Financial Sector and Output Dynamics in the Euro Area: Non-linearities Reconsidered

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Abstract

We analyze the feedback mechanisms between economic downturns and financial stress for several euro area countries. Our study employs newly constructed financial condition indices that incorporate banking variables extensively. We apply a non-linear Vector Smooth Transition Autoregressive (VSTAR) model for investigating instabilities in the link between the financial sector and economic activity. The VSTAR model allows for non-linear dynamics and regime changes between low and high stress regimes. It can also replicate the regime-specific amplification effects shown by our theoretical model. The amplification effects, however, change over time. Specifically after the Lehman collapse, we observe the presence of strong non-linearities and amplification mechanisms for some euro area countries. Thus, these strong amplification effects appear to be related to rare but large events, and to a low-frequency financial cycle. Prior to the financial crisis outbreak we find corridor stability even if the financial sector shock takes place in a high stress regime. More important seems to be the shock propagation over time in the economy. Only with the occurrence of the rare but large events we find strong endogenous feedback loops and a loss of stability as described by the high stress regime of our theoretical model. The economy leaves the corridor of stability and is prone to adverse feedback loops.

JEL *classification:* E2, E44, G01

Keywords: Vector STAR, financial stress, financial cycle, real economy, regime-switching, euro area

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1   Introduction

The financial and economic crisis has drawn attention to the need for a better understanding of destabilizing effects that arise in the financial sector and spill over to the real economy. In turn, weakening economic conditions are likely to feed back to the financial sector, thus giving rise to an adverse feedback loop.

Recent studies incorporate financial market frictions into theoretical models and analyze the spillover mechanisms from the financial sector to the real economy. Non-standard amplification mechanisms such as the credit channel or financial stress to economic activity have recently started to become more important in theoretical modeling. Besides the financial accelerator mechanism of Bernanke *et al.* (1999), mostly applied to firms in the past, there is a more recent literature concentrating on the banking sector as a source for business cycle dynamics. Such theoretical studies have started with Stiglitz and Greenwald (2003) and continued with Adrian and Shin (2009), Geanakoplos and Farmer (2009), Adrian *et al.* (2010), Gorton (2010), Geanakoplos (2011), Brunnermeier and Sannikov (2013), and Mittnik and Semmler (2013). The latter studies examine the balance sheets of banks, showing that a downward spiral is triggered through overleveraging, financial interdependencies, and contagion effects. The new theoretical models are similar in that they highlight (1) the critical impact exerted by financial sector dynamics and (2) amplification and destabilizing effects of the financial sector on economic activity.

Mittnik and Semmler (2013) as well as Brunnermeier and Sannikov (2013) emphasize that a theoretical analysis based on traditional log-linearization techniques is likely to be inadequate due to local instabilities and non-linear amplification mechanisms which do not arise near the steady state but can generate switches to different regimes. Their theoretical models and simulation results are in contrast to the DSGE model tradition where amplifying effects occur locally around a stable unique steady state. In our paper, a theoretical model that allows for regime-switching between low and high financial stress is introduced which is solved by a recent numerical procedure called Non-linear Model Predictive Control. In the low stress regime, the interest rate on borrowing is at a low level and remains constant. Then, the solution path of the debt to capital ratio converges to the steady state and the economy faces sustainable debt dynamics. In the high stress regime, however, the interest rate to be paid on debt is a non-linear function of the leverage ratio. We show that, if the leverage ratio moves beyond a certain threshold, debt becomes unsustainable. As a consequence, there is no convergence and a loss of stability. This will motivate our empirical work employing a regime-switching Vector Smooth Transition Autoregressive (VSTAR) model.

As to empirical work, there is a growing econometric research that also deals with the impact of financial conditions on economic activity. This recent research strand is based on multivariate, non-linear models since those are able to capture this kind of interdependent, regime-switching dynamics described by theoretical models (see, for instance, Hubrich *et al.* (2013), Mittnik and Semmler (2013), van Roye (2013), Holló *et al.* (2012), Hubrich and Tetlow (2012), and Davig and Hakkio (2010)).

The results of these studies indicate that financial stress—which is a reflection of vulnerability and instability in the financial system—has a strong, but regime-specific impact on the real economy. In particular, all studies find extreme negative effects of an increase of financial stress on economic activity in a distressed period, whereas the effects in a low stress period are relatively small or even negligible. Besides the stronger effect, Hubrich and Tetlow (2012) point out that the negative impact on the economy is longer-

lasting in high stress periods. The model outcomes of Mittnik and Semmler (2013) imply additionally that the size and sign of shocks may matter.

What has been lacking in the literature so far is work on non-linear linkages and asymmetric dynamics as they may unfold over time. For instance, effects of financial sector instability on economic activity may depend on the actual state of the financial sector. During some downswings this effect may be more severe than during others. These amplification effects on the real economy might not matter much for a considerable time period, but then a triggering event may generate a rare and adverse response such as the one experienced recently.

In our empirical work we analyze the feedback and amplification mechanisms between economic downturns and financial conditions in several euro area countries. Based on a new data set for extracting financial condition indices, that now extensively includes banking variables, we explore how the financial-real economy nexus behaves over time.

The hitherto theoretical and empirical findings suggest the need for an empirical approach that can accommodate varying dynamic patterns across alternative states of the economy. We propose a non-linear multivariate VSTAR model framework, developed by Teräsvirta and Yang (2013a;b), which has not been used within this literature so far. In contrast to previous studies it is able to capture regime changes in a more flexible way.

Using a Vector STAR model, we confirm the relevance of non-linearities in the link between the financial sector and output. In most countries, a shock to the financial market leads to a long-lasting negative response in economic activity. A high financial stress regime amplifies negative effects on output. Thus, it is important to distinguish between periods of low and high financial stress when assessing the impacts of financial shocks on real economic activity, as the results of shocks are regime-dependent. Yet, the negative effect that we find in our study is not as pronounced as it is in some other studies. Moreover, we show that the amplification effects change over time in the euro area countries. This holds true specifically for the time before the Lehman collapse. After the crash, however, we observe the presence of strong non-linearities and amplification mechanisms, particularly in the larger euro area countries. This suggests that events leading to a major economic breakdown are rare but large events, and they are related to a low-frequency financial cycle.

Thus, our contribution is threefold: first, we use new financial condition indices which are comprehensive and put a stronger focus on the banking sector. Second, we apply a non-linear VSTAR model which has not been used before in this literature. Third, we comprehensively investigate the (potentially changing) dynamics between the financial sector and the real economy over time for selected euro area countries.

The remainder of the paper is organized as follows. Section 2 motivates our empirical analysis with a theoretical model which allows for regime-switching between a low and a high stress regime. Section 3 presents empirical results of the relation between the financial sector and the macroeconomy. Section 3.1 describes the ZEW Financial Condition Indices. The non-linear VSTAR model and its characteristics are discussed in section 3.2. In section 3.3, we first compare results of linear and non-linear models. Then, we analyze the financial market – output nexus over time. Section 4 concludes.

2 Theoretical Model

Next, we introduce a financial – real interaction model with an essential role of the financial sector which motivates our empirical work employing a regime-switching model.

The theoretical model introduced here resembles Brunnermeier and Sannikov (2013) and represents an extension of the model by Mittnik and Semmler (2013). Both models focus on the balance sheets of the banking system, whereas the former authors stress the volatility of asset prices and contagion effects that generate destabilizing feedback loops, the latter study's feedback loops arise from leveraging, financial linkages and sudden jumps in credit spreads. A similar line of research is proposed by Stein (2012) where overleveraging of the banking sector, as compared to optimal leveraging, is made central and can trigger a high stress regime.

In this type of model, when leveraging and payouts are less constrained, and financial stress and risk premia are high the banking system is vulnerable and more prone to instabilities. With stronger decision restrictions on leveraging, low interest rates and low credit spreads a regime of less financial stress, stability of the banking system and a good macro performance might emerge. Yet, as Stein (2012) points out this is likely to be also a period—because of the low interest rate, low credit spread, rising capital gains and higher leveraging—that gives rise to the vulnerability of the banking sector, creating the conditions for a fragile future banking - macro link. Thus, those financial sector – macro feedback loops can create a regime of low financial stress, stable environment and expansionary periods, but are also likely to generate destabilizing forces generating contractions and recessions. This might occasionally occur when the financial sector starts to come under stress, risk premia rise and capital gains, due to a collapse of asset prices, rapidly fall making themselves felt on aggregate demand and output.

There are numerous extensive studies on those vulnerable regimes and destabilizing feedback loops (see for example, Stein (2012) and Mittnik and Semmler (2013)). Many studies have called this a vicious cycle, see for instance Brunnermeier and Sannikov (2013), Geanakoplos (2011), Stein (2012), Mittnik and Semmler (2013). What, however, recently has been explored is a "diabolic loop". This has become relevant particularly in Europe where the financial crisis of 2008/9 was quickly followed by a sovereign debt crisis. Then, there is not only the relationship of banks with the private sector, but there is a triangle relationship between private borrowing, bank leveraging, and sovereign debt, see Brunnermeier and Oehmke (2012). Banks give loans not only to the private sector, but also keep treasury bonds on their asset side. Banks vulnerability can arise due to a threat of private loan losses or an asset price fall, or due to the deterioration of the fiscal position of the sovereign. When the banks are threatened by insolvency and a bank bail out by the public occurs, sovereign debt as well as sovereign insolvency threat rises, which make the banks even more vulnerable, and they cut their loan supply to the private sector, which in turn generates less revenue for the state with greater threat of insolvency risk and so on. Moreover, both the private sector and public sector borrowing are usually accompanied by an increase in external liabilities, see Stein (2012: Ch. 8).

In our modeling strategy we refer to two strands of literature. First, we build on the literature about these aforementioned complex feedback loops which can create vulnerable regimes. This is best understood in a multi-period model where one allows for leveraging of economic agents and asset price movements. There are several reasons why the choice of a multi-period model is insightful:

- The evolution of debt and the sustainability of debt can only be tracked over a longer horizon, though we do not assume an infinite decision horizon here.

- Leveraging and the evolution of debt is frequently seen to be interconnected with asset prices and net worth (see Geanakoplos (2011), and Stein (2012)). To have

a multi-period payoff function either for consumers, banks or firms, is essential in asset pricing theory.

- The outcomes of such an intertemporal decision model with finite decision horizon can then be compared to standard macro models with infinite horizon. One can also easily evaluate policy effects in this context.

Second, we also take into account regime-specific amplification and feedback loops that are mentioned as essential, for example in Brunnermeier and Sannikov (2013), Mittnik and Semmler (2013) and Stein (2012). Such macroeconomic amplification mechanisms have been known since a long time but they are rare in DSGE models, since mean reversion is usually assumed. The following magnifying effects could be at work in certain regimes, possibly triggering a regime-switch:

- On the real side there could be strong multiplier effects in certain regimes, generating stronger feedback loops, for example if multipliers turn out to be stronger in recessions than in expansions (Mittnik and Semmler 2012).

- Interest rates and credit spreads could also be regime dependent (and different from the interest rate that results from the Taylor rule), moving counter-cyclically, as often described by the literature on the financial accelerator.

- The Fisher debt-deflation-effect might become relevant, for example triggering a rise of the fraction of households deleveraging in contractionary periods, see Eggertsson and Krugman (2012).

- There could be price expectation and real interest rate effects that could be more destabilizing, for example due to deflationary pressures, pointed out by Tobin (1975)'s work.

- There are wage channel effects that can trigger amplifying forces in downturns (this depends on the shape of the Phillips curve, see Charpe *et al.* (2013)).

- The asset price channel could also be amplifying, through wealth effects on aggregate demand (for example amplifying an upswing with asset prices rising, but also accelerating a downswing in periods of large asset price losses).

- There could be banking vulnerability due to overleveraging, loan losses and asset price fall, with externality and contagion effects, which could trigger what has been called "diabolic loop".

