Macroeconomic Dynamics, **22**, 2018, 4–32. Printed in the United States of America.
doi:10.1017/S1365100516000080

OVERLEVERAGING, FINANCIAL FRAGILITY, AND THE BANKING–MACRO LINK: THEORY AND EMPIRICAL EVIDENCE

STEFAN MITTNIK
Ludwig-Maximilian-Universität München

WILLI SEMMLER
New School for Social Research,
ZEW,
and
University of Bielefeld

We analyze the consequences of overleveraging and the potential for destabilizing effects from financial- and real-sector interactions. In a theoretical model, we demonstrate that, in the presence of regime-dependent macro feedback relations, a highly leveraged banking system can result in instabilities and downward spirals. To investigate this question empirically, we analyze time series from eight advanced economies on industrial production and the components of the country-specific financial stress indices constructed by the IMF. Employing nonlinear, multiregime vector autoregressions, we examine how industrial production is affected by the individual risk drivers making up the indices. Our results strongly suggest that financial-sector stress has a substantial, nonlinear influence on economic activity and that individual risk drivers affect output rather differently across stress regimes and across groups of countries.

Keywords: Financial-Real Linkages, Regime Dependent Macro Feedbacks, Financial Stress Measures, Multiregime VAR

1. INTRODUCTION

Financial-sector instabilities are believed to be central in causing or amplifying economic crises [see Reinhart and Rogoff (2009)]. In the past, financial and

A previous version, entitled “Estimating a Banking–Macro Model for Europe Using a Multi–regime VAR,” was presented at a conference on “The Future of the Euro and Europe,” Sapienza University, Rome, July 2013, organized by Giovanni Di Bartolomeo, at the 7th International Conference on Computational and Financial Econometrics, University of London, December 2013, and at the conference of the Society of Nonlinear Dynamics and Econometrics, New York, April 2014. We want to thank Lilia Cavallari and participants of the conferences for valuable comments. We are especially grateful for communications with Markus Brunnermeier, James Ramsey, and Timo Teräsvirta. Willi Semmler would also like to thank the Centre for European Economic Research (ZEW) for financial support. The research for this paper was partly conducted while Willi Semmler was a visiting researcher at the European Central Bank. Address correspondence to: Willi Semmler, New School for Social Research, 79 Fifth Avenue, New York, NY 10003, USA; e-mail: semmlerw@newschool.edu.

 1365-1005/17

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 as well as adverse shocks in asset values and overall financial stress [see Brunnermeier (2009)].[1] In line with the asset price view of banks' vulnerability is the financial-accelerator model of Bernanke et al. (1999). It 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 (2014), henceforth BS, argue that, because of 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 in Adrian et al. (2010), Stein (2011, 2012), He and Krishnamurthy (2013), and Mittnik and Semmler (2013).

DSGE-type models have also been used in an attempt to empirically capture the relationship between asset prices, financial intermediaries, and output. Prevailing modeling approaches employ stationary linear (or linearized) models where, by construction, departures from the steady state are mean-reverting. Although the economy might accelerate, ultimately it will revert to the steady state. Related empirical analyses are often conducted by means of linear vector autoregressions (VARs), as, for example, in Christensen and Dib (2008) and Gilchrist et al. (2009). However, if, because of a highly leveraged banking system with low net worth, large shocks to asset prices or, more generally, to financial markets are of a destabilizing rather than mean-reverting nature, the question is: To what extent do such financial instabilities impact real economic activity and what are, in turn, the reverse feedback effects on the banking sector or the financial sector at large?

Various studies have explored different amplifying mechanisms. The approach in BS (2014) focuses more specifically on the banking sector. In their view, it is a shock to asset prices that creates a vicious cycle through the banks' balance sheets. 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 delever to stay liquid. This can ultimately lead to fire sales, depressing asset prices further, decreasing net worth, and thus trigger endogenous jumps in risk and, possibly, further downward spirals.

In Mittnik and Semmler (2013), henceforth MS (2013), the vulnerability of banks and downward instability essentially depend 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 may induce more risk taking and risk transfer, generating higher (endogenous) aggregate risk and higher risk premia. Initially, banks may have loan losses, arising from defaults of firms, households, or sovereigns. Financial stress, triggered by security price movements and higher credit spreads, may subsequently draw banks into a downward spiral.

Stein (2011, 2012) argues similarly by allowing 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. Banks' operating income is composed of normal returns and stochastic capital gains or losses. Debt tends to rise with excess return on capital income over and above some normal returns—at least if there are persistent capital gains available; see Stein (2012, Chap. 4). This can hold as long as the central bank keeps interest rates down and credit spreads are low. Furthermore, interest rates and capital gains are frequently highly negatively correlated.[2] Borrowing is likely to exceed debt capacity, resulting in excess borrowing. Stein (2012) introduces a measure of overleveraging, namely, leveraging above the optimal level.[3] When the borrowing bubble bursts, the process reverses, as asset prices and net worth fall, and the risk premia and credit spread suddenly rise, reducing lending, borrowing, and financial intermediation.

The model presented in the following builds upon both BS and MS and refers to the risk drivers behind Stein's (2012) overleveraging and excess debt approach. We start with a stochastic version, but to better understand the macro feedback loops and contrasting our view with BS and Stein, employ nonstochastic variants. We distinguish between low- and high-stress regimes. Overleveraging and excess debt, for example, create vulnerability for a high-stress regime. The regimes also depend on other covariates, such as jumps in credit spreads, rise of aggregate financial stress, and adverse feedback from real economic activity to banks' balance sheets. A regime change will be triggered when financial stress jumps because of adverse feedback from real activity to banks' operating income, causing loan losses and a fall in net worth. Thus, the banking–macro feedback loops are characterized by a regime of low financial stress and a stable environment for expansionary periods and booms. In a high-stress regime, however, destabilizing forces, triggering contractions, and recessions due to macro feedback loops can prevail.[4]

We can account for destabilizing macro feedback loops in a model of a shorter horizon. We think that 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 and long-run transversality conditions. Yet, as macro theories suggest, there could be forces at work triggering instability in finance–macro linkages. Such dynamic processes can easily amplify real, nominal, and asset–price feedback loops; see Section 2.[5]

MS (2013), using nonlinear, multiregime vector autoregressions, find that responses to financial-sector shocks tend to be state-dependent and to vary disproportionately with the size and sign of a shock. Their analysis focuses on an aggregate measure of financial stress, namely, the financial stress index (FSI) developed by the IMF, and some measure of output. The IMF stress index is designed to capture overall financial stress for a range of countries [see Cardarelli et al. (2011)]. Although this overall measure can provide valuable insight into the interdependence of financial-sector stress and economic activity, because of its aggregate nature, it neither provides insight into the role of specific risk drivers and transmitters nor gives rise to specific policy recommendations. The question of which risk factors are particularly influential or may serve as early warning signals for policy makers cannot be answered by an analysis based on a highly aggregate stress index.

To overcome this deficit, we first introduce variants of the banking–macro linkage with leveraging and investigate the interactions between financial stress and output. We then explore empirically the role of individual risk drivers for output in general and across regimes. By exploring the individual components of the stress index, we expect to gain a better understanding of the implications of the individual risk factors for the vulnerability of the banking sector as well as for the financial–macro link. 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 United States, Canada, Japan, the United Kingdom, and the four largest Eurozone countries, Germany, France, Italy, and Spain.

Given that standard linear dynamic econometric models, such as VARs, cannot capture the rich dynamic behavior implied by the theoretical model outlined in the following, our empirical analysis follows MS (2013) and uses nonlinear multiregime VARs (MRVARs). This model class can capture complex dynamics and allows us to assess the implications of individual risk factors and their consequences in different states of the economy.

Stein (2011, 2012) is more concerned with a banking sector that is exposed to sector-specific overleveraging (as in real estate and the agricultural sector) through the supply of loans. The degree of overleveraging in the banking sector is not directly measured.[6] Also, this may not be a sufficient indicator for high financial stress. Overleveraging makes the banking sector vulnerable and can lead to a precarious regime as financial instability builds up. Here, we do not employ a direct measure of overleveraging, but rather use risk drivers of banks' balance sheets representing good proxies for overleveraging and financial stress of banks.

The MS (2013) model implies that state-dependent risk premia and credit spreads are drivers and indicators of financial risk, with particular amplifying consequences for the real economy. The empirical results reported in the following, in particular the strong state dependence of responses to spread variables (i.e., TED spreads, term spreads, and corporate bond spreads), are broadly consistent with MS (2013).

One of our empirical findings is that the amplifying mechanisms discussed in BS (2014), namely that the banks' balance sheets and the endogenous generation of risk through fire sales and asset–price volatility can induce financial instability and downward spirals, are broadly consistent with our data. Our results indicate, however, that asset–price volatility by itself, playing a prominent role in BS (2014), is not a strong driver of risk and regime shifts.[7]

The paper is organized as follows. In Section 2, building upon BS (2013), we introduce a banking sector vulnerable to overleveraging and show the potential for regime shifts in the presence of banking–macro feedback loops. Section 3 describes the data. Section 4 introduces our empirical modeling strategies and presents the results from causality and selected MRVAR-based response analyses.[8] Section 5 concludes.

