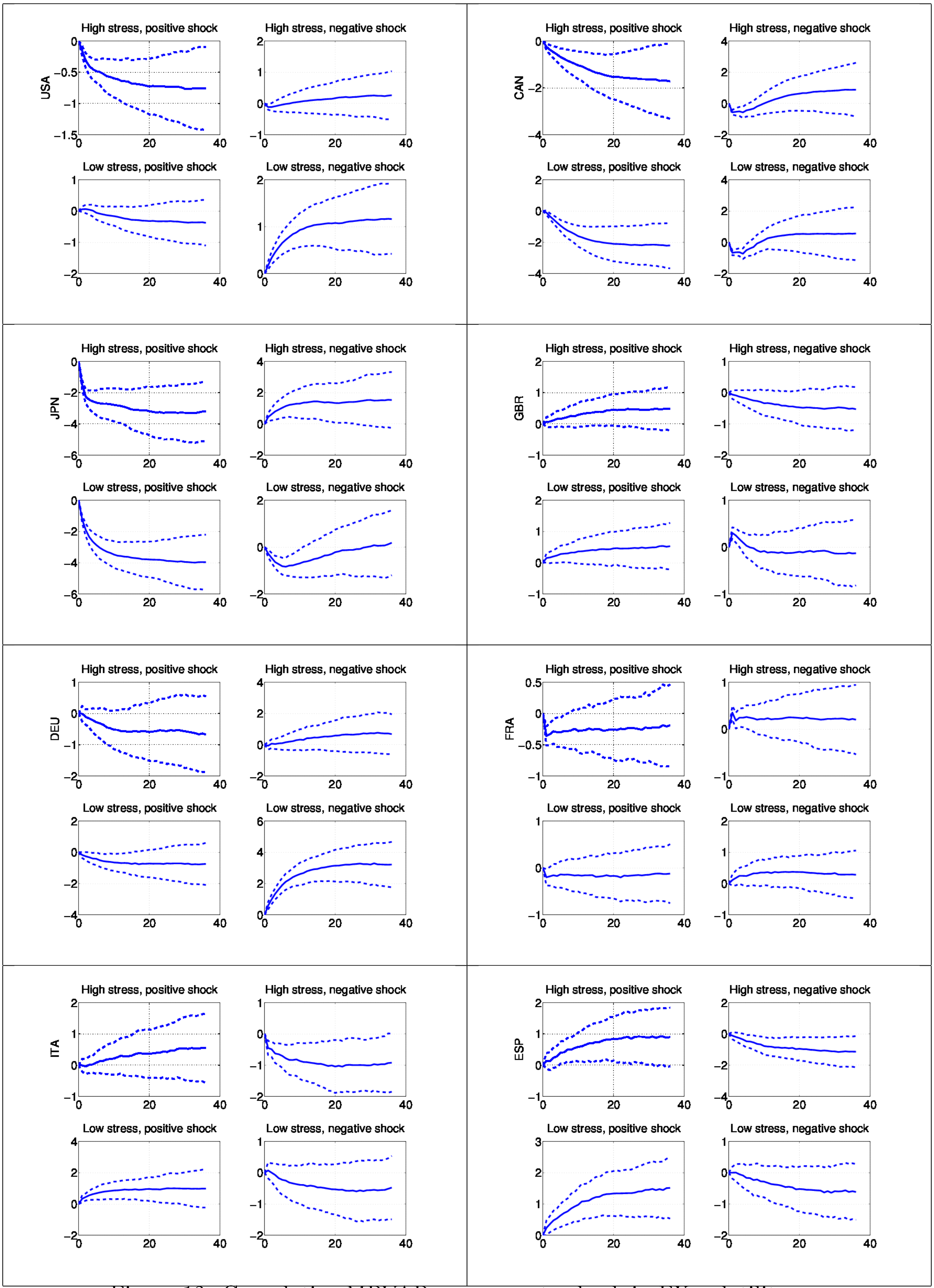

Figure 12: Cumulative MRVAR responses to shock in FX volatility