Brunnermeier and Oehmke (2012: p.30) in particular stress the importance of amplifying mechanisms arising from externalities and contagion effects. They ask why does a shock "...propagate across so many sectors of the economy? The reason is amplification. In the presence of amplification, even a modest triggering event can cause large spillovers across the financial system. Amplification can occur because of direct spillovers, such as so-called domino effects, or indirect spillovers that work through prices, constraints, and the endogenous responses of market participants."

Stein (2012) has highlighted such important amplification mechanisms with respect to certain countries. In the US and also in Spain, so Stein's view, the sectors with a strong asset price boom, such as financial intermediaries and real sectors, have helped to service the debt from high capital gains. On the other hand, the high leveraging and over-borrowing will then trigger at some point high risk premia, high interest rates and credit

spreads and collapse of financial linkages. This is then likely to be accompanied by a fall in asset prices and stronger losses in capital value and net worth, finally generating, through macro feedback loops, an economic contraction.

Those amplification mechanisms can easily generate a regime-switch from low to high financial stress and a banking triggering a strong downturn.[1] Furthermore, one might want to understand the above sketched adverse feedback loops in an open economy setting. A framework for this is provided in Blanchard and Fischer (1989). Recent empirical evidence of the relevance of external debt on the macrodynamics in Europe is shown in Stein (2012: ch.8). This as well as the central banks' policy responses are taken into account in our model.

Most of the recent dynamic models, such as DSGE models and the Brunnermeier and Sannikov (2013) and Mittnik and Semmler (2013) models, as well as Blanchard and Fischer (1989), are working with an infinite horizon model. In our context, as we will show, an infinite-horizon model is not needed. We here propose a model with a receding finite horizon that is solved by a new numerical procedure, the NMPC method, see Grüne et al. (2013), summarized in Appendix A. This is a new solution procedure that allows for a multi-period model, but also better includes some of the above discussed macroeconomic feedback loops and amplification mechanisms. Yet, it approaches, with longer horizon, the usual infinite horizon solution.

2.1 Regime of Low Financial Stress

In a first model variant we presume that the interest rate on borrowing is at a low level and remains constant. This can be seen as equivalent to a regime where the central bank is pursuing a low—or near zero—interest rate policy. By this policy, the central bank is aiming to keep the economy in a low financial stress regime (see Christiano et al. (2011), and Woodford (2011)). The detailed measure of financial stress that also includes banking as well as sovereign risk variables, will be discussed in the next section. Our model variant for the low stress regime reads as follows:

$$V(k,b) = \max_{c_t, g_t,} \int_0^T e^{-rt} U(c_t) dt \tag{1}$$

s.t.

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

$$db_t = (rb_t - (y_t - c_t - i_t - \varphi(g_t k_t)))dt \tag{3}$$

In equ. (1) there are preferences over log utility. The policy variables in equ. (1) are consumption (c_t), and growth rate of capital stock (g_t).[2] The horizon T does not have to be very large, or go to infinity.[3]

Equ. (2) represents the capital stock. It increases due to investment but declines due

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[1]A similar model of asset price credit market boom is also presented in Semmler and Bernard (2012).

[2]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 lie between 0 and 1.

[3]For details of such a model with short time horizon, approximating well models with longer time horizons but needing much less information, see Grüne et al. (2013). Those type of models are called Nonlinear Model Predictive Control, see Grüne and Pannek (2011), where the basic theory is developed without discounting.

to a capital depreciation rate δ. Brunnermeier and Sannikov (2013) model this as a Brownian motion and volatility dependent asset prices. We can also admit stochastic shocks occurring along the path, represented by the second term in equ. (2). Though we will neglect it in our current version when we solve the model. Equ. (3) represents the dynamics of aggregate debt (households, firms, banks and the public sector).[4] Our debt dynamics are written here in a way which is standard if one allows for borrowing of households, firms and the sovereign. As mentioned we allow here for external debt where the excess borrowing of the private and the public sector add up to external borrowing.

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 through a surplus.[5] Hereby we have $i = g_t k_t$. Note that consumption and investment are separate decision variables. Moreover, $\varphi(g_t k_t)$ is the adjustment cost for investment. Overall the model has two decision variables and two state variables. Note also that we have quadratic adjustment cost of investment and we could permit a difference of interest and discount rates.[6]

One can allow the income y to be split up into y = normal return on capital + capital gains + wage income. Note that the capital gains could be positive or negative; for a more detailed specification of those, see Stein (2012). Then the excess return on capital income over the interest rate, generated through capital gains, can be used to service the debt.

Now we solve our above model by using NMPC. A sketch of the algorithm is presented in the Appendix A. Assuming here $r = 0.04, \delta = 0.07$ and quadratic adjustment cost of investment, we obtain the following solutions using NMPC, yet, setting the shock in equ. (2) equal to zero.
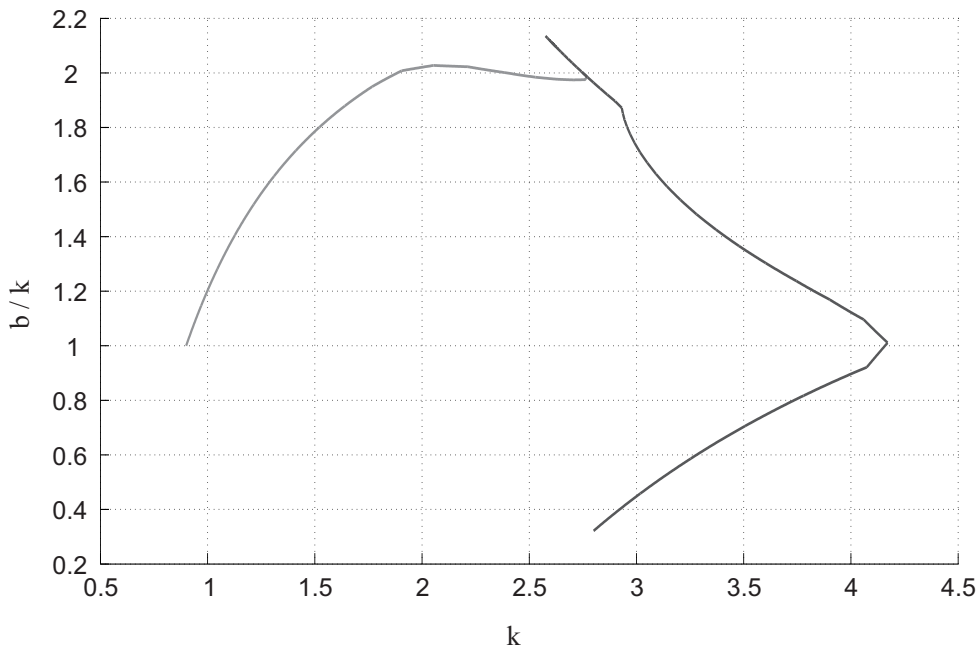
Figure 1: debt dynamcis for constant interest rate, for two initial conditions, $k(0) = 0.9$, $b(0) = 0.9$ (left) $k(0) = 2.8, b(0) = 0.9$ (right, bold), convergence to steady state, with $r = 0.04$.

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[4]Brunnermeier and Sannikov (2013) have the debt dynamic formulated as a net worth dynamics but a closed economy framework. In our open economy framework, we can also allow for sovereign debt here.

[5]How this works for an open economy, and what the stylized facts for Europe are can be found in Stein (2012: ch.8).

[6]This is frequently done in a two type of agent model, as Eggertsson and Krugman (2012).

For a regime of low financial stress, in Figure 1 the vertical axis shows the debt to capital stock ratio, the horizontal is the capital stock. Here the paths are shown for different initial conditions. The upper end of the two paths represents the steady state which is unique where both the trajectories end up. 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 the eqs. (2)-(3) are zero. So, with the central bank keeping the interest rate low there is a regime of low financial stress where debt is sustainable.[7]

Figure 1 gives the solution paths for two different initial conditions, but the same discount and interest rates. We could also assume that the central bank is able to reduce the discount rate and interest rates through appropriate monetary instruments even to a lower rate. The results of the NMPC solution for example, with a temporarily different interest rate, or credit spread, can also easily be obtained. Results from our solution method have shown that the solution paths converge toward the steady state, yet for a smaller interest rate there is a lower debt to output ratio on the out of steady state path.

In this first regime we keep the interest rate on leveraging persistently low, by assuming that there is low financial stress and the central bank can sufficiently reduce not only the interest rate but also credit spreads by reducing financial stress. This may generate a tranquil period where there are large capital gains and an asset price boom, where risk premia are low and asset prices rising. Yet, when an overleveraging occurs and the asset price bubble bursts and capital gains become negative, then net worth maybe rapidly deteriorating. As the debt ratio rises and the capital gains 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 quickly vanish or become negative.

2.2 Regime of High Financial Stress

We next allow the yields on bonds, sovereign or private, and financial stress, to be endogenous. This presumably will then also entail stronger endogenous feedback loops of the financial stress to macroeconomic variables, possibly giving rise to the loss of stability. This is somewhat equivalent to the central bank not attempting—or not being able—to pursue a monetary policy to reduce asset market stress and to bring down credit spreads. Let our model now be defined as follows

$$V\left(k,b\right) = \max_{c_t, g_t,} \int_0^T e^{-rt} U(c_t) dt \tag{4}$$

s.t.

$$dk_t = (g_t - \delta)k_t dt + \sigma_t k_t dZ_t \tag{5}$$

$$db_t = r(s_t|\gamma, c^*)b_t - (y_t^a - c_t - i_t - \varphi(g_t k_t)))dt \tag{6}$$

The difference to the model of low stress regime is here now that we assume state depending financial stress, represented by the banking sector, securities and exchange

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[7]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 sovereign 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.

rate market variables. Since we want to have the function to be bounded we define financial stress to be given by the following function:[8]

$$r(s_t|\gamma, c^*) = [1 + \exp(-\gamma(s_t - c^*))]^{-1} , \gamma > 0 \tag{7}$$

This function makes the credit cost depending on the state variable financial stress, s_t, a threshold variable, c^*, and a slope parameter, γ. The above represents the logistic function often used in STAR models and further discussed in our specification of the VSTAR model in sect. 3.2 below. It is also roughly the function that has been empirically observed in De Grauwe (2012),[9] but one can also derive from Roch and Uhlig (2012).[10] In our numerical solution procedure we will approximate this function above by a closely related function.[11]

Now if 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. So if the capital gains shrink, the source for debt services declines, and surpluses would shrink, the debt service rise with higher interest rates and debt sustainability becomes threatened. For a scenario like this, see Stein (2012) where this is exemplified with macroeconomic data for Spain and Ireland.

Note also that when we allow the income y^a in (6) to include capital gains, aiding to service the debt, there is an advantage for borrowing agents as long as there is little financial stress and no risk premium to be paid. We want to remark that low interest rates and capital gains are frequently highly (negatively) correlated. This points to a kind of low-frequency financial cycle scenario[12] where financial stress and financial fragility may arise in a period of tranquility where low stress and zero risk premia can be observed, as for example were seen from the 1990s to 2007. Implicitly, in this case, on the asset side, as Stein (2012) shows, the present value of the assets will tend to become very large, because there is no correction through risk premia,[13] as it should be, and net worth will be high.

The reversal of this process is likely to trigger macroeconomic instabilities when financial stress is significantly driven by asset prices and banking vulnerability. Note that asset prices are likely to fall with higher interest rates, rising risk premia and credit spreads, and higher discount rates. Asset prices falling means capital losses. Yet, a sudden loss of capital gains generate lower income to service debt, at a time when debt service rises through rising financial stress and credit spreads. The asset price bubble may burst in a period when high debt services emerge (Stein 2012). There are now endogenous risk

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[8]Note that empirically we will introduce a multitude of factors generating financial stress. For the shape of the function in equ. (7) see Figure 8.

[9]Presenting EU debt and bond yield data, see also Corsetti *et al.* (2013).

[10]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 Gilchrist and Zakrajšek (2012).