2. THE MODEL

Commonly adopted dynamic policy models, such as DSGE models, tend to smooth out potentially destabilizing feedback mechanisms by assuming infinite-horizon decisions. Here, we propose a framework with finite horizon that allows destabilizing feedback loops. To solve such a model, we use a recently developed numerical procedure, the nonlinear model predictive control (NMPC) method; see Gruene et al. (2015) and Mittnik and Semmler (2015). It provides solutions that, when specifying very long horizons, approach the usual infinite-horizon solutions.

2.1. Bank Leveraging without Adverse Macro Feedback Loops

To study leveraging, net worth dynamics, and risk drivers for financial intermediaries in a finite-horizon decision model, we start with a low-dimensional stochastic model specification, which will be modified in Section 2.2. The essential model features we employ can be found in Stein (2011, 2012) and in BS (2013, Section 2). Both specifications are stochastic, but they do not explicitly model macroeconomic feedback loops.

The models of BS and Stein are similar in the sense that payouts and leveraging are choice variables, and the main state variable is net worth, denoted in the following by $x_{1,t}$ and specified in (3). To solve such a stochastic model through NMPC, one needs to add a stochastic shock sequence, defined in (4), which represents another state variable. In BS capital returns are—because of capital gains—stochastic, as is the interest rate. BS start with a model where only the capital return is stochastic, and they add a stochastic interest rate later by referring to time-varying borrowing cost, reflecting screening and monitoring cost.

Whereas BS model in continuous time, we adopt a discrete-time framework with a discounted instantaneous payout, c_t, and leveraging, α_t, as decision variables.[9] In a discrete-time framework and assuming a decision horizon of N periods, our model is given by

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

s.t.

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

https://doi.org/10.1017/S1365100516000080 Published online by Cambridge University Press

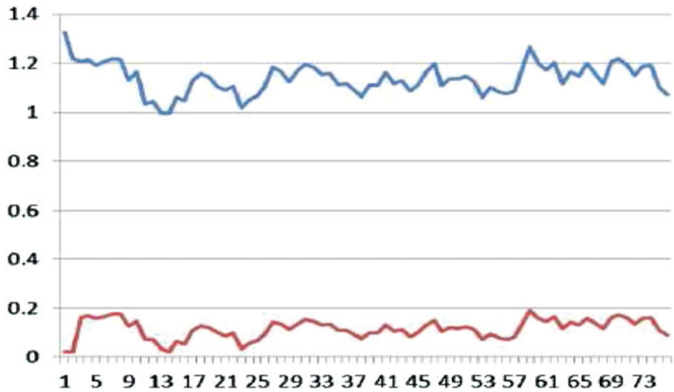

FIGURE 1. Optimal payout (c_t, lower line) and leveraging (α_t, upper line) paths.

$$x_{1,t+1} = x_{1,t} + hx_{1,t}[\alpha_t(y + \nu_1 lnx_{2,t} + r) + (1 - \alpha_t)(i - \nu_2 lnx_{2,t}) - \varphi(x_{1,t}) - c_t] \quad \textbf{(3)}$$

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

where preferences are given by (1), the dynamics of the aggregate capital stock by (2), net worth by (3), and the stochastic shock process by (4). Variables c and α are the two decision variables,[10] with the pay-off $c = C/x_1$, and $\alpha = 1 + f$, where $f = d/x_1$ is the leverage ratio, measured as liability over net worth. Moreover, d denotes debt, y capital gains, driven by the stochastic shock $\nu_1 \log x_{2,t}$. Furthermore, r, is the return on capital, i, the interest rate, also driven by a stochastic shock, $\nu_2 \log x_{2,t}$,[11], $\varphi(x_{1,t})$ is a convex adjustment cost, h, the step size, ρ, a persistence parameter, with $\rho = 0.9$, and z_k is an i.i.d. random variable with zero mean and a variance, $\sigma = 0.05$.

We solve (1), (3)–(4) through a stochastic version of NMPC, see Gruene et al. (2015) and Mittnik and Semmler (2015). Figure 1 presents the path of the payout, c_t, lower line, and leveraging, $\alpha_t = 1 + f_t$, upper line. As can be observed, the stochastic capital gains and interest rates generate volatility of both payout and leveraging. Note that we solve here only for optimal leveraging. The payouts tend to move with leveraging. Because α_t is a choice variable, both BS and Stein assume that debt is redeemed in each period and, without cost, reobtained on the market without frictions.

In Figure 2, the smooth line is the path of net worth, modeled by (3), and the ragged line the process of stochastic shocks, with expected value of one, modeled by (4). One can observe that the volatility of net worth is considerably lower than that of the stochastic shocks.[12]

Note that in BS (2014) there is only implicitly a macro feedback loop stylized, namely an externality, i.e., endogenous volatility, that is triggered below the steady state. This makes the steady state unstable downward and non-mean-reverting, in contrast to in Bernanke et al. (1999). In BS, the feedback loop arises from large

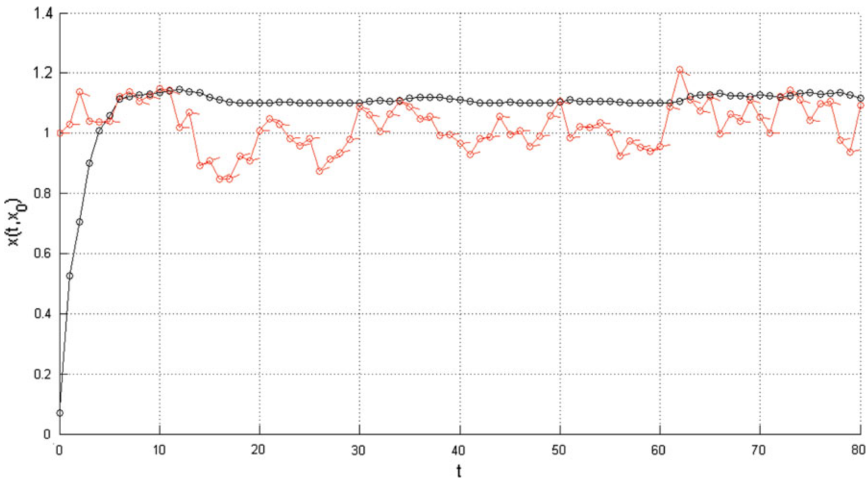

FIGURE 2. Paths of net worth, smooth line, and shock process, ragged line, with initial net worth below stochastic steady state.

shocks, triggering a fire sale of assets, a fall of asset prices and net worth, generating a downward spiral.[13] Although the system (1), (3)–(4) does not yet directly model instability, Figure 1 depicts the volatility of x_t, the optimal leveraging, and the payouts, c_t.[14]

Our numerical approach allows us to derive leveraging, defined in BS (2004, p. 23), directly as the ratio of assets to net worth (upper line in Figure 1). As BS 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, even in the stochastic steady state. This also contributes to endogenous risk. What is missing in BS and Stein is the specification of aggregate amplifying macro feedback mechanisms in the finance–macro link. Such feedback relations will be studied next.

2.2. Bank Leveraging and Adverse Macro Feedback Loops

We now modify the model in Section 2.1 by explicitly considering the capital-stock dynamics (2).[15] In addition, we consider more specifically a state-dependent leveraging by defining debt as a state variable, allow for feedback effects of leveraging on households' welfare,[16] and introduce regime dependence. Specifically, we study two regimes, a regime of low debt and low financial stress, and a regime of high leveraging and high stress.

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

https://doi.org/10.1017/S1365100516000080 Published online by Cambridge University Press

regime and allows banks to increase leveraging and reduce loan losses.[17] Our model specification for the low-stress regime is given by

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

s.t.

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

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

where $\mu_t = b_t/k_t$ and μ^* is the leveraging rate in the steady state. In (5), there are preferences over log utility, and, in (5), we have added a penalty term whereby welfare is penalized by some excess leveraging.[18] The decision variables in (5) are payouts (for consumption), c_t, and the growth rate of capital stock, g.[19] The horizon, N, does not need to be very large, but can go to infinity.[20] As with (2), equation (6) represents the evolution of the capital stock. It increases because of investments but is dampened by δ because of the resources used to manage the assets. Note that BS (2013) have normally distributed shocks and volatility-dependent asset prices. Here, we present and solve a nonstochastic but nonlinear version.

Equation (7) represents the dynamics of banking leveraging,[21] where $y = Af(k)$ is the return on capital with $A > 0$.[22] The interest payment on debt, rb_t, increases debt, but the surplus, the excess of income over spending, $y_t - c_t - i_t - \varphi(g_t k_t)$, reduces debt. Here, we define $i_t = g_t k_t$. 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.