[11]Since in our numerics we cannot directly read in the financial stress, s_t, we approximate (7) by an arctan function such as $r(b_t/k_t) = \beta arctan(b_t/k_t)$, We hereby have set $\beta = 0.1$. Here too, the credit cost rises in a non-linear way with the debt to capital stock ratio, first slowly, then more rapidly but is finally bounded. Yet, this function behaves the same way as the above logistic function, except that 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. It is also numerically easier to solve in our NMPC algorithm.

[12]Financial cycles as rather long cycles are studied in Schularick and Taylor (2012).

[13]Stein (2012) suggests then to make corrections by suggesting to take the trends/drifts in capital gains and interest rates in such a model, that would better measure some debt capacity. The borrowing exceeding that debt capacity would amount to excess borrowing.

premia, rise of interest rates and prices of asset declining.

This triggers important macroeconomic feedback loops that often can be observed during periods of rising financial stress, as mentioned above. This is frequently accompanied by a decline in aggregate demand and output.[14] Though optimal consumption and investment plans might be targeted, actual income, consumption and investment are likely to decline due to rising financial stress—falling asset prices, rising risk premia and credit spreads. So, overall we may experience that actual output (y_t^a) adjusts downward:

$$y_t^a = g\big(r(s_t|\gamma, c^*)\big)(i^{opt} + c^{opt}) \tag{8}$$

Note that in equ. (8) we have now defined actual output to be driven by aggregate demand, where consumption and investment demand, responding to financial stress are affecting actual output. The optimally chosen consumption and investment demand for each time period of the state variables are actually not realized, but only the consumption and investment demand under the impact of financial stress are executed. This can easily be solved by our NMPC algorithm. What is modeled here is what Blanchard and Leigh (2013) call the feedback of financial market stress on aggregate demand.[15]

We can note that if risk premia and credit spreads and thus financial stress rise, but are bounded as in (7), y_t^a will decline due to lower consumption and investment demand, but if demand and output falls, income, and thus tax revenue, as well as capital gains, and the surplus, to service the debt, are likely to fall, too. This might make then debt and bond issuing – if bonds are sold on the market – unsustainable, because of further jumps in financial risk.

Next we solve our model (4) – (8) numerically using again NMPC. We illustrate the outcome by two variants. In both variants we are in a regime of high financial stress. First, we are setting the macro feedback loops on aggregate demand, $g\big(r(s_t|\gamma, c^*)\big)$, to be very weak. We get the following results.

As the solution path for the capital stock and leveraging in Figure 2 (right graph) shows the credit spread below a certain threshold permits a higher capital stock and higher leveraging. Yet as the credit spread rises—in our case caused by financial market stress— and if it reaches a certain threshold, we observe that with an increasing leveraging risk premia rise, capital stock stops rising but the leverage ratio is rising further. Thus, if the credit spread is moving beyond a certain threshold, debt becomes unsustainable since capital gains fall and the interest payments become higher than the surplus to service the debt, see eq. (6).[16]

Stronger macroeconomic feedback loops[17] may arise due to the following:

- There is the wealth effect reducing aggregate demand – when the capital appreciation falls, or becomes negative, both consumption and investment demand are likely to fall.

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[14]See Blanchard and Leigh (2013) and Corsetti *et al.* (2013). The latter show how empirically sovereign debt and banking risk also increases private borrowing cost.

[15]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.* (2013).

[16]This maybe be magnified by the reversion of the effect as mentioned before: namely the risk and risk premia rising, discount rates rising and falling (or negative) capital gains, not supporting the debt repayments any more. So debt would rise faster.

[17]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).
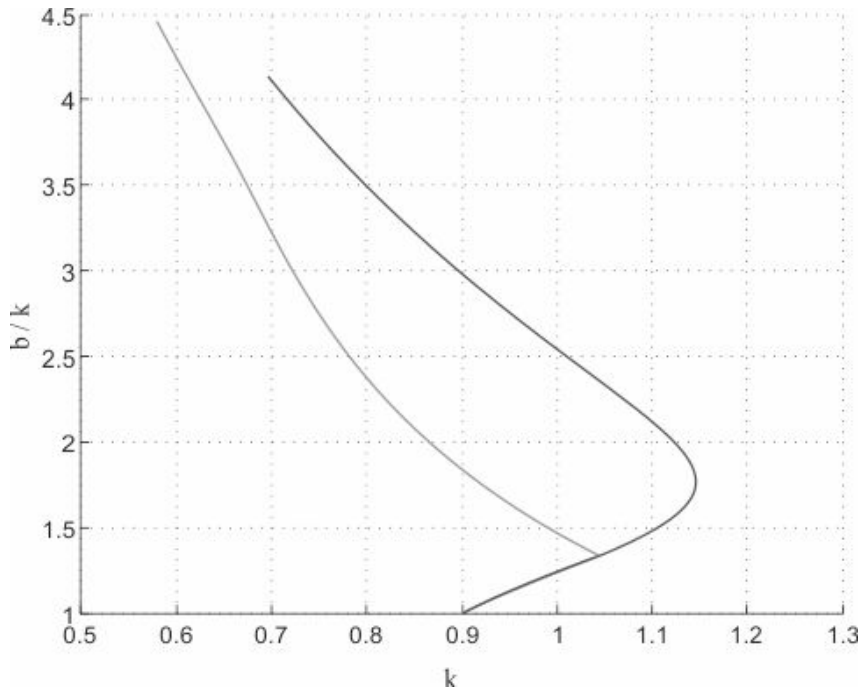
Figure 2: Debt dynamics for non-linear financial stress effects; weak effects on aggregate demand (right graph, bold); strong effect on aggregate demand (left graph), for initial conditions $k(0) = 0.9, b(0) = 0.9$

- The share of households that are income and credit constrained, in the sense of Galí *et al.* (2007), and households that are higher leveraged and are under financial stress,[18] are significantly rising in a contraction period of the business cycle, see also Mittnik and Semmler (2013; 2012).

- As the financial market forces trigger banking and financial stress,[19] 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, for example by purchasing bad assets and bonds to drive down asset market risk and risk premia.[20]

- The fraction of private households start strongly deleveraging that reduces income and liquidity of other households and firms, which might be accompanied by a Fisher debt deflation process, see Eggertsson and Krugman (2012).

- 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.[21]

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[18]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).

[19]See the ZEW financial condition index.

[20]The ECB in Europe was for example constrained by the Maastricht Treaty not to purchase sovereign bonds. Later this was relaxed by allowing it to purchase sovereign bonds on the secondary market, though there a number of programs that by-passed the Maastricht Treaty.

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

Whereas the first four destabilizing mechanisms have been known in the literature and are often viewed to generate a vicious cycle, the last one, which has recently been discussed, adds a more dangerous mechanism which has been, as mentioned, called "diabolic loop".[22]

Now we expect, starting with a debt to capital stock ratio roughly above normal that the above feedback mechanisms lead to higher financial market stress and higher risk yields, higher credit spreads and lower output, leading to a contraction in the utilization of the capital stock, and capital stock itself, and to an increasing debt to capital stock ratio.[23]

The debt dynamics with endogenous credit spread and endogenous demand and output contraction of system (4) – (8) are shown in Figure 2 (left graph), using again the NMPC solution method. The situation is sketched here also assumes that the central bank cannot – or is not authorized to – bring down the financial market stress through financial market interventions.

Figure 2 (left graph) shows, starting with a debt to capital stock ratio of roughly unity, the feedback mechanisms of higher financial market stress – higher risk premia, higher yields and higher credit spreads – and lower output leading to a contraction of capital stock and increasing debt to capital stock ratio.[24]

Given those above sketched macro feedback loops and an insufficient central bank's reaction it is easily explained why there might be a regime-switch from a low to a high stress regime where vulnerabilities increase and a faster deterioration of demand and output as well as unsustainable debt dynamics are likely to occur, as shown in the two graphs in Figure 2.

3   Empirics

We next conduct an empirical analysis of amplification effects in the relation between the financial sector and economic activity in several euro area countries. The theoretical model points towards a low and high financial stress regimes and asymmetric effects of shocks in the different regimes. We pick up this type of non-linearity in our empirical study by employing a VSTAR model. It is able to replicate the dynamics shown by our theoretical model and relies on a transition function which is numerically by and large identical.

We first present new ZEW Financial Condition Indices for several euro area countries. Subsequently, we introduce the VSTAR model, the modeling cycle and the evaluation strategy. The VSTAR model has not been used in the literature dealing with the link between the financial sector and output dynamics before. The Vector STAR model is able to capture the relevant non-linear dynamics in a more sophisticated way. The last subsection discusses initially linear vs. non-linear model outcomes. Then, we analyze the financial sector – output link and its amplification mechanisms over time.

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[22]See Figure 5 in Brunnermeier and Oehmke (2012) and see also Bolton and Jeanne (2011).

[23]This could equivalently create a downward spiral in net worth, if the model is written in terms of net worth, as Brunnermeier and Sannikov (2013) and Stein (2012).

[24]Note that a contractionary effect could be accelerated if the creditors become unwilling to lend when a certain leverage ratio is reached and new borrowing or rolling over of old debt will be discontinued. For a model including such a sudden rise of credit market constraint, see Ernst and Semmler (2012).

3.1 Financial condition indices for selected euro area countries

In this section, we briefly describe the *ZEW Financial Condition Indices (FCI)* for the euro area which are subsequently used in the empirical analysis .[25] They reflect financial sector conditions and stress and have a stronger focus on the banking sector. The data set relies on 21 financial condition variables for each country.[26] Some of the variables are neglected in individual indices but, in our view, play an important role in describing financial stress and the way as it unfolded, for example, after the Lehman collapse. Our index also tracks market volumes, particularly within the banking sector. Clearly, there are strong interdependencies between the banking sector, and the performance of both the financial sector and the real economy (Brunnermeier and Sannikov 2013; Mittnik and Semmler 2013). Furthermore, our additional measures incorporate the insights from the theoretical model introduced in section 2, including the annual growth rate of assets over liabilities, which represents available bank collateral; the ratio of short- over long-term debt securities issued by banks[27]; and the annual growth rate of bank lending to the private sector. For these reasons, we believe the inclusion of banking-related factors with a strong link to the economic downturn improves the accuracy of our indices. We would like to emphasize that it is not sufficient to only construct an aggregate euro area indicator. Such an index would not adequately take into account the heterogeneity of the financial sector in individual euro area states (see also Bijlsma and Zwart (2013)).[28]

The FCIs are available for Belgium, Germany, Austria, Finland, France, Greece, Ireland, Italy, Netherlands, Portugal and Spain from 1980m01 to 2013m01 on a monthly basis (for a graph of the indices see Figure 7 in Appendix B).

The ZEW FCIs cover three (standard) categories: banking sector, securities market and foreign exchange market. The following variables represent the banking sector: interbank rate spread, Eonia/Euribor spreads, TED spread, bank stock-market returns, beta of the banking sector, CMAX interacted with the inverse price-book ratio, inverted term spread, ratio of short over long debt securities issued, bank lending to private sector, the ratio of total assets over liabilities, excess reserves, the inverse marginal lending facility, money market spread, spread of main refinancing rate and euro area 2-year government benchmark bond yield, and write-offs. The variables related to stress in the securities market are given by share price returns and their volatility, corporate debt spreads and volatility of government bond returns. Volatility of real effective exchange rates is included to reflect risk in the foreign exchange market. Most of the variables are available on country level, some are Eurozone aggregates. For a detailed description of the data see

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[25]Kliesen *et al.* (2012: p.372) state that there is a high degree of overlap between financial *stress* and *condition* indices (FSI vs. FCI). They point out that stress indices contain more price variables, whereas condition indices are broader indices including also quantities. "As such, an FSI can be considered a snapshot of the level of fragility in the financial market and an FCI a mapping of financial conditions onto macroeconomic conditions." Nevertheless, there is no clear-cut distinction of financial stress and condition indices. The ZEW indices are comprehensive indices with a fairly high negative correlation to the growth of industrial production, so they are called ZEW financial *condition* indices. They reflect both vulnerability of the financial market and a link to the macroeconomy. In the following we will refer to financial stress and financial conditions synonymously.

[26]In building our index we were inspired by Grimaldi (2010), Elekdag *et al.* (2009), Holló *et al.* (2012), and van Roye (2013).

[27]Following Geanakoplos (2011), we do not include the assets over equity ratio variable but use flows due to their more reasonable ability in explaining stress in balance sheets of banks. The former may deliver an unreasonable measure: equity is high in a boom leading to a decline in the ratio and vice versa in a bust.

[28]See also Kappler and Schleer (2013) for a more theory-related discussion of the data set.

Table 12 in Appendix B.

To account for a fairly high correlation across some variables, we use a dynamic factor model to extract the common factor which we call *ZEW Financial Condition Index*. We apply the two-step estimation approach of Doz *et al.* (2011) which has the ability to account for ragged edges of the data sample. The dynamic factor model looks as follows:

$$X_t = \Lambda_0^* F_t + \xi_t \tag{9}$$

F_t are the common factors, Λ_0^* is the matrix of factor loadings, X_t is the vector of observables, and ξ_t is the idiosyncratic component. The common factor F_t follows a (V)AR-process $A(L)F_t = u_t$. In the initial step, the factor loadings are estimated as principal components. Subsequently, the Kalman filter is applied.

To model economic activity, we use monthly growth rates of industrial production indices that are expressed in constant prices and seasonally adjusted. The data is taken from the OECD and available from 1980m01 till 2013m01.

The FCIs for the euro area countries properly capture country-specific as well as euro area-wide stress periods. This means that they accurately indicate financial stress in response to experienced financial market and banking turmoil. They also properly reflect the risk associated with the financial market breakdown in Europe in 2008, as well as the sovereign debt crisis that began to unfold in 2011. The ZEW FCIs are negatively correlated with the growth rates of industrial production in each respective country. We therefore believe that the ZEW FCIs can furnish valuable new insights into the link between financial sector turmoil and economic dynamics in several euro area countries.

Table 1: Correlations of FCIs and IP

	AUT	BEL	FIN	FRA	GER	GRE	IRE	ITA	NLD	PRT	ESP
corr(IP,FCI)	-0.0851	-0.0505	-0.1271	-0.1249	-0.2028	-0.0426	-0.0438	-0.0523	-0.0593	-0.0425	-0.0286

3.2 A non-linear Vector STAR approach

The Vector STAR model is able to replicate the mechanisms described in the theoretical model before. It can capture smooth or abrupt regime-switching based on an observable transition variable which allows for a straightforward economic interpretation. The VS-TAR model can model asymmetric amplification effects in different regimes. The hitherto studies, which incorporate non-linearities, apply Markov Switching or Threshold Vector Autoregressive (TVAR) models. We prefer a model with an observable transition variable such that we can define a meaningful set of regimes for a particular state of the economy or the financial market (e.g. low/high stress). Hence, we do not work with Markov Switching models which do not easily offer a direct economic interpretation. Moreover, the speed of transition from one regime into the other like it can be modeled in a TVAR model does not appear plausible in our application. An economy which currently faces high financial market stress may likely not abruptly switch to a low stress regime but the transition may take a while. For a comprehensive survey on non-linear Vector models see Hubrich and Teräsvirta (2013).

3.2.1 The VSTAR Model

The logistic Vector STAR model looks as follows[29]:

$$\mathbf{y_t} = \Big\{ \sum_{i=1}^{m} (\mathbb{G}_{\mathbf{t}}^{\mathbf{i-1}} - \mathbb{G}_{\mathbf{t}}^{\mathbf{i}}) \mathbf{F}_{\mathbf{i}}' \Big\} \mathbf{x_t} + \varepsilon_{\mathbf{t}} \tag{10}$$

where $\mathbf{y_t}$ is a $k \times 1$ column vector, $\mathbf{x_t} = (\mathbf{y_{t-1}'}, \ldots, \mathbf{y_{t-p}'}, \mathbf{d_t'})'$, and $\mathbf{d_t}$ a vector containing deterministic components. $\mathbf{F_i} = (\mathbf{A_{i1}'}, \ldots, \mathbf{A_{1p}'}, \mathbf{\Phi_i'})'$ includes coefficient matrices. The error term $\varepsilon_{\mathbf{t}}$ is assumed to be independent normal with zero mean and variance-covariance matrix Ω. $\mathbb{G}_{\mathbf{t}}^{\mathbf{i}}(.)$ is a diagonal matrix of transition functions such that different transition function across equations can be modeled:

$$\mathbb{G}_{\mathbf{t}}^{\mathbf{i}}(.) = \mathrm{diag}\big\{ \mathbf{g}(s_{1it}|\gamma_{i1}, c_{i1}), \ldots, \mathbf{g}(s_{kit}|\gamma_{ik}, c_{ik}) \big\} \tag{11}$$

for $i = 1 \ldots, m-1$, where m determines the number of transitions across equations and $\mathbb{G}_{\mathbf{t}}^{\mathbf{0}} = \mathbf{I_k}, \mathbb{G}_{\mathbf{t}}^{\mathbf{m}} = \mathbf{0}$. The transition function are assumed to be of logistic type which is monotonically increasing in s_{ijt} and bounded between zero and one.

$$\mathbf{g}(s_{ijt}|\gamma_{ij}, c_{ij}) = [1 + \exp(-\gamma_{ij}(s_{ijt} - c_{ij}))]^{-1}, \ \gamma_{ij} > 0 \tag{12}$$

The transition function depends on the transition speed (γ_{ij}), the location parameter (c_{ij}) and the transition variable (s_{ijt}). Usually, a d-times lagged endogenous variable is used. There is also the special case where only one transition function governs the whole system, then, $\mathbb{G}_{\mathbf{t}}^{\mathbf{i}}(.) = \mathbf{g}(s_{ijt}|\gamma_i, c_i)\mathbf{I_k}$. The latter specification associated with $m = 2$ will used in the application in the next section. The slope parameter γ_{ij} and thereby, the Vector STAR model is redefined by

$$\gamma_{ij} = \exp(\nu_{ij}), \tag{13}$$

where ν_{ij} is the parameter to be estimated following Schleer (2013). Redefining γ_{ij} facilitates the construction of a grid because one can build an equidistant grid in the dimension of ν_{ij}. The search space (grid) for γ is then automatically dense in the beginning and less so when it becomes large which is a sensible choice for estimating the Vector STAR model. In order to make γ a scale-free parameter, it is divided by the standard deviation of the transition variable when the parameters of the VSTAR model are estimated following Teräsvirta (2004).

We use a logistic function since it is able to capture the kind of asymmetries we are interested in and resembles the non-linearities shown by our theoretical model. The effects of shocks can vary across low and high stress scenarios. If the economy is already in a distressed period, an increase in financial stress might have different, e.g. stronger and longer lasting, effects on the real economy than in a low stress scenario due to the previously described endogenous feedback mechanisms. Destabilizing effects may set in such that economy does not converge to a stable equilibrium again. Technically, the logistic function is bounded between zero and one. If γ tends to infinity it converges to a pure threshold model and if γ approaches zero it collapses to a linear VAR model. The location parameter c defines the threshold.

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[29]The notation is taken from Teräsvirta and Yang (2013a).

3.2.2 The Modeling Cycle

A Vector STAR model has the advantage of having a fully specified modeling procedure at hand consisting of three steps: testing linearity, specifying and estimating the Vector STAR model and finally, evaluating the model.[30] We proceed as follows:

Unit root tests: We check stationarity of the individual FCI and IP series by applying two tests: ERS DF-GLS and ERS point-optimal developed by Elliott *et al.* (1996). Those tests have better power properties and lower size distortions in comparison to the standard ADF test (Hayashi 2000: p.601). Moreover, we test the stability condition of the linear VAR model, that its reverse characteristic polynomial has no roots in and on the complex unit circle (Lütkepohl 2005: p.16). To the best of our knowledge, unit root or stability tests derived for a Vector STAR with logistic type transition function are not available. Consequently, we stick to tests for univariate series and a linear model.

Testing linearity: We apply a joint linearity test of the whole Vector STAR system as recommended by Camacho (2004), Weise (1999) and formalized by Teräsvirta and Yang (2013b). Therefore, we rely on Rao's statistic which is recommended by the latter authors due to satisfying size properties. The lag length is selected by the Schwarz Information criterion (Schwarz 1978) and the maximum lag length is set to maxlag = round($12(T/100)^{(1/4)}$) which is the formula suggested by Schwert (1989). We rely on the full lag structure, as otherwise the power of linearity tests is harmed (see Teräsvirta (2004: p. 225)). Based on the implications of our theoretical model, we use the ZEW FCIs reflecting financial market stress as transition variable for both the FCI and IP equation. To determine the lag of the transition variable, its maximum is set to 3. We do not expect that a higher lag, i.e. a state of the transition variable several months ago, is economically reasonable in defining the "stress regime".[31] We choose the lag which rejects linearity at the 5% level and has the smallest p-value across the tested lags.

Selecting the lag length and estimation: A constant is always included in our model. We select the lag length by the Schwarz Information criterion based on a linear VAR model, generate starting-values by using the differential evolution algorithm in a multivariate framework suggested by Schleer (2013) and estimate the model by Maximum Likelihood (interior-point algorithm). If there is still serial correlation in the residuals—we test serial correlation of order one to twelve—, we add another lag until the serial correlation test of Teräsvirta and Yang (2013b) with wild-bootstrapped p-values cannot reject the null of no serial correlation. The wild-bootstrap is based on Godfrey and Tremayne (2005).

We bound our estimation problem with respect to the γ and c by using 0.5 and 30 as bounds for the slope parameter γ. The former implies a very smooth transition, whereas the latter results in model already close to a TVAR. To get the bounds of c, we rely on the approach of Schleer (2013) defining c as a function of the transition speed: $c = f(\gamma)$. If γ is high, implying a low number of observations around the threshold, we use a truncated sample of the observations of the transition variable for c. For a low γ, we use the full support of the transition variable.

Moreover, in our application there are three additional features which should be considered for finding the optimal location parameter. First, a value of zero means neutral financial market conditions. Second, the transition variable, the ZEW FCIs, are strongly positively skewed as can be seen in Table 2. Third, high stress occurs less often than low

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[30]Teräsvirta (1998) describes the modeling cycle for a univariate procedure and Teräsvirta and Yang (2013a;b) extend it for a multivariate Vector STAR model.

[31]This is confirmed by the results as the most frequent lag chosen by the selection procedure is one (see section 3.3).

stress. If we used a symmetric range to get the support of the transition variable, we would exclude most of or even the complete high stress regime. As a consequence, we take the value which is closest to zero as center (separating negative and positive values) and use the lower 20% and upper 40% percentile around this value for finding the threshold c. The asymmetry of the intervals accounts for the skewness of the indices.

Table 2: Skewness of ZEW Financial Condition Indices

	AUT	BEL	FIN	FRA	GER	GRE	IRE	ITA	NDL	PRT	ESP
skewness	1.928	1.871	1.502	2.004	2.010	1.137	1.995	1.621	2.183	1.855	0.595

Evaluation stage: As discussed above, we ensure that our estimated VSTAR models do not suffer from serial correlation in the residuals.

3.2.3 Empirical Strategy

To get insights into financial market – macro linkages, we conduct several analyzes. We apply a bivariate VSTAR model with $y_t = [\Delta \log IP, FCI]$ for each country based on the FCI as transition variable. Assuming one transition function governing the whole system, the VSTAR model has two different histories (regimes)[32]:

$$
\begin{aligned}
&\text{FCI}_{t-d} < c \text{ (low stress regime)} \\
&\text{FCI}_{t-d} \geq c \text{ (high stress regime)}
\end{aligned}
\tag{14}
$$

Initially, we perform Granger causality tests which are based on the VSTAR model, thus, taking the non-linearity into account. Since we rely on a model with two regimes, we technically can "divide" the model in a linear and non-linear part. Hence, we can test Granger causality based on the linear parameters only and on the linear plus non-linear parameters.