The model has two decision and two state variables. One could formulate the second state equation in terms of net worth and leveraging—the latter as a decision variable as in BS. We prefer leveraging as a state variable, so that debt can only sluggishly be redeemed and reissued. We can also distinguish, as before in the banking model of Section 2.1, between the discount rate and the interest rate, with the latter affected by leveraging.[23]

We solve (5)–(7) via NMPC as sketched in Mittnik and Semmler (2015). Setting $r = 0.04$ and $\delta = 0.03$, and assuming quadratic adjustment cost of investment, we obtain the solutions shown in Figure 3. For a regime of low financial stress, the vertical axis shows the degree of leveraging and the horizontal 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 a low operating-income flow, $A = 0.1$ (left trajectory), and the higher operating income, $A = 0.2$ (right trajectory). The third initial condition is chosen to be rather low, $k(0) = 0.2$, $b(0) = 0.08$, which also converges to the steady state.

Our NMPC approach guarantees the transversality condition to hold—the trajectories are nonexplosive and converge to a steady state, where the left-hand side of (7) is zero.[24] We have global stability, if the central bank manages to keep

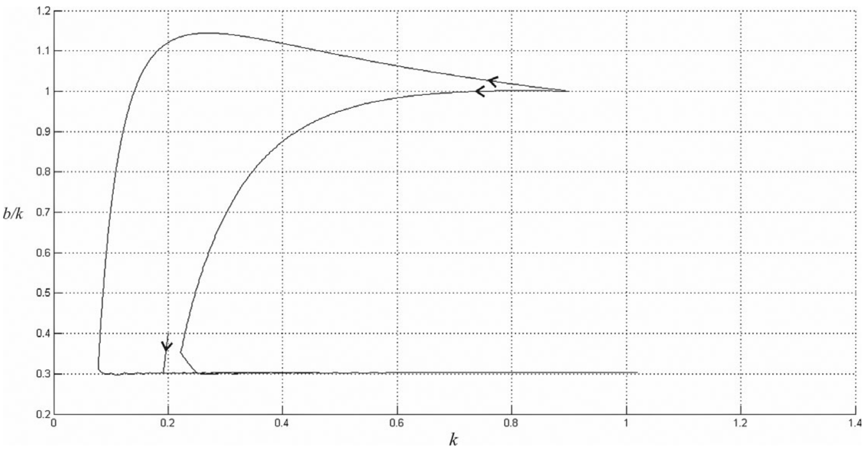

FIGURE 3. Dynamic paths of assets and leveraging for low and constant interest rate, for three initial conditions; two initial conditions $k(0) = 0.9$, $b(0) = 0.9$ (large), the left trajectory with $A = 0.1$, the right with $A = 0.2$, and initial condition $k(0) = 0.2$, $b(0) = 0.08$ (small); all trajectories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

interest rates and credit spreads low. In such a regime of low financial stress, debt sustainability is prevailing.[25]

Such tranquil conditions may generate large capital gains and entail an asset price boom and low risk premia—all favorable conditions for bank leveraging. When overleveraging occurs and the asset price bubble bursts, capital gains become negative and net worth may quickly deteriorate. As the debt ratio rises and capital gains fall, and interest rates and credit spreads are likely to rise—the latter being negatively correlated with the capital gains—the net worth of the assets can also quickly vanish.[26] These phenomena may result in a regime shift in the economy.

High leveraging and high financial stress. Next, we consider financial stress and credit spread to be endogenous. We employ economic mechanisms that entail endogenous feedback from financial stress to macroeconomic activity, making banks vulnerable and inducing overall instability. This is likely to occur if monetary policy fails to reduce financial market stress and bringing down credit spreads.

To model this scenario, we specify the model as follows:

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

s.t.

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

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

https://doi.org/10.1017/S1365100516000080 Published online by Cambridge University Press

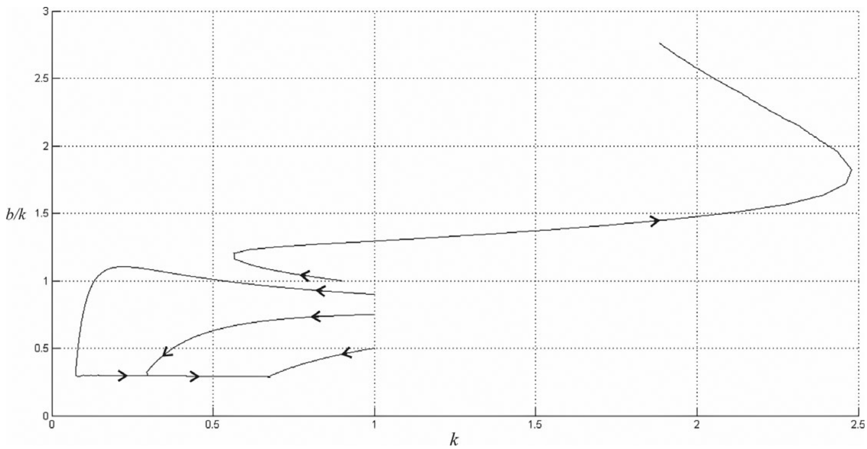

FIGURE 4. Debt dynamics for nonlinear stress effects; the three lower trajectories for the low-stress case with borrowing cost below a threshold, for three initial conditions, converge to some steady state, even in a high-stress regime but for low credit costs; the upper trajectory is triggered by high financial stress and adverse macro feedback, for initial conditions $k(0) = 0.9,\ b(0) = 0.9$, but note that the trajectory with $k(0) = 1,\ b(0) = 0.9$ is still stable.

The difference from the specification for the low-stress regime is the assumption that the credit spread is state-dependent. Financial stress builds up as a nonlinear function of the leverage ratio via[27]

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

making credit cost dependent on a state variable, s_t, a threshold variable, c^*, and a slope parameter, γ. A relationship as in (11) finds empirical support in De Grauwe and Ji (2012); see Schleer and Semmler (2015).

In Figure 4, we present two cases. In the first, there are state-dependent risk premia and credit spreads, but leveraging (expressed by initial conditions) is low. Credit risk and financial stress do not build up, banking stress drivers are not built up, and there are only weak adverse macro feedback loops. The lower three trajectories represent this case, with initially low stress and low borrowing cost below some threshold. These three initial conditions converge to the steady state. Since there is a corridor of stability.

In the second case, represented by the upper trajectory, the initial leveraging is higher. Function (11), representing the steeply rising credit spread, implies higher credit costs as financial stress increases. With respect to the asset side of the economy, we expect asset prices to fall (or not to grow), capital gains could become negative and income needs to adjust to a lower level, surpluses would shrink, debt service rise with higher interest rates, and debt sustainability become threatened.[28] Moreover, as discussed in Section 2.1, adverse macro feedback effects, arising from financial stress, can affect banks' vulnerability. Thus, not only are there endogenous risk premia, rising interest rates, and declining asset prices, but also macro feedbacks are likely to trigger a decline in aggregate demand and output,[29] which feed back on banks' operating income and market valuation. All of this causes a further reduction of credit supplies by banks. Hence, the real sector starts to affect the financial sector and vice versa.

Thus, for the upper trajectory of Figure 4, outside the region of stability we assume that, although optimal payouts and investment might be targeted, actual operating income of banks is likely to decline and loan losses are likely to rise, triggering adverse macro feedbacks. Consequently, actual gross income, specified in (13), adjusts downward and so does aggregate demand:

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

$$y_t^a = [1 - r(s_t|\gamma, c^*)]y_t. \qquad \textbf{(13)}$$

In (13), actual operating income is driven by aggregate activity in the regime of financial stress, $[1 - r(s_t|\gamma, c^*)](i^{\text{opt}} + c^{\text{opt}})$, where actual payouts and investment, responding to financial stress via $[1 - r(s_t|\gamma, c^*)]$, determine actual income. The optimally chosen decision in each time period of the state variables are not implemented, but only the actual constrained outcome, which depends on the degree of financial stress and the macro feedbacks triggered by this. This feedback from financial-market stress to aggregate demand and output is described in a recent IMF study as follows [Corsetti et al. (2012)]: "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."

The upper trajectory in Figure 4 shows the switch to a regime of high leveraging, high financial stress, and stronger macro feedback loops. The solution path can still be stable when the debt-to-capital-stock ratio is reduced from $b(0)/k(0) = 0.9/0.9$ to $b(0)/k(0) = 0.9/1.0$. The regime switching at such a threshold is triggered by stronger macro feedbacks, but it also can reduce the region of stability.[30]

The economic intuition for the stability region to shrink and the instable region to grow could be manifold. First, when capital appreciation falls or becomes negative, aggregate demand falls and, with lower-valued collateral, banks, with net worth falling, reduce loans or increase funding cost (wealth effect). Second, the share of households that are income and credit constrained, in the sense of Gali et al. (2007), and of households that are more highly leveraged and under financial stress,[31] rises significantly in a contraction period of the business cycle, causing demand to fall. Third, some households deleverage more strongly [cf. Eggertsson and Krugman (2012)], which 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 prices are expected to fall (Tobin effect). Fourth, as financial-market forces trigger banking and financial stress,[32] the central bank may not be capable or willing to force interest rate further down and/or to reduce risk premia and credit spreads. This will adversely affect bank lending and demand and output. With loan losses rising and asset prices falling, banks' vulnerability increases.[33] Further externalities and contagion effects can result in a vicious downward spiral. Finally, more adverse feedback could arise from a weak financial sector that holds risky sovereign or other debt, when default occurs. As a consequence, banks reduce lending to the real economy or, worse yet, may even default themselves [cf. Brunnermeier and Oehmke (2012) and Bolton et al. (2011)].