Second, we construct non-linear IRFs, namely "Generalized" IRFs, following the method of Koop *et al.* (1996) and Weise (1999) who applies the approach to Vector STAR models. There are important differences between linear and non-linear IRFs: the latter are history-dependent, their future shocks may not necessarily be zero, and, they are not invariant to the size and the sign of a shock. We use $B = 100$ bootstrap repetition and $R = 100$ Monte Carlo replications. By using "Generalized" IRFs, we are able to model asymmetric dynamics with respect to the regime in which the shock has taken place. The non-linear IRFs are not restricted to remain in one regime. In other words, we allow for regime-switching after the initial shock.

We use a Cholesky decomposition to derive structural responses. There are two possible factorizations. First, the financial condition index has a contemporaneous effect on industrial production, whereas a shock to industrial production does not affect the financial sector in the same period. Holló *et al.* (2012) and van Roye (2013) apply this setting arguing that the current level of IP cannot be observed by market participants due to the publication lag. Hence, the realization cannot be reflected in the variables underlying the FCI. On the contrary, Mittnik and Semmler (2013) and Hubrich and Tetlow (2012) rely on the reverse ordering. In this case, a variable representing financial market dynamics

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[32]From an economic perspective, it does not seem to be reasonable to distinguish between more than two financial stress regimes. Something of the kind of a "medium" stress regime is not indicated by economic theory as well. There is either convergence or a loss of stability which are labeled as low and high financial stress regimes.

as the FCI is considered to be fast reacting to change in output, whereas output is rather sluggishly adjusting. The latter ordering seems to be more plausible from our point of view, hence, we stick to that form of orthogonalization.

3.3   Results

Before we discuss the results of Granger causality tests and impulse response functions, we first present the outcomes of the model selection tests—unit root and linearity tests—, beginning with the former. Except of the FCI of Portugal, Spain and Ireland, the FCI and IP growth series of all countries are confirmed to be stationary by at least one test.[33] Recall that we perform two tests: ERS DF-GLS and ERS point-optimal. Mostly, both test results coincide indicating stationarity of the time series which is perfectly in line with our expectation that neither IP growth nor FCI exhibit a trend-like behavior.

Non-stationarity of the FCI of Portugal, Spain and Ireland was found at the 5% level. We exclude Ireland from our analysis, whereas we adjust the sample for Portugal and Spain as non-stationarity in the FCI series appears to be a more recent phenomena. The FCI indices of those two countries are steadily increasing after the financial market breakdown due to the sovereign debt crisis setting in quite heavily as well. We assume that the underlying DGPs change essentially. This seems plausible due to the recent economic development in Spain and Portugal with significant distortions in various sectors and unsustainable paths of sovereign debt. We take this as weak evidence that the series are stationary up to a certain point in time, but check carefully in the estimation stage whether the VSTAR model exhibits unstable or explosive behavior. The sample periods for each estimated model can be seen in Table 3. The stability condition of a (linear) VAR model is satisfied for each country.

Table 3: Sample Periods

	AUT	BEL	FIN	FRA	GER	GRE	ITA	NDL	PRT	ESP
1980:01 –	2013:01	2012:12	2013:01	2013:01	2013:01	2013:01	2012:12	2013:01	2011:07	2011:09

Rejecting linearity is a necessary condition for estimating a non-linear VSTAR model. If a linear relation is estimated by means of a non-linear model, this model would contain unidentified parameters. The null of the linearity test (Rao's test statistic) is rejected confirming non-linearities in the financial sector output dynamics for each country. For the majority of models the lag length of the transition variable was chosen to be one indicated by the smallest p-value across the tested lags. This is in line with our expectation that a more recent FCI, in terms of its delay, is appropriate for determining the regime in the financial market – output nexus. The only exception is Spain, for which the smallest p-value was found for lag three. Overall, joint non-linearity has been detected allowing us to estimate multivariate VSTAR models for all countries.[34]

3.3.1   Linear vs. Non-linear Analysis

In the following, we present results of Granger causality tests and impulse response functions for the whole sample period contrasting linear and non-linear outcomes. Although

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[33]The results can be found in Table 13 in Appendix C.

[34]In section 3.3.2 we will discuss the results of the linearity tests in more detail, particularly, their evolution over time.

the linearity tests confirm our conjecture of a non-linear relation, we derive further insights into linear and non-linear model specifications for two reasons: (1) to check whether differences between linear and non-linear models are qualitatively and quantitatively relevant, and (2) to compare the VSTAR outcomes with those derived by means of different model types in the literature.

In the following, we discuss results of Granger causality tests for a linear VAR model and a non-linear VSTAR model. Table 4 presents the results for a linear model. The FCIs Granger cause industrial production in all euro area countries except for Greece and Portugal at a 5% level of significance. On the contrary, output does not Granger cause financial market conditions in all countries except for Spain. These results give us a fairly clear picture indicating that the FCI is useful in forecasting industrial production, whereas the reverse is not the case. Based on a linear VAR model, industrial production does not comprise statistically relevant information for the future situation of financial conditions. Moreover, we cannot detect strong cross-country heterogeneity. The overall picture is rather identical for the euro area countries.

Table 4: p-values of Granger causality tests – linear VAR model

country	FCI $\rightarrow$ IP	IP $\rightarrow$ FCI
Austria	**0.0145**	0.5674
Belgium	**0.0045**	0.8418
Finland	**0.0000**	0.1984
France	**0.0051**	0.9289
Germany	**0.0000**	0.4707
Greece	0.2022	0.7701
Italy	**0.0408**	0.4434
Netherlands	**0.0001**	0.3591
Portugal	0.1008	0.8529
Spain	**0.0062**	**0.0401**

Bold numbers indicate significance at the 5% level.

As linearity tests indicate non-linear behavior, we contrast the VAR with Granger causality VSTAR-results. We test Granger causality based on both linear parameters and linear plus non-linear parameters. The results for the non-linear Vector STAR models differ clearly from those generated by the linear VAR model as can be seen in Table 5. This holds for both the linear and the linear plus non-linear part. Focussing on the second column of Table 5 which describes the whole (non-linear) model dynamics, we detect significant interdependent financial market output relations for Austria, Belgium, Spain, Germany, and the Netherlands. This insinuates the existence of an adverse feedback loop, as it was called by the chairman of the FED Bernanke: a shock to the financial sector may result in a long-lasting detrimental effect on output, but the economic contraction may also feedback on the financial sector again.

This effect might be neglected if one relies on a linear VAR model which is not able to capture a regime change. It can therefore not switch to a financially distressed regime which in turn yields negative effects for economic activity. The latter is also shown by our theoretical model. Moreover, the results based on the non-linear VSTAR model point towards more heterogeneity across the euro area countries than linear Granger causality does. In particular, Greece and Italy do not show any significant Granger causality. We will keep this in mind for later analyses as this questions feedback effects between the financial sector and economic activity in these countries, at least for the full

sample. Overall, this emphasizes the importance of non-linearities in the financial market output nexus once more and points out that the differences between linear and non-linear outcomes are qualitatively relevant.

Table 5: p-values of Granger causality tests – non-linear VSTAR model

	linear parameters		linear and non-linear parameters	
country	FCI $\rightarrow$ IP	IP $\rightarrow$ FCI	FCI $\rightarrow$ IP	IP $\rightarrow$ FCI
Austria	0.0607	**0.0026**	**0.0151**	**0.0000**
Belgium	0.2777	0.1516	**0.0000**	**0.0167**
Finland	0.0557	0.2845	**0.0000**	0.1039
France	0.2895	0.9939	**0.0064**	0.4726
Germany	0.1286	**0.0355**	**0.0001**	**0.0171**
Greece	0.8831	0.1124	0.2396	0.0971
Italy	0.4042	0.7364	0.1495	0.2224
Netherlands	**0.0056**	0.9980	**0.0000**	**0.0305**
Portugal	0.4954	0.0340	0.0756	**0.0161**
Spain	**0.0006**	0.3766	**0.0002**	**0.0100**

Bold numbers indicate significance at the 5% level.

Having found further empirical evidence for considerable distinctions between linear and non-linear model outcomes, we compute impulse response functions based on a one standard deviation shock in FCI and report the accumulated response of economic activity after 6,12,18, and 24 months. This is done for both a linear VAR model and non-linear VSTAR model. Results for the former are shown in Table 6. The linear IRF show the expected results of a, in most cases significant, negative response of industrial production after a shock which worsens financial conditions. After 24 months industrial production is for all countries on average 0.75% lower indicating a long-lasting permanent negative effect on the real economy.

Table 6: Accumulated responses of IP after shock in FCI, VAR model

	AUT	BEL	FIN	FRA	GER	GRE	ITA	NLD	PRT	ESP
6 m	-0.29%	-0.47%	-0.44%	-0.34%	-0.67%	-0.30%	-0.39%	-0.44%	-0.39%	-0.38%
12 m	-0.51%	-0.54%	-0.88%	-0.52%	-1.10%	-0.51%	-0.57%	-0.63%	-0.57%	-0.50%
18 m	-0.66%	-0.58%	-1.13%	-0.61%	-1.24%	-0.61%	-0.57%	-0.67%	-0.65%	*-0.43%*
24 m	-0.76%	-0.61%	-1.29%	-0.66%	-1.28%	-0.68%	*-0.56%*	-0.64%	*-0.70%*	*-0.32%*

Italic numbers indicate statistically insignificant responses, Monte Carlo confidence bands, +/- 2 S.E.

In a linear VAR model set-up, however, we cannot differentiate between different regimes which may likely influence the outcomes. Linear models can only handle symmetric effects, whereas a non-linear model set-up is able to capture potential asymmetric dynamics within the financial sector – output relation. It is a priori not clear how non-linearities influence the relation between the financial sector and the real economy. The negative response in a high (low) stress regime could be higher (lower) due to feedback effects from the real sector to the financial market which cannot be taken into account adequately by a linear model. On the contrary, allowing for regime-switching could also lead to smaller negative effects on the macroeconomy. After 6 or 12 months the economy may likely be faced by at least one regime shift or another shock hitting the economy. The initial shock has taken place in a high stress regime, but it may propagate by facing different regimes. Hence, a

shift to a low stress regime may dampen the negative consequence on the real economy. In any case, different regimes may alter results and their consideration is important for understanding the financial sector output nexus.

Before results of the VSTAR-IRFs will be discussed, the values of the optimized location and slope parameters for each country are shown in Table 7. These parameters clearly vary across countries. Moreover, a smooth rather than an abrupt change takes place for most countries.[35] The optimized slope parameter which determines the transition speed is on a moderate level. Only Italy constitutes an exception showing a rather high transition speed from one to the other regime. The overall finding is in line with our expectation that regime-switching takes place rather smooth. A financially distressed economy will likely not abruptly switch to a low stress regime but the transition may take some time. This result is particularly important for the interpretation of the results of multi-regime VAR or Threshold VAR models which model a sudden regime-change. The type of non-linearity in the financial market – output relation may be different as suggested by the VSTAR model. This may produce misleading results of those kind of models. The location parameter is also very heterogenous across countries. In most countries it is above or close to zero which is reasonable. The higher the threshold, the worse the financial conditions of an economy need to be, so that the economy enters a high stress regime. The location parameters cannot be easily compared across countries. The FCIs are country-specific; thus, the support for the optimization problem differs.