In the presence of such adverse macro feedback mechanisms, shifts from low- to high-stress regimes are a plausible scenario. If the region of stability shrinks, even smaller shocks can have a serious negative impact; see BS (2014) and Dimand (2005). With larger debt, greater vulnerability of banks, and higher financial stress, there is a greater probability of runs and of a jump to a debt crisis equilibrium; see Lorenzoni and Werning (2013). In such a slow-moving debt crisis, credit spreads, bond price, and bond yield dynamics tend to reflect other risk factors also, rather than solely leveraging.

The empirical analysis that follows examines to what extent interactions between the real and the financial sector may be characterized by such more complex, nonlinear feedback mechanisms, and whether there is evidence for regime-dependent responses to shocks.

3. 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 monthly frequency, the growth rate of industrial production (IP) is a reasonable measure for real activity. Though the IP is the best high-frequency measure for economic activity, it should be kept in mind that the relative sizes of the industrial sector differ across countries, which could induce heterogeneity in our empirical finding.

As to capturing the financial market stress, and regime changes there, a number of stress indices have been developed for the United States and other countries. Yet most of them do not have the range of coverage in terms of countries, time periods, and detailed individual risk drivers that the IMF financial stress index (FSI) has. We thus use for our empirical analysis the components of the financial stress index the IMF constructs on a monthly basis for advanced economies as measures of financial-sector risk.[34] The advantage of the FSI constructed by the IMF is that it is consistently defined across all the countries under investigation here.

The index is composed of seven country-specific risk indicators, which can be grouped into three segments, relating to banking, securities markets, and foreign-exchange markets. Banking-related are the *TED spread*, i.e., the 3-month LIBOR or commercial paper rate minus the government short-term rate; the *inverted term*

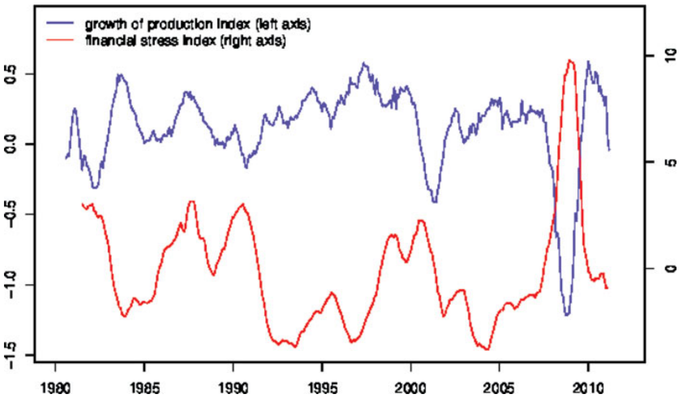

FIGURE 5. U.S. aggregate FSI index (bottom line) and industrial production (top line).

spread, i.e., the government short-term rate minus the government long-term rate; and the *banking-sector beta*, i.e., the standard capital asset pricing model (CAPM) beta, computed in a 12-month rolling window.[35] Securities-markets-related are *corporate debt spreads*, i.e., the corporate bond yield minus the long-term government bond yield; *stock market returns*[36]; and *stock market volatility*, measured as the 6-month (backward-looking) moving average of the squared month-on-month stock-index returns. Finally, foreign-exchange-markets-related is the *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.[37]

The aggregate FSI is simply the (standardized) sum of the seven components, and hence has the same interpretation as the individual stress indicators. Figure 5, as an example, shows the time series of the aggregate stress index together with the (scaled) IP levels for the United States. At the aggregate level, one can clearly observe two regimes: High growth–low stress and low growth–high stress regimes [see MS (2013)]. In contrast to MS (2013),we will focus subsequently on economic activity and individual components of the FSI.

4. EMPIRICAL ANALYSIS

To better understand how individual risk factors affect economic activity, our empirical analysis focuses on the individual components of the FSI. To assess whether or not variations in the individual FSI components generally have an influence on an economy's IP growth, we first conduct standard bivariate tests for Granger causation with respect to the FSI components. In view of the nonlinear dynamic effects of the aggregate FSI on IP reported in MS (2013), we turn to nonlinear analyses and conduct bivariate tests for *nonlinear* Granger causality and assess the possible presence of dynamic dependencies beyond linear relations. We then fit nonlinear MRVARs and examine whether causal relationships within

https://doi.org/10.1017/S1365100516000080 Published online by Cambridge University Press

TABLE 1. p-values from Granger–causality tests, testing the null hypothesis that IP growth is not Granger-caused by the stress indicators

	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

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.

4.1. Testing for Causality

Linear Granger causality. To conduct bivariate tests for Granger causality, 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 a significant role only for the United States and Japan.

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 United States, Canada, and Germany; in addition, the term spreads Granger-cause banking stress in the United Kingdom and in Italy. FX volatility appears to affect IP growth in Canada and Japan.

Testing for nonlinear Granger causality. Granger causality is defined in terms of linear predictability. To assess the possible presence of nonlinear predictability,

TABLE 2. p-values from Granger–causality tests that 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

we also test to what extent a nonlinear specification of the stress components is supported. 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. That is, for each country, we estimate

$$\mathrm{ip}_t = \alpha + \sum_{i=1}^{p} \beta_i \mathrm{ip}_{t-i} + \sum_{i=1}^{p} \gamma_i \mathrm{si}_{t-i} + \sum_{i=1}^{p} \delta_i \mathbf{1}_{\{\mathrm{si}_{t-i} > \mathrm{si}_{\mathrm{thresh}}\}} \mathrm{si}_{t-i} + u_t, \tag{14}$$

where si_{t-i} represents a generic stress indicator and $\mathbf{1}_{\{\mathrm{si}_{t-i} > \mathrm{si}_{\mathrm{thresh}}\}}$ 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 the threshold.[38] Thus, the regression coefficient of si_{t-i} amounts to $\gamma_i + \delta_i$ if si_{t-i} is above the median, and γ_i otherwise. In line with the standard approach to Granger causality, we test the joint significance of $\delta_1, \ldots, \delta_p$.

The results, shown in Table 2, demonstrate that already this crude check indicates the presence of nonlinear dynamics. Whereas linear tests do not suggest that the banking beta causes growth, it turns out that the European economies—except Spain—are affected by large beta values. IP growth rates in Japan and the United Kingdom, which do not appear to be linearly affected by TED spreads, seem 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 also found to 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 United States 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.

4.2. Regime Dependence of Economic Activity on Financial Risk

The MRVAR approach. The tests for Granger causality reported in the previous section gives insights into the question of *whether* above-median levels of a stress indicator affect real activities differently than below-median ones. They do not provide information, however, 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 induced by infinitesimal disturbances. In general, 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 (MRVARs) in the form of threshold vector autoregressions in the vein of Tong (1978, 1983) and Tsay (1998) to allow for regime-dependent phenomena.[39] The threshold-based MRVAR approach is a simple and parsimonious strategy for nonparametric function estimation and for modeling multiequilibrium 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.[40]

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, which depend on the overall state, z_t, the nature of the shock, v_t, and the response horizon, h, so that $\mathrm{GIR}_h(z_t, v_t) = \mathrm{E}\,(y_{t+h} \mid z_t, u_t + v_t) - \mathrm{E}\,(y_{t+h} \mid z_t, u_t)$, where the overall state, z_t, reflects the relevant information set.

For each of the risk components[41] and all eight countries, we derive generalized, cumulative responses from estimated MRVARs with regimes 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 earlier, where the estimated MRVARs served as a descriptive tool for detecting possible non-linearities. That is, we were interested in obtaining regimes that yield the best piecewise linear fit—and, thus, probably the most distinct regimes—in order to obtain high diagnostic power. When conducting response analysis with an application to policy intervention in mind, we 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.[42]

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 the Appendix.

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 the impact of stress shocks on IP for the spread variables, i.e., TED spreads, term spreads, and corporate bond spreads. For TED spreads (see Figure A.1 in the Appendix) we find that a positive stress shock in a high-stress regime mostly has a stronger impact on IP than in a low-stress regime, and a stress-reducing negative shock has, as a rule, a stronger impact in high- than in low-stress regimes. This holds especially for the United States, Canada, Germany, and, to some extent, Italy. For other countries, such as Japan, the United Kingdom, France, and Spain, the hypothesis holds only partially or the responses lack significance.

Stronger results are obtained for term spreads (Figure A.2 in the Appendix). 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 banking sector stability. For most of the countries (except Italy), a positive stress shock in an already high-stress state, arising from term-structure shocks, reduces 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.[43]

As to corporate bond spreads (Figure A.3 in the Appendix), we find that the signs of the responses are mostly as expected and the size of the effects of shocks is different in the high-stress than in 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 risk drivers. As to the role of (negative) stock returns as stress factors (Figure A.4 in the Appendix), with the exception of the United States 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 [such as 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 A.5 in the Appendix), which shows the expected impacts only in the high- and low-stress regimes for the United States 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 shocks in FX volatility (Figure A.6 in the Appendix) have the predicted outcome for "standalone" countries, meaning countries that have their own currency. The responses in countries that are members of the Euro currency zone are mostly insignificant.

5. CONCLUSIONS

We have investigated potential effects of overleveraging and financial- and real-sector interactions on economic stability. Our theoretical model, building upon Stein (2011, 2012), Mittnik and Semmler (2013), and Brunnermeier and Sannikov (2014), allows overleveraging and adverse asset–price movements to induce shifts to high- or low-risk regimes, financial-sector instabilities, and downward spirals. Such phenomena are more prevalent when strong, adverse real-sector feedback mechanisms exist. In contrast to infinite-horizon models, we have adopted the NMPC approach of Gruene et al. (2015) in order to allow for short- and medium-term amplifying and destabilizing forces, forces that are typically smoothed out in conventional dynamic models.

In an empirical multicountry study, we have assessed conjectures of our theoretical model by investigating how various types of financial-stress variables affect real economic activity. The stress variables considered are 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 multiregime vector autoregressions to evaluate model-implied conjectures about banking–macro linkages.

Our empirical results from eight economies—the United States, Canada, Japan, the United Kingdom, and the four largest Eurozone economies, 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 is typically captured by conventional linear modeling techniques. As was to be expected, with eight countries and six risk factors under investigation, the risk drivers affect economic activity somewhat differently across countries. However, there is strong empirical indication 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.

Our results contribute to the current debate on monetary-policy effectiveness. The view that a zero or near-zero interest rate policy may not have been sufficient to counteract the consequences of the financial market meltdown in the United States in 2007/2008 and the ongoing debt crisis in the Eurozone is supported by our theoretical and empirical analysis. Financial-stress-reducing policies (also referred to as "unconventional monetary policies"), where central banks buy "bad assets" in order to bring down risk premia and interbank credit spreads in situations of high financial stress, seem justifiable.[44]

The sole focus on zero or near-zero interest rate policies has been criticized for not being very effective in stimulating persistent output and employment growth; see Gavin et al. (2013) and literature therein. This criticism is plausible, as it is not the near-zero interest rate that determines the effective funding cost for banks, firms, and households, but rather the risk-premium-augmented credit spreads, among them TED and corporate bond spreads and loan rates that are relevant for decisions on borrowing, lending, and spending and for debt sustainability.

In a low-growth/high-stress period, monetary policy and a general increase of the balance sheets of the central bank may not be sufficient to trigger lending and economic activity, as Brunnermeier and Sannikov (2015) argue. Specific credit policies are needed to handle specific risk drivers. Liquidity mismatch, resulting from low-growth/high-stress regimes, is not overcome when interbank lending rates are high. There can also be impaired balance sheets of households, firms, or the government, as well as sectoral impairments that are not easily overcome by extensive purchases of treasury bonds. If asset markets do not function properly, more selective credit policies, affecting specific credit spreads and funding cost, and quantity measures might be needed to encourage credit flows helping to overcome credit bottlenecks. More research on specific risk drivers and how to mitigate their negative impact on economic activity appears to be in order.

NOTES

1. For an empirical study of overleveraging of the banking system in the European Union, see Schleer et al. (2014).

2. See Stein (2012, Chap. 5) and also Chen and Semmler (2013).

3. For an empirical study of overleveraged banks, following the Stein methodology, see Schleer et al. (2014).

4. The possibility of such loops for the Euro zone has been discussed recently. One of the loops has been called the "diabolic loop," where there is not just the relationship between banks and the private sector but rather a triangular relationship between private borrowing, bank leveraging, and sovereign debt [see Brunnermeier and Oehmke (2012)].

5. See also Semmler and Bernard (2012).

6. This is done in Schleer et al. (2014) for EU banks.

7. Though it it fair to assume that BS (2014) focus more on explaining the rare and large event during 2007/2008 rather than the more moderate effects occurring in average above- or below-median states.

8. The Appendix presents the full set of MRVAR-response plots. The working paper by Mittnik and Semmler (2015) provides a description of the NMPC algorithm that is used to solve the model variants of Section 2 and further details of the destabilizing finance–macro feedback loops.

9. Note that BS (2014) use x_t for their decision variable leveraging and assume that $x_t > 1$.

10. Here, we neglect the dynamics of (2). In BS, it represents the aggregate capital of financial specialists and households (with g the growth rate of capital, another decision variable, and δ the resource use for managing the assets). A larger fraction of the assets will be held by financial specialists, because, with $\alpha_t > 0$, they can borrow. Those details can be neglected here. Aggregate capital written here as differential equation, will be considered in Section 2.2.

11. Stein (2012) posits that interest rate shocks are highly negatively correlated with capital gains shocks. Thus, we have a negative sign in (3). Here, we also assume that the interest rate shocks have smaller variance than the capital gains shocks.

12. Note that the more volatile line represents the stochastic shock, which is—because it is a flow—more volatile than a stock variable, given by the smoother line.

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

14. In Stein (2011, 2012) the actual leverage over and above the optimal leverage is caused by a sequence of high capital gains and a sequence of low interest rates, both highly negatively correlated, giving rise to excess leveraging. In this sense, he explores only the vulnerability of the overleveraged sector, but does not model particular, possibly amplifying feedback loops, such as MS (2013). However, Stein's model can distinguish between optimal debt, actual debt, and excess debt. For empirical measures of these, see Schleer et al. (2014).

15. In BS, the capital stock is shared by households and banks, but remains relatively passive.

16. See Blanchard (1983) and Roch and Uhlig (2012).

17. Note that low interest rates, capital gains, and loan losses, affecting the returns of banks, are essential for the net worth dynamics in (1), (3)–(4).

18. Roch and Uhlig 2012) allow for a one-time cost of default, so that $\chi(\mu_t - \mu^*)^2$ occurs only once. We stretch this default cost over time, making it dependent on the excess leveraging. An approach similar to ours was proposed in Blanchard (1983).

19. In the numeric solution, we can take $\tilde{c} = c/k$ and multiply it by k in the preferences, so that the two choice variables can be confined to reasonable constraints between 0 and 1.

20. For details of such a model with short decision horizon, approximating models with longer time horizons well, but requiring much less information, see Gruene et al. (2015).

21. This can be justified by assuming a model with two types of agents, as in BS (2013).

22. In earlier versions of BS return on capital was linear in capital. We set, instead, $y = Af(k) = Ak^{\gamma}$.

23. One can also allow income, y, to be split into the sum of normal return on capital and capital gains, as in Section 2.1. Then the excess return on capital income over the interest rate, fueled through capital gains, can be used to service the debt; see also Stein (2012, Chs. 4–5).

24. This is consistent with Bohn (2007), where debt is mean-reverting when the reaction coefficient (the response of the surplus with respect to debt) in the debt dynamics is greater than the interest rate.

25. This may not hold if asset prices and capital gains rise and subsequently credit spreads jump (see the next section).

26. For details of such scenarios in certain sectors of the economy, see Stein (2012).

27. Because we cannot observe financial stress, s_t, directly, the empirical analysis that follows considers a range of proxies as drivers for financial stress. Also, in the numerical algorithm, we approximate (11) by an arctan function of the form $r(b_t/k_t) = \beta \arctan(b_t/k_t)$, with $s = b/k$ $\beta = 0.1$. In (11), credit costs rise in a nonlinear fashion with leveraging: first slowly, then more rapidly, but ultimately bounded. The arctan function behaves in the same way, except that it is flatter in the upper and lower branches. Also, it is is not bounded by 1 and 0, but can move within reasonable bounds, as needed to approximate credit cost.

28. For a scenario of this nature and reference to data from Spain and Ireland, see Stein (2012).

29. See Blanchard and Leigh (2013) and Corsetti et al. (2012). They show that sovereign debt and banking risk increase private borrowing cost, leading to a decline in aggregate demand. As here, they employ spillover effects of risk spreads to aggregate demand.

30. For more details on those macro feedback mechanisms, see Mittnik and Semmler (2015).

31. There is empirical evidence that the drop in demand will be larger for households with larger debt, which are then forced to deleverage more; see Eggertsson and Krugman (2012).

32. This is, for example, documented by the ZEW financial-condition index presented in Schleer and Semmler (2015).

33. See De Grauwe and Macchiarelli (2013) and Gerali et al. (2010).

34. The samples cover the period from 1981 through mid-2012.

35. 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 enter only when returns on bank stocks are lower than the overall market return. Otherwise it is set to zero, so that the truncated paths, after de-meaning and standardization, arise.

36. 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.

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

38. 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 the 25% quantile of the remaining observations.

39. For an MRVAR application assessing the fiscal multiplier see Mittnik and Semmler (2012).

40. For details on MRVAR specification and estimation and a discussion of the advantages of specification (15) over Markov-switching VARs, see MS (2013).

41. In view of its truncated nature and the fact that about half of the observations are zero (before de-meaning), we omit the banking beta from the analysis, because the interpretation of a positive and negative shock becomes dubious.