Table 7: Optimized location and slope parameter, VSTAR models

	AUT	BEL	FIN	FRA	GER	GRE	ITA	NLD	PRT	ESP
c	2.03	2.58	-0.55	1.56	1.29	-0.59	-0.29	1.48	1.36	1.63
std.dev.	1.3115	2.2819	0.0350	0.0610	0.4194	0.0882	0.0014	0.0267	0.5392	0.0365
γ	0.50	0.50	2.20	4.11	0.50	1.43	30.00	2.09	0.50	3.95
std.dev.	0.3915	0.5073	0.0735	0.2200	0.2338	0.1156	0.0454	0.0490	0.2638	0.1309

In Table 8 the accumulated responses of IP after a one standard deviation FCI shock for a non-linear VSTAR model are presented. Our IRF-setting allows for regime-switching and further shocks which is a reasonable scenario and neglected in some studies. The interpretation is as follows: a shock took place either in a low or high stress regime and the (average) response is calculated without setting future shocks to zero. For Germany, Austria, Belgium, Finland, the Netherlands and Portugal, we find a negative response of IP after a shock in the high financial stress regime which more detrimental than in the low stress regime. This is line with the hitherto empirical literature applying Markov Switching models or Multi-regime VARs (e.g. van Roye (2013); Hubrich and Tetlow (2012); Mittnik and Semmler (2013)). Except for Portugal, the responses both for a low and high stress regime shock are smaller than for the linear VAR. This may likely come from allowing for regime-switching, not setting future shocks to zero and modeling more flexible transmission mechanisms in the economy. As a consequence, the regime-switching dampens the effect on the real economy, although we allow for non-linear feedback effects of industrial production.

For France and Greece, we cannot find a negative reaction of IP after a financial sector shock. This may be only surprising in the first instance. The share of manufacturing of GDP for Greece and France is below 20% and by far the lowest across the considered euro area countries. Hence, the economy of both countries may likely suffer from a financial

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[35]This can also be seen in Figure 8 in the Appendix.

sector shock but this might be rather reflected in different sectors of the economy. Portugal and Spain show the strongest negative effect in IP after the shock. This is in line with the recent economic developments. Portugal and Spain suffer dramatically from the financial market turmoil and sovereign debt crisis. Surprisingly, the results for Spain are stronger if the shock took place in the low stress regime. In Italy the response of IP is negative in both regimes, but it does not influence the results much in which regime the shock has taken place. This may be explained by the fact that the Italian economy has faced many shocks and has not remained in a regime for a long time.

Bijlsma and Zwart (2013) have classified countries with respect to their financial market structure as market based or bank-based by using a wide-range of indicators. According to them, Germany, Austria, Spain, Italy, Greece and Portugal belong to the latter group. France, Belgium, Finland and the Netherlands have market-based financial sectors. By taking the mean of each group 24 months after a shock, the economies with a bank-based financial sector show a lower mean of -0.43% than the ones with a market-based financial sector -0.05% after a shock in a low stress regime as well as in a high stress regime -0.77% vs. -0.25%. This gives some empirical evidence that recessions are more severe and recovery takes longer when shocks emanate from bank-based rather than market-based financial sectors (see also Boissay *et al.* (2013)).

Table 8: Average of accumulated responses of IP after shock in FCI, VSTAR model

	AUT	BEL	FIN	FRA	GER	GRE	ITA	NLD	PRT	ESP
	low stress									
6 m	0.15%	0.28%	-0.35%	0.04%	-0.31%	0.18%	-0.25%	-0.40%	-0.57%	-0.61%
12 m	0.02%	0.41%	-0.28%	0.01%	-0.37%	0.21%	-0.25%	-0.50%	-0.50%	-0.96%
18 m	-0.06%	0.46%	-0.30%	0.00%	-0.38%	0.16%	-0.17%	-0.32%	-0.06%	-1.13%
24 m	-0.10%	0.39%	-0.30%	0.00%	-0.38%	0.19%	-0.10%	-0.30%	-0.95%	-1.25%
	high stress									
6 m	-0.16%	-0.10%	-0.81%	-0.12%	-0.53%	0.37%	-0.22%	-0.58%	-0.94%	-0.26%
12 m	-0.20%	-0.16%	-0.57%	0.11%	-0.59%	0.33%	-0.29%	-0.40%	-0.82%	-0.69%
18 m	-0.23%	-0.19%	-0.62%	0.11%	-0.60%	0.06%	-0.18%	-0.19%	0.76%	-0.92%
24 m	-0.26%	-0.20%	-0.61%	0.08%	-0.59%	0.43%	-0.08%	-0.25%	-3.08%	-1.04%

Overall, we identify regime-specific, non-linear dynamics. These are not as different across regimes and as negative as it was found by previous studies (see, for instance Aboura and van Roye (2013) for France, Hubrich *et al.* (2013), and Holló *et al.* (2012) for the Eurozone). This may not only come from rather smooth regime-changes, but the allowance for regime-switching and further shocks after the initial shock may likely dampen the negative effect over time and give us a more realistic picture of the dynamics within economies. Yet, also the time period under study may play a crucial role for the results. This issue will be discussed next.

3.3.2 Non-linearities over time

To identify potentially changing transmission and amplification mechanisms in the relation between the financial sector and economic activity, we first analyze whether non-linearities constitute a permanent feature in that relation by means of linearity tests. Second, we compute rolling impulse response functions (RIRF) to analyze the evolution of potentially altering dynamics.

Before the non-linear model is estimated, we check whether the relation between the financial condition indices and industrial production is indeed non-linear. In order to circumvent unidentified parameters and derive valid results, it is crucial to ensure that non-linearities receive also statistical support.

We start at the beginning of 1995 and estimate the country-specific bivariate VSTAR models with increasing sample size. Starting in 1995 aims at balancing the trade-off between the econometric validity and the economic interest. The former requires a sample period which is as long as possible to reliably estimate the VSTAR model. The latter favors starting the rolling analysis as early as possible to get broad insights in potentially changing dynamics. Starting in 1995:01 leaves us with 180 observations for the first VSTAR model which appears to be a good compromise.

Stationarity tests, lag selection and estimation strategy are as described above. Based on the (rolling) unit roots tests, we excluded Ireland in our analysis as the FCI series suffers from non-stationarity over a significant time period. For some other countries, we adjusted the sample if the VSTAR model shows unstable behavior.[36]

The results of the rolling linearity tests based on Rao's statistic are discussed in the following and reported in Table 9. Belgium, Finland, France and Portugal show highly non-linear dynamics in the financial sector output link over the complete rolling sample. Linearity is rejected at a 1% level of significance. For the second group of countries, comprising of Germany, Greece and the Netherlands, the null of linearity is rejected mostly at a 1% or 5% level of significance. There are few exceptions for Germany and the Netherlands for which linearity can only be rejected at the 10% level. Nevertheless, we take this as empirical evidence that also these three countries exhibit non-linear dynamics in the financial market – macro link. Spain, Austria, and Italy constitute the third group. Before the financial crisis outbreak, we cannot reject the null of linearity at a usual level of significance. Yet, after the collapse Austria, Italy and partly Spain exhibit non-linear dynamics in the financial market – output relation. The pattern which is most clear for the latter three countries, a decrease in the p-value after the Lehman collapse, is qualitatively identical across most euro area countries. The average of pre-crisis p-values is clearly higher than for the crisis period. Hence, non-linearities become "(more) evident".[37] Except of Austria, Italy and Spain, the countries also exhibit non-linear dynamics before the collapse, whereas the latter group switches from linearity to non-linearity.

Table 9: Mean of p-values of rolling linearity tests (Rao's statistic)

	AUT	BEL	FIN	FRA	GER	GRE	ITA	NLD	PRT	ESP
full sample	0.26772	0.0000	0.0000	0.00001	0.00628	0.0000	0.10902	0.00590	0.00002	0.30138
pre-crisis sample	0.35425	0.0000	0.0000	0.00001	0.00812	0.0000	0.14141	0.00774	0.00002	0.33038
crisis sample	0.00000	0.0000	0.0000	0.00000	0.00000	0.0000	0.00389	0.00000	0.00004	0.17286

Full sample refers to 1980m01:2013m01 (exceptions see Table 14), the pre-crisis sample to 1980m01:2008m08 and the crisis sample to 2008m09:2013m01.

The drop in the p-value after 2008m08 may indicate that the non-linearities in the financial market – output relation may not be present or weaker before.[38] For most countries the (whole sample) relation appears to be non-linear. When focussing on subsamples,

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[36]The exclusions are reported in Table 14 in Appendix D.

[37]Belgium, Finland, and Greece may be seen as an exception. The p-values are extremely low before such that a significant further drop cannot be observed.

[38]It further stands out that if linearity is rejected, the test selects lag one of the FCI as transition variable in 76%. This further confirms our conjecture that a FCI with a more recent delay determines the regime.

this is not necessarily the case. However, conditional on being only in a low stress regime the interplay between FCI and IP should be only linear. This may likely be the rationale behind the shift to a non-linear relation after the Lehman collapse as can be seen most clearly for Austria, Italy, and partly Spain. Spain, however, does mostly not show a non-linear link in both the pre-crisis and crisis period. Nevertheless, we cannot rule out that the reasoning for Austria and Italy also holds for Spain. For most other countries the tests permanently support regime-switching dynamics. We can take away from the linearity tests that the financial sector – output nexus does not always exhibit inherent non-linearities in each country. Declining p-values from the pre-crisis to the crisis sample point towards a change in the dynamic behavior and amplification mechanisms.

To investigate the evolution of non-linearities further, we compute rolling non-linear IRFs for those countries exhibiting non-linearities over the whole sample period. Those countries are Belgium, Finland, France, Portugal, Germany, Greece, and the Netherlands. We compute RIRFs for Spain, Italy, and Austria as well. We cannot rule out that in those countries the relation is linear before 2008m09 because their economies have permanently been in a low stress regime before. Hence, for all countries except Ireland we analyze whether amplification effect differ in the relation between the financial sector and the real economy over time.

Results are presented in more detail for Germany in the following. Results of France, Greece, the Netherlands, Finland, Spain, Italy, Austria and Belgium are discussed in the following as well and can be found in Appendix D.[39] In Figure 3 the rolling impulse response functions for Germany show a highly interesting pattern. Before the Lehman collapse, up to September 2008, a shock to the financial sector does not lead to a significant, long-lasting or even negative response of industrial production in Germany. This holds for a shock in both the low and high stress regime. The financial crisis looks like a structural break in the financial sector output relation. The dynamics are clearly changing after the financial sector is dramatically under strain as a result of the Lehman collapse. From September 2008 on, the response of economic activity is clearly negative and persistently remains on a lower level. The dot-com bubble, an event which also puts the financial market in Germany under pressure, does not result in remarkable and persistent consequences on the real economy. From that perspective, the financial crisis 2008 appears as an "outlier event". Note that the recession had multidimensional sources and was supported by worsening macro conditions as it is argued in Abadir (2011). The financial sector shock may then likely be the ultimate source and triggering event generating adverse feedback loops and a loss of stability.

The mean of rolling IRFs for 6,12,18 and 24 months after the initial shock has taken place is shown in Table 10. We compare the mean of the RIRFs across regimes and across periods: the full sample 1980m01 – 2013m01, the pre-crisis sample 1980m01 – 2008m08 and the crisis sample 2008m09 – 2013m01.

In the period after the Lehman collapse, which we call the crisis period, the IRFs show the expected and in the hitherto literature described results of asymmetric significant, negative responses across high and low stress regimes. Our results suggest counterintuitively that prior to the crisis, impacts on output were stronger during low than high stress periods. This indicates that in a low stress regime the consequences for the real economy are more negative which is at odds with the results of the hitherto theoretical

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[39]The financial sector output nexus of Portugal shows instabilities which may come from explosive behavior due to non-stationarity of the system. Hence, we do not present those results. Recall that we test non-stationarity of the individual series but we cannot test non-stationarity of the whole VSTAR system as econometric theory has not been developed so far.
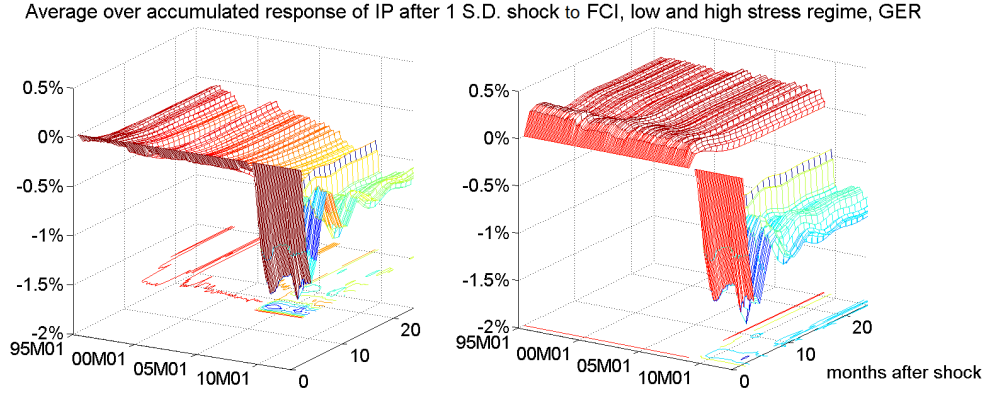
Figure 3: Rolling IRFs of IP, 1 S.D. shock, Germany

and empirical literature. Before the crisis non-linearities in the financial sector output link may not have been present or had perhaps been rather weak previously. Moreover, further (smaller) shocks or frequent regime-switches may result in undistinguishable outcomes between regimes. The stronger amplification effects after the Lehman collapse may likely come from the fact that the economy remains in a high stress regime for a substantially long time, and thus, an adverse feed-back loop may have been triggered. Before the Lehman collapse there may have not been such a "high" stress situation so that detrimental feedback effects have been generated.