42. 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.

43. See the discussion in MS (2013) for why the Spanish economy may behave differently as a result of the delayed enforcement of IFRS accounting standards.

44. Though one has to keep in mind that our response analysis is confined to bivariate reduced-form modeling and to a 36-month horizon.

REFERENCES

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 428.

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*, pp. 211–241. Amsterdam: North-Holland.

Bijlsma, M. J. and G. T. J. Zwart (2013) The Financial Market in Europe, the United States and Japan. Bruegel working paper 2013/02.

Blanchard, O. (1983) Debt and the current account deficit in Brazil. In Rudiger Dornbusch and Maurice Obstfeld (eds.), *Financial Policies and the World Capital Market: The Problem of Latin American Countries*, pp. 187–198. Chicago, IL: University of Chicago Press.

Blanchard, O. and D. Leigh (2013) Growth Forecast Errors and Fiscal Multipliers. IMF working paper WP/13/1.

Bohn, H. (2007) Are stationarity and cointegration restrictions really necessary for the intertemporal budget constraint? *Journal of Monetary Economics* 54, 1837–1847.

Brunnermeier, M. (2009) Deciphering the liquidity and credit crunch 2007–2008. *Journal of Economic Perspectives* 23, 77–100.

Brunnermeier, M. K. and M. Oehmke (2012) Bubbles, Financial Crises and Systemic Risk. NBER working paper 18398.

Brunnermeier, M. and Y. Sannikov (2014) A macroeconomic model with a financial sector. *American Economic Review* 104(2), 379–421.

Brunnermeier, M. and Y. Sannikov (2015) Monetary Analysis: Price and Financial Stability. Manuscript, Princeton University.

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* 17, 17–25.

Cardarelli, R., S. Elekdag, and S. Lall (2011) Financial stress and economic contractions. *Journal of Financial Stability* 7, 78–97.

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.

Christensen, I. and A. Dib (2008) The financial accelerator in an estimated New Keynesian model. *Review of Economic Dynamics*, 11, 155–178.

Corsetti, G., A. Meier, and G. Mueller (2012) What Determines Government Spending Multipliers? IMF working paper 12/150, International Monetary Fund.

De Grauwe, P. and Y. Ji (2012) Self-Fulfilling Crises in the Eurozone: An Empirical Test. Center for European Policy Studies.

De Grauwe, P. and C. Macchiarelli (2013) Animal Spirits and Credit Cycles. CESIFO working paper 4480, November.

Dimand, R. W. (2005) Fisher, Keynes, and the corridor of stability. *American Journal of Economics and Sociology* 64, 185–199.

Eggertsson, G. B. and P. Krugman (2012) Debt, Deleveraging, and the Liquidity Trap: A Fisher–Minsky–Koo Approach. Manuscript, Princeton University.

Gerali, A., S. Neri, L. Sessa, and F. Signoretti (2010) Credit and banking in a DSGE model of the euro area. *Journal of Money, Credit and Banking* 42(1), 107–141.

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.

Gruene, L., W. Semmler, and M. Stieler (2015) Using nonlinear model predictive control for dynamic decision problems in economics. *Journal of Economic Dynamics and Control* 60, 112–133.

Hansen, B. E. (2000) Sample splitting and threshold estimation. *Econometrica* 68, 575–603.

He, Z. and A. Krishnamurthy (2013) Intermediary asset pricing. *American Economic Review*, 103(2), 732–770.

Koop, G., M. Pesaran, and S. Potter (1996) Impulse responses in nonlinear multivariate models. *Journal of Econometrics* 74, 119–147.

Lorenzoni, G. and I. Werning (2013) Slow Moving Debt Crises. Manuscript, MIT.

Mittnik, S. and W. Semmler (2012) Regime dependence of the fiscal multiplier. *Journal of Economic Behavior and Organization* 83, 502–522.

Mittnik, S. and W. Semmler (2013) The real consequences of financial stress. *Journal of Economic Dynamics and Control* 37, 1479–1499.

Mittnik, S. and W. Semmler (2015) Overleveraging, Financial Fragility and the Banking–Macro Link: Theory and Emprical Evidence. ZEW, discussion paper 14-110.

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.

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

Roch, F. and H. Uhlig (2012), The Dynamics of Sovereign Debt Crises and Bailouts. Working paper, University of Chicago, CentER, NBER, CERP.

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

Schleer, F. and W. Semmler (2015) Financial sector and output dynamics in the Euro area: Non-linearities reconsidered. *Journal of Macroeconomics* 46, 235–263.

Schleer, F., W. Semmler, and J. Illig (2014) Overleveraging in the Banking Sector: Evidence from Europe. ZEW, Discussion Paper 14-066

Semmler, W. and L. Bernard (2012) Boom–bust cycles; Leveraging, complex securities and asset prices. *Journal of Economic Behavior and Organization* 81, 442–465.

Stein, J. L. (2011) The Diversity of Debt Crises in Europe. CESIFO working paper 3348, Category 6: Fiscal Policy; Macroeconomics and Growth, February.

Stein, J. L. (2012) *Stochastic Optimal Control and the US Financial Crisis*. Heidelberg, Germany: Springer Publishing House.

Tong, H. (1978) On a threshold model. In C. H. Chen (ed.), *Pattern Recognition and Signal Processing*. Amsterdam: Kluwer.

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

Tsay, R. S. (1998) Testing and modelling multivariate threshold models. *Journal of the American Statistical Association* 93, 1188–1212.

APPENDIX: CUMULATIVE RESPONSE PLOTS FROM MRVAR MODELS

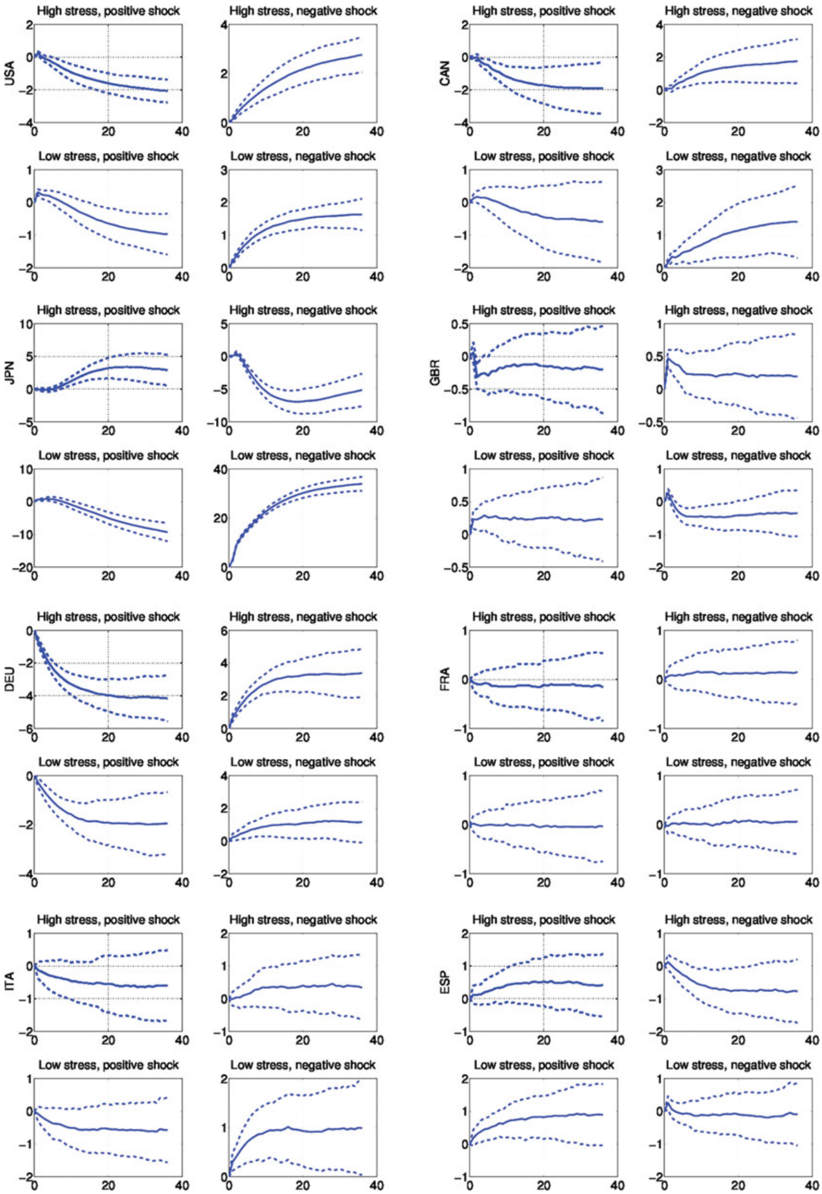

FIGURE A.1. Cumulative MRVAR responses to shock in TED spreads.

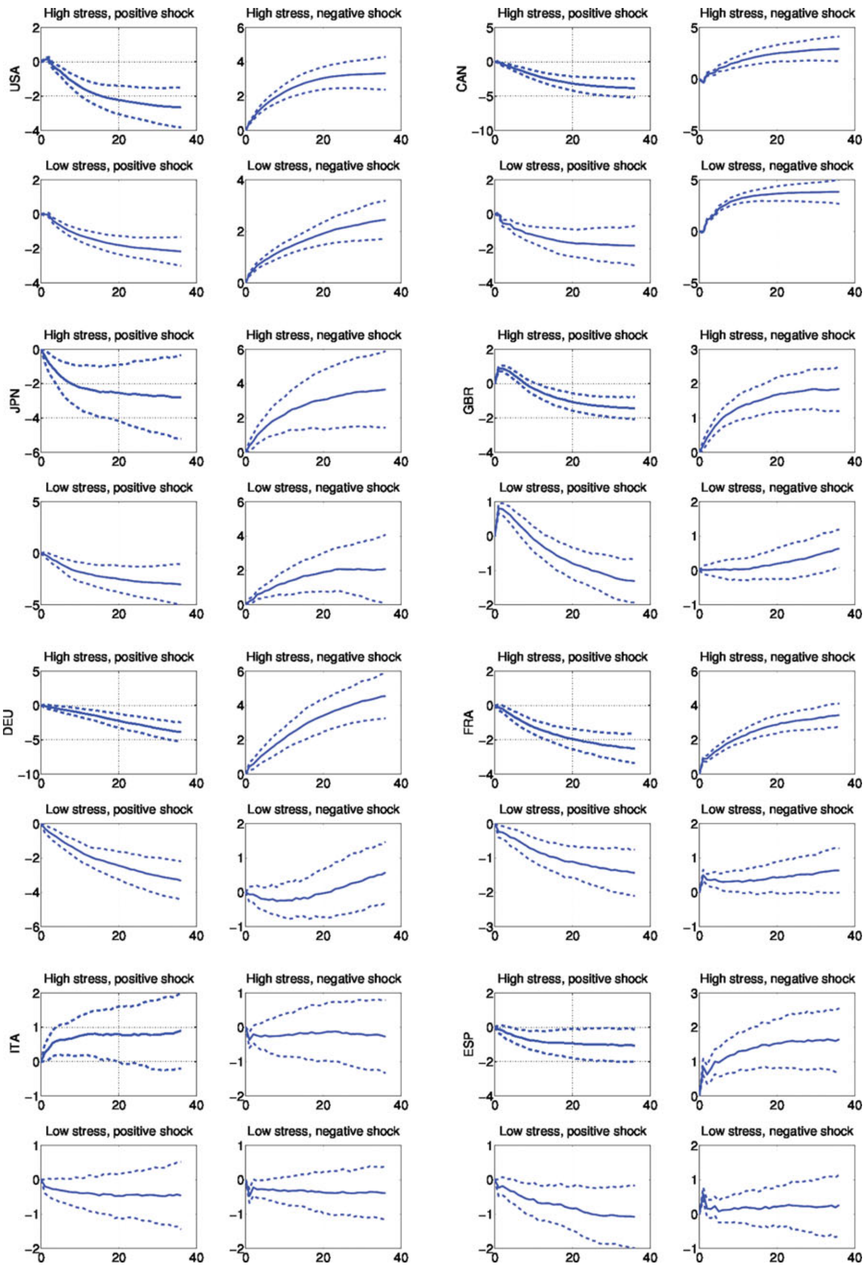

FIGURE A.2. Cumulative MRVAR responses to shock in (negative) term spreads.

https://doi.org/10.1017/S1365100516000080 Published online by Cambridge University Press

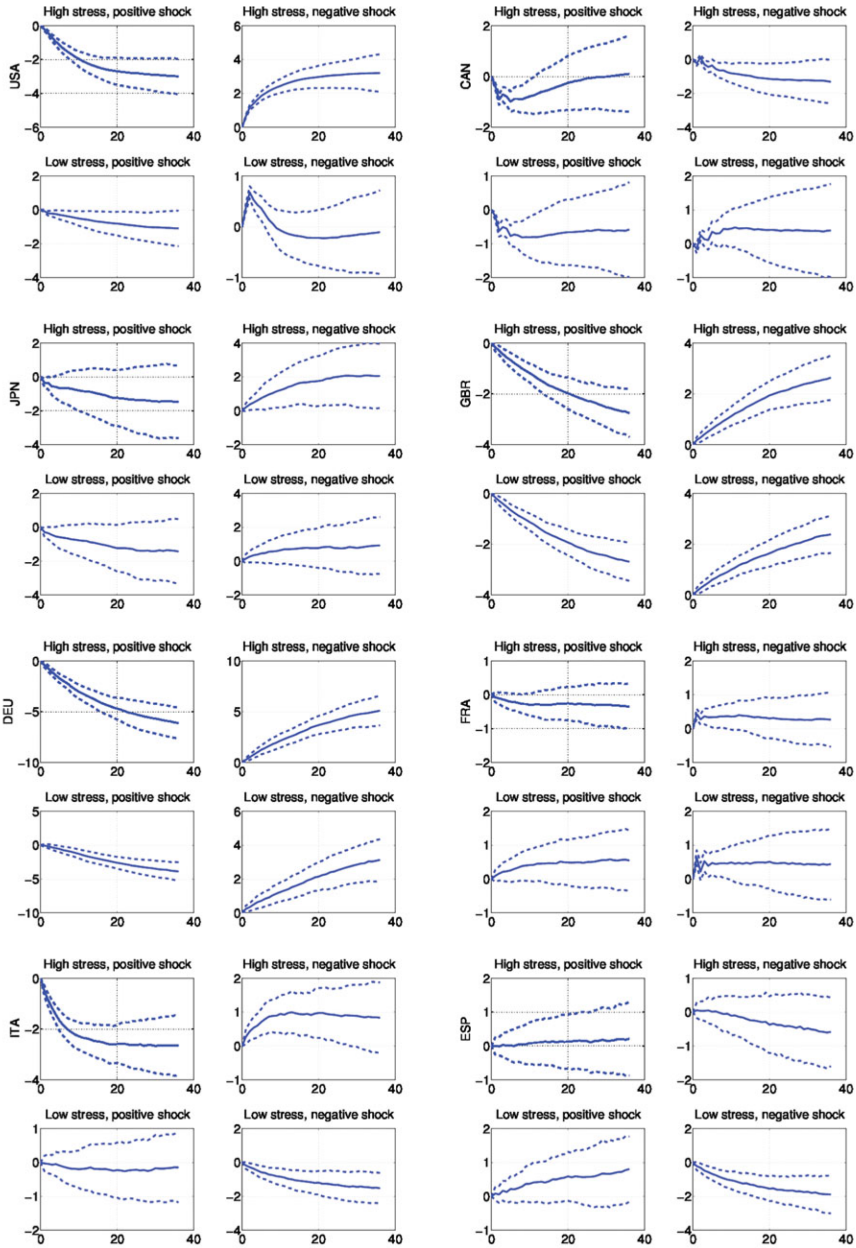

FIGURE A.3. Cumulative MRVAR responses to shock in corporate spreads.

https://doi.org/10.1017/S1365100516000080 Published online by Cambridge University Press