Table 10: Average over accumulated response of IP after 1 std.dev. shock in FCI, Germany

	full sample		pre-crisis sample		crisis sample	
	low stress	high stress	low stress	high stress	low stress	high stress
6 months	-0.27%	-0.06%	-0.22%	0.13%	-0.44%	-0.66%
12 months	-0.36%	-0.09%	-0.28%	0.13%	-0.62%	-0.84%
18 months	-0.39%	-0.10%	-0.30%	0.13%	-0.67%	-0.88%
24 months	-0.39%	-0.10%	-0.31%	0.13%	-0.68%	-0.88%

Full sample refers to 1980m1:2013m1, the pre-crisis sample to 1980m1:2008m08 and the crisis sample to 2008m09:2013m1.

This effect has not been discussed in the literature so far. It leads to the questions whether the financial crisis is only a larger shock or whether the amplification mechanisms changed after the Lehman collapse. Based on our results, the shock propagation and dynamics have clearly changed. Yet, the shock size is always one standard deviation, which is significantly increasing in the course of time as can be seen in Figure 4. Figure 9 in the Appendix shows that this holds for most other countries as well.

To analyze whether the change in the dynamics and intensity of the negative response of the real economy is solely driven by the size of the shock, we also calculate RIRF where we control for the shock size. We normalize the shock size to be 0.2348 for all RIRFs which is the mean of the (one standard deviation) shock of the rolling window sample from 1995:01 to 2013:01 for Germany.

As can be seen from Figure 5, it is obviously not only the size of the shock which matters. There have been also systematic changes in the amplification mechanisms compared to previous times. Although we control for the size of the shock, the dynamics clearly change after the Lehman collapse independent of the regime in which the shock took place. This is in contrast to results derived by Benati (2013). He argues that financial crisis results in
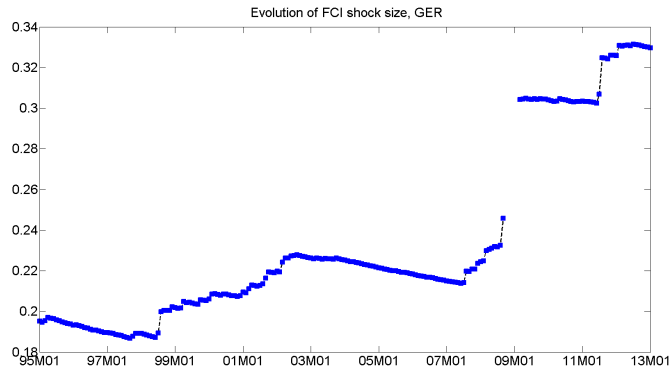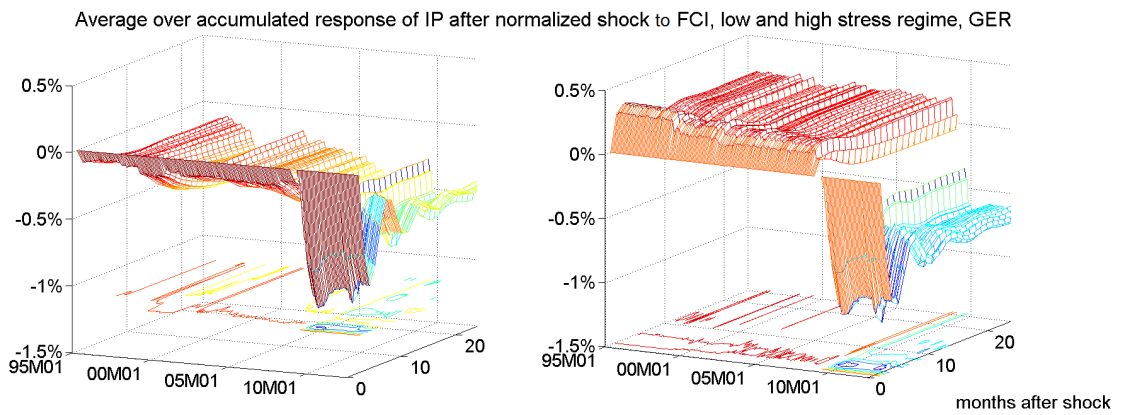
Figure 4: Shock size of FCI, Germany

Figure 5: Rolling IRFs of IP, normalized shock, Germany

25

very similar macro fluctuations as they are in normal times, but only the size of the shock matters. Yet, Benati (2013) does not account for a stochastic regime-switching, hence non-linear behavior, which most likely does not capture the dynamics adequately. The sample-specific means confirm those results derived with non-normalized shocks (see Table 11). In line with our theoretical model, we find that the amplification effects are weaker for a shock in a low stress regime. Moreover, prior to the financial crisis outbreak we find convergence and corridor stability even if the shock takes place in a high stress regime. More important seems to be the shock propagation over time in the economy. If the economy does not shift to a period of low financial stress, we detect endogenous feedback loops and a loss of stability as described by the high stress regime of our theoretical model. Therefore, the economy leaves the corridor of stability and is prone to adverse feedback loops.

Table 11: Mean of accumulated response of IP after normalized shock in FCI, Germany

	full sample		pre-crisis sample		crisis sample	
	low stress	high stress	low stress	high stress	low stress	high stress
6 months	-0.26%	0.00%	-0.24%	0.14%	-0.33%	-0.49%
12 months	-0.34%	-0.03%	-0.31%	0.15%	-0.47%	-0.62%
18 months	-0.37%	-0.04%	-0.33%	0.15%	-0.51%	-0.65%
24 months	-0.38%	-0.04%	-0.34%	0.15%	-0.51%	-0.66%

Full sample refers to 1980m01:2013m01, the pre-crisis sample to 1980m1:2008m08 and the crisis sample to 2008m09:2013m01.

The results are similar for the other countries, but they differ with respect to their magnitude and clarity. We present the normalized shock response in Appendix D. After 2008m09 the response of industrial production for France, Finland, Italy, and Belgium is negative although we control for the shock size, whereas it varies around zero before. Accordingly, the change in the dynamics and intensity of the negative impact on the real economy is not solely driven by the size of the shock. The wavelike behavior of the RIRFs in some countries might likely be a result of further—albeit smaller—shocks which take place. In Italy, we observe only a initially negative response in the high stress regime, whereby this effect does not seem to be very persistent. For Austria and Spain, the results change after the financial crisis as well, but we also identify some periods with harmful effects for the real economy after a financial sector shock before. Note that from our previous results it is not clear whether the link between the financial sector and output in Austria and Spain should be modelled by a non-linear regime-switching model before the financial crisis. Hence, we should interpret the results with caution.

For Greece and the Netherlands the results are not as unambiguous as for the latter countries. The Greek results might be likely driven by the economic structure in Greece which is not heavily dependent on industrial production. As a consequence other sectors might be more seriously affected than manufacturing. This result also confirms the in-significant relation between the financial sector and economic activity in Greece shown by the Granger causality test. Moreover, the FCI of Greece might also rather reflect not only the Greek financial market pressure, but also contagion effects and the potential danger of the euro zone exit. For Greece in particular we might not be able to disentangle Greek and Euro area risk which then explains the negligible influence on industrial production. In the Netherland the relation between financial sector and economic activity appears to be de-linked as well. The economic growth in the Netherlands is mainly driven by Germany through the export-channel. Hence, this factor might be unobserved in our model and

the financial sector and the macroeconomy appear to be de-linked. The latter argument may hold for all smaller countries we consider in our analysis.

Most importantly, we show that the negative effect of financial stress on output is not always present. This holds specifically for the time before the Lehman collapse. After the crash we do observe the presence of strong amplification mechanisms for some euro area countries. The underlying FCIs also captures euro area and, to some extent, global risk. Hence, the financial sector shock may be seen as a source of the financial and economic crisis, but the severe economic downturn may then have been reinforced by global effects influencing one another and interdependencies between financial markets. The outlier event "Lehman Brothers collapse" and the subsequent euro area crisis constitute situations of greater real-economy sensitivity to financial market fragility. While it would be possible to have a period of high stress without consequences for the real economy if the amplification effects are weaker, the recent crisis points to systematic changes in output fluctuations and financial sector dynamics when compared to previous periods. This is also confirmed by Figure 6 that shows the value of the location parameter over time. The value remains on a low level before it rises strongly after the financial crisis outbreak. The optimized location parameter for the other countries, confirming the pattern, can be found in the Appendix D. In contrast to Germany, the threshold value is even further increasing recently in some countries.

The outcomes lead to the question whether we really capture "high" financial stress before September 2008 or the amplification mechanisms were weaker. From our view, there are periods of high stress without consequences for the real economy where the amplification effects were weaker. But the recent crisis points to systematic changes in output fluctuations and financial sector dynamics when compared to earlier times.
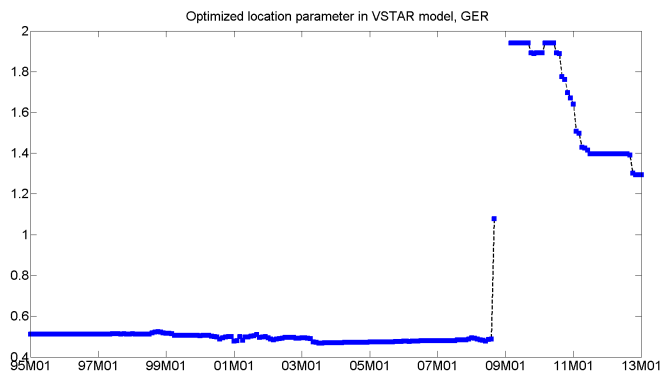

Figure 6: Optimized location parameter VSTAR model, Germany

We suggest that our findings are in line with the financial cycle interpretation in the sense of Jordà *et al.* (2011) and Schularick and Taylor (2012): events leading to a major economic breakdown appear to be related to a financial cycle which is of low frequency and hence, its effects on downturns are rare but then have a large impact. The negative output effect may not always be present although we are in a model-defined "high stress" regime. The degree of amplification effects is of crucial importance to determine negative consequences for the real economy. Our results suggest, that stronger amplification effects and adverse feedback loops may likely be triggered if an economy remains in a high stress regimes for a significant long time period.

4 Conclusion

We confirm the relevance of non-linearities in the relation between the financial sector and economic activity by a Vector STAR model and gain some essential new insights concerning amplification effects of financial sector shocks over time. The Vector STAR model is able to replicate the dynamics shown by our theoretical model that points towards non-linearities and regime-specific amplification effects. The analysis is based on the data sample from 1980m01 to 2013m01 and uses novel financial condition indices. Our data set is comprehensive in terms of its broadness of financial stress categories and country coverage. While some of the banking variables are neglected in hitherto existing indices, those are included in our index since they play an important role in describing financial market stress and the way it has unfolded, for example, after the Lehman collapse.