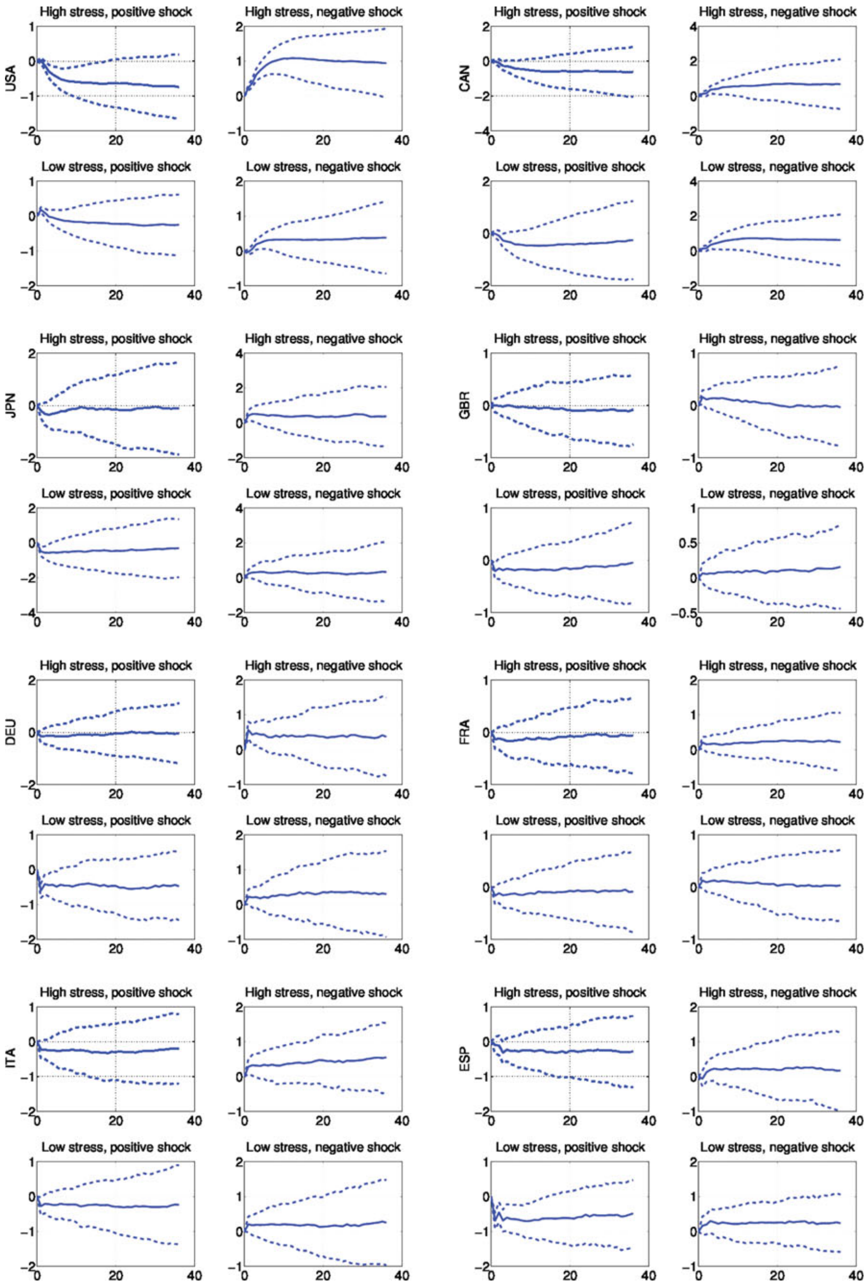

FIGURE A.4. Cumulative MRVAR responses to shock in (negative) stock returns.

https://doi.org/10.1017/S1365100516000080 Published online by Cambridge University Press

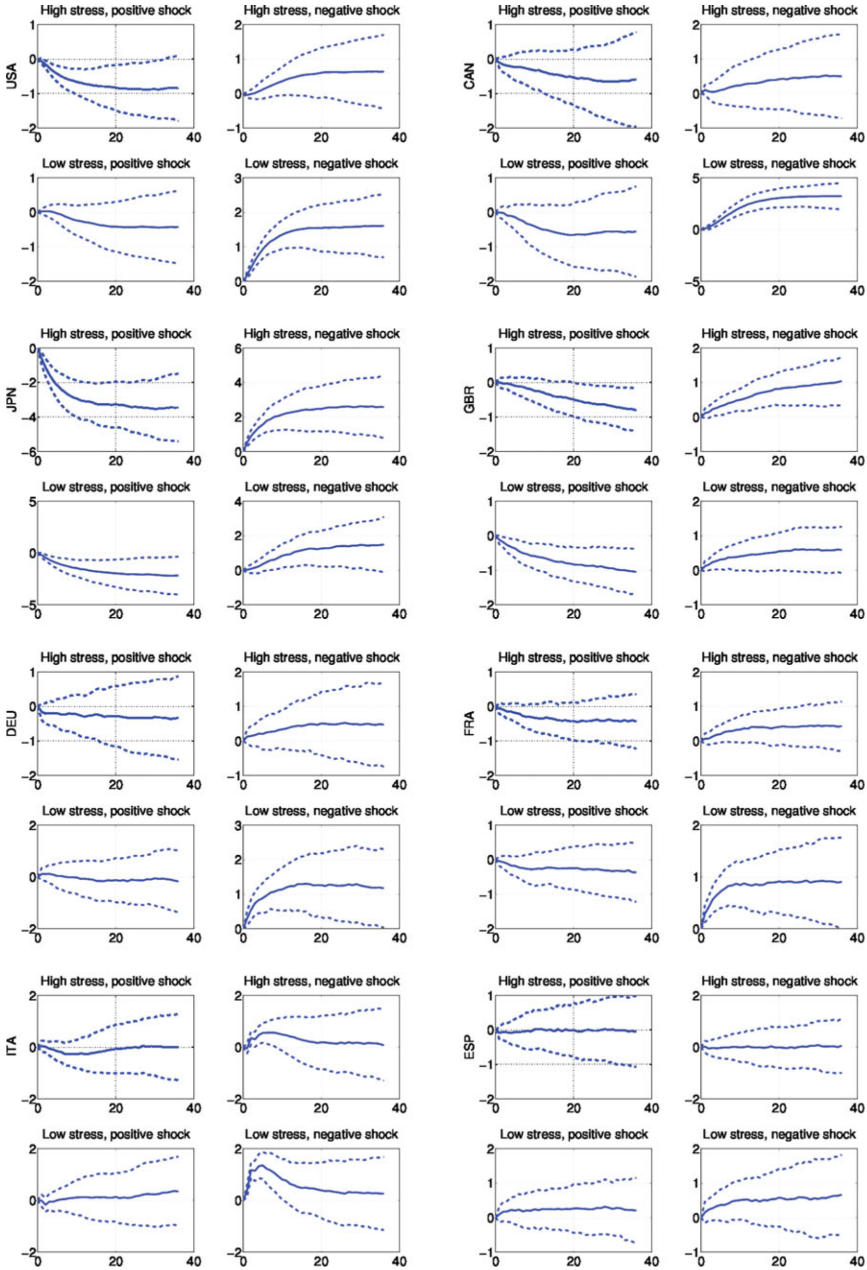

FIGURE A.5. Cumulative MRVAR responses to shock in stock-market volatility.

https://doi.org/10.1017/S1365100516000080 Published online by Cambridge University Press

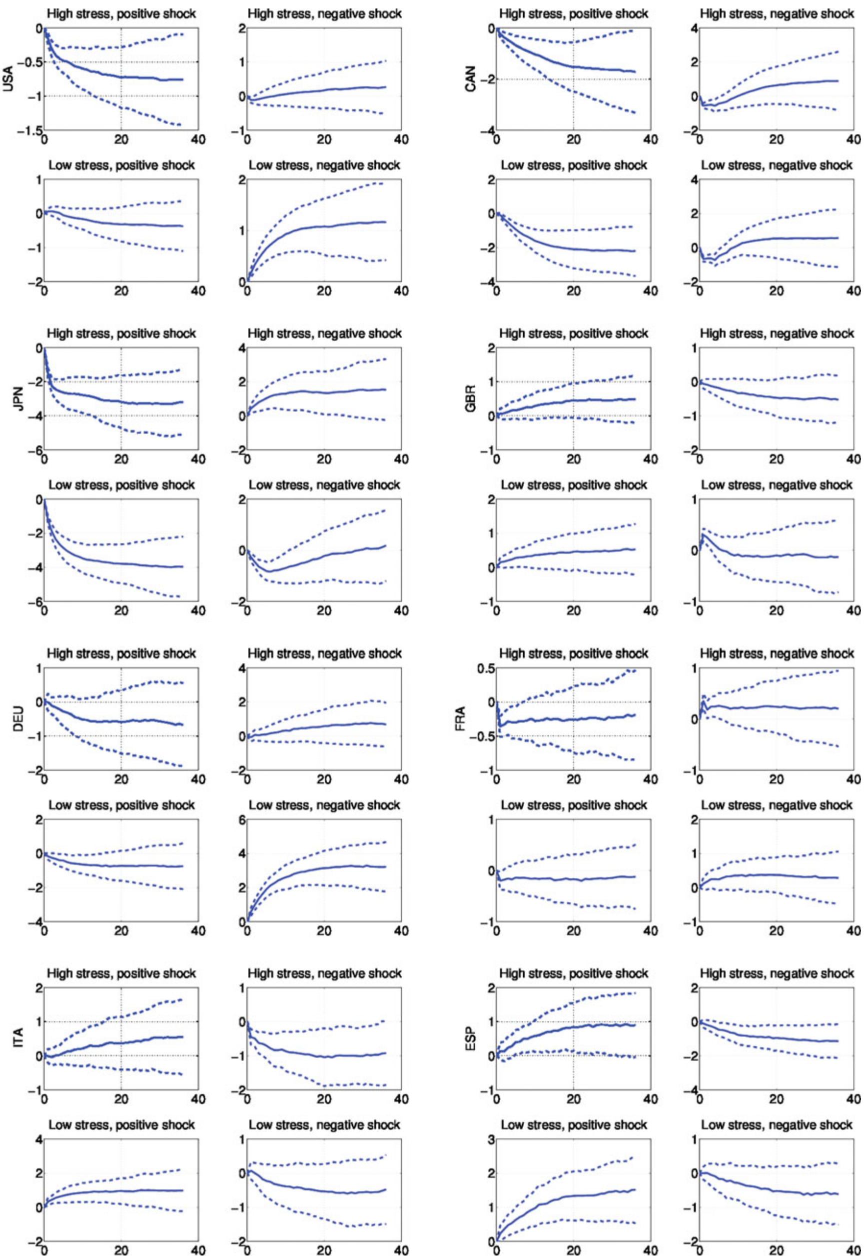

FIGURE A.6. Cumulative MRVAR responses to shock in FX volatility.

https://doi.org/10.1017/S1365100516000080 Published online by Cambridge University Press