In most countries, a shock to the financial market leads to a long-lasting negative response in economic activity. It is particularly harmful for the real economy if the shock takes place in a period of high financial market stress. The negative response that we have obtained is not as pronounced as it is in other studies. Economies may switch rather smoothly from one stress regime to the other. The effect of shocks in the presence of smooth regime-changing may be dampened so that the negative effect on economic activity is weaker. This effect could be even more diluted if after the initial financial sector shock frequent regime-switches and further shocks take place. We find evidence for the latter as the effects between high and low stress regimes do differ, but not substantially.

Most importantly, the outcomes crucially depend on the time period under study. We show that dynamics and amplification effects in the link between the financial sector and the macroeconomy vary over time in the euro area countries. Linearity cannot be rejected for some euro area countries over time. Declining p-values of linearity tests point towards increasing importance of non-linearities with the financial crisis outbreak. Even if linearity is rejected, the negative output effect of financial sector shocks typically observed is not always present. After September 2008—when Lehman Brothers collapsed and the financial markets in most advanced economies crashed—the response of industrial production is clearly negative, whereas it varies around zero before for some countries, although we are in a model-defined high stress regime. This suggests that events leading to a major economic breakdown are rather related to a low-frequency financial cycle and its effects on downturns are rare but then have a large impact.

Our results do not confirm the argument that the financial crisis was only an unusually large shock that resulted in macroeconomic fluctuations similar to those expected during normal times. The change in the dynamics and intensity of the negative response of the real economy is not solely driven by the size of the shock. The stronger amplification mechanisms arising after the Lehman collapse that we obtain for some countries describe an asymmetric behavior in the financial sector – output link which may not have been present or had perhaps been rather weak previously. Prior to the financial crisis outbreak we find stability even if the shock takes place in a high stress regime. More important seems to be the shock propagation over time in the economy. Only with the occurrence of the rare but large events we find strong endogenous feedback loops and a loss of stability as described by the high stress regime of our theoretical model. The economy leaves the corridor of stability and is prone to adverse feedback loops.

A   The Numerical Procedure

For the numerical solution of our dynamic decision problem we employ a new procedure. Usually one uses DYNARE or Dynamic Programming to solve models such as presented in section 2, see Grüne and Semmler (2004). DYNARE linearizations work with first or second order approximation and eliminates global non-linearities. Though DP may be superior, but its numerical effort typically grows exponentially with the dimension of the state variable. Hence, even for moderate state dimensions it may be impossible to compute a solution with reasonable accuracy. A remedy to this problem can be obtained by using non-linear model predictive control (NMPC), which is the method we use in this paper, see Grüne *et al.* (2013). Instead of computing the optimal value function for all possible initial states, NMPC only computes single trajectories.

In order to describe the method, let us abstractly write the dynamic decision problem as

$$\text{maximize} \quad \int_0^T e^{-\rho t} \ell(x(t), u(t)) dt,$$

where $x(t)$ satisfies $\dot{x}(t) = f(x(t), u(t))$, $x(0) = x_0$ and the maximization takes place over a set of admissible decision functions. By discretizing this problem in time, we obtain an approximate discrete time problem of the form

$$\text{maximize} \quad \sum_{i=0}^T \beta^i \ell(x_i, u_i) dt, \tag{15}$$

where the maximization is now performed over a sequence u_i of decision values and the sequence x_i satisfies $x_{i+1} = \Phi(h, x_i, u_i)$. Here $h > 0$ is the discretization time step, $\beta = e^{-\rho h}$ and Φ is a numerical scheme approximating the solution of $\dot{x}(t) = f(x(t), u(t))$ on the time interval $[ih, (i+1)h]$. For details and references in which the error of this discretization is analyzed we refer to Grüne *et al.* (2013).

The idea of NMPC now lies in replacing the maximization of the above large horizon functional, where we could have $T \Rightarrow \infty$, by the iterative maximization of finite horizon functionals

$$\text{maximize} \quad \sum_{k=0}^N \beta^i \ell(x_{k,i}, u_{k,i}) dt, \tag{16}$$

for a truncated finite horizon $N \in \mathbb{N}$ with $x_{k+1,i} = \Phi(h, x_{k,i}, u_{k,i})$ and the index i indicates the number of the iteration, cf. the algorithm below. Note that neither β nor ℓ nor Φ changes when passing from (15) to (16), only the horizon is truncated.

Problems of type (16) can be efficiently solved numerically by converting them into a static nonlinear program and solving them by efficient NLP solvers, see Grüne and Pannek (2011).

Given an initial value x_0, an approximate solution of (15) can now be obtained by iteratively solving (16) as follows:

(1) for i=1,2,3,...
(2)   solve (16) with initial value $x_{0,i} := x_i$ and denote the
        resulting optimal control sequence by $u_{k,i}^*$
(3)   set $u_i := u_{0,i}^*$ and $x_{i+1} := \Phi(h, x_i, u_i)$
(4) end of for-loop

This algorithm yields an infinite trajectory x_i, $i = 1, 2, 3, \ldots$ whose control sequence u_i consists of all the first elements $u_{0,i}^*$ of the decision sequences for the finite horizon

subproblems (16).

Under appropriate assumptions on the problem, it can be shown that the solution (x_i, u_i) (which depends on the choice of N above) converges to the correct solution of (15) as $N \to \infty$. The main requirement in these assumptions is the existence of an equilibrium for the infinite horizon problem (15). If this equilibrium is known, it can be used as an additional constraint in (16), in order to improve the convergence properties. However, recent results have shown that without a priori knowledge of this equilibrium this convergence can also be ensured, see Grüne *et al.* (2013), and this is the approach we use in the computations in this paper.

B The Data
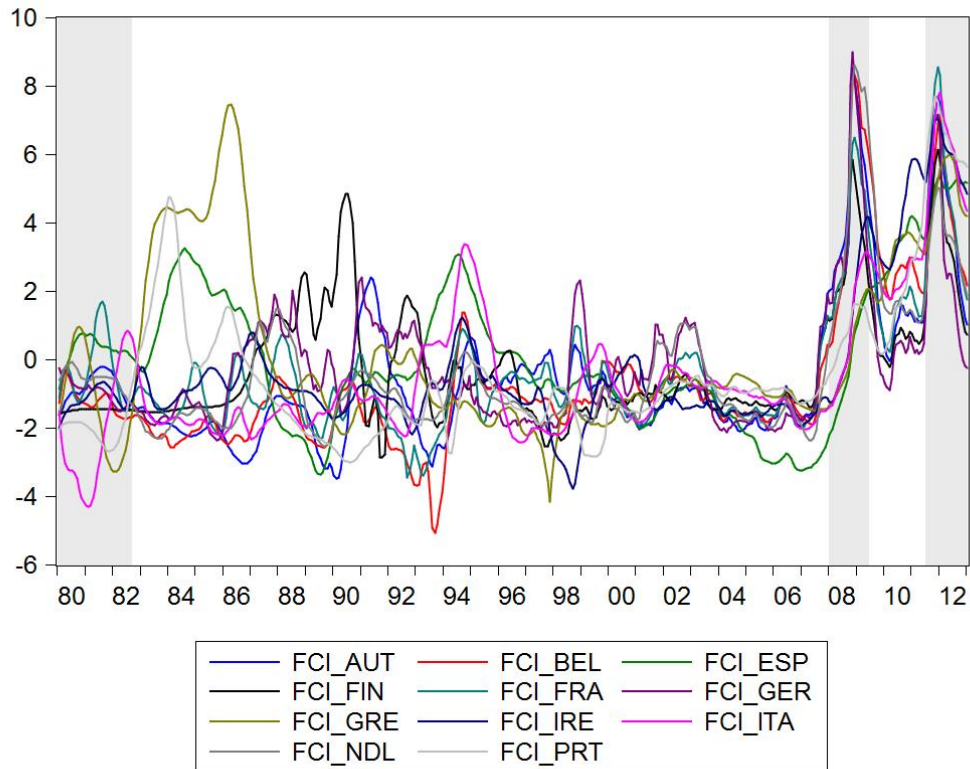
Figure 7: FCIs of euro area countries, periods of recessions dated by CEPR Business Cycle Dating Committee in grey

In Table 12 follows a brief description of variables used to extract the ZEW FCIs. They are divided into three groups, namely, the banking sector (variables related to the money and interbank market, credit conditions and constraints, balance sheet structure of banks, and bank's profitability situation), securities market and foreign exchange market. We also report the transformation which were used to make the series stationary, the native frequency, the source (D=Datastream; ECB=European Central Bank; BIS=Bank of International Settlements), a note if the series is a euro area (EA) aggregate and the first observation if the series is an euro area aggregate and not country-specific.[40]

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[40]A similar table can be found in Kappler and Schleer (2013).

Table 12: Data description

Indicators	Description	Tcode	N. Freq.	Source	First obs.	Notes
BANKING SECTOR						
Interbank Rate Spread	Interbank Offered Rate 12 m. - Interbank Offered Rate 1 m.	0	daily	D	country-spec.	From 99 EA agg.
Excess Reserves	Bank reserves in excess of the central banks' reserve requirement	1	monthly	ECB	2000M01	EA agg.
Euribor-Eonia Spread 1	Interbank Offered Rate 1 m. - Eonia (effective overnight rate, unsecured lending)	0	daily	D	country-spec.	From 99 EA agg.
TED Spread	Interbank Offered Rate 3m. - government short term rate	0	daily	D	country-spec.	
(Inverse) Marginal Lending Facility	To obtain overnight liquidity from ECB	2	daily	D (ECB)	1999M01	EA agg.
Main refinancing rate spread	euro area 2-y. benchmark bond yield - minimum bid rate	0	daily / monthly	D	1999M01	EA agg.
Money Market Spread	Euribor 3m. - EUREPO	0	daily	D (ECB)	1999M05	EA agg.
Ratio of short / long term debt	Debt securities issued < 1year (short-term) and 1-2 years (medium-term) divided by > 2 years (long-term) of MFIs	0	monthly	ECB	country-spec.	
Bank lending to Private Sector	Bank lending to private sector in constant prices	3	monthly	D	country-spec.	
Write-offs	MFIs, Loans to Nonfinancial Corporations and Households, Write-offs/write-down	1	monthly	D	2002M01	EA agg.
Total Asset / Liabilities	MFIs Total Assets/Liabilities; Index of Notional Stocks	3	monthly	ECB	country-spec.	
Bank stock market returns	Bank stock market returns	3	daily	D	country-spec.	
Beta of Banking sector	Measure of banking risk relative to market risk	4	daily	D	country-spec.	
CMAX/PB	Financial intermediary risk interacted with stock market valuation	5	daily	D	country-spec.	
Inverted term spread	Slope of yield curve: short term government yield - long term government yield	0	monthly	D	country-spec.	
SECURITIES MARKET						
Share Price Returns	Stock markets returns	6	monthly	D	country-spec.	
Share Prices Volatility	Stock markets volatility	7	monthly	D	country-spec.	
Corporate Debt Spread I	AAA country specific corporate bond yield- euro area AAA corporate bond yield	0	monthly	D	country-spec.	
Corporate Debt Spread II	BBB euro area corporate bonds- AAA euro area corporate bonds	0	monthly	D	1999M04	EA agg.
Government Bond Volatility	Volatility of long-term government bonds	7	monthly	D	country-spec.	
FOREIGN EXCHANGE MARKET						
Foreign exchange market volatility	effective exchange rates, narrow index (27 economies), real cpi	7	monthly	D (BIS)	country-spec.	

0 - levels, no transformation
1 - annual log differences / annual growth rate
2 - multiplicative inverse
3 - annual log differences multiplied by −1
4 - $\beta = \frac{cov(r,m)}{var(m)}$; r and m are total returns, at annual rates, of the banking sector index and the overall market index. Beta is calculated by using a one-year rolling time-frame. The banking beta was recorded only when it was greater than one, else it is set to 1.
5 - (1-current value of stock market index/maximum value over last 12 months) multiplied by book-to-price ratio
6 - monthly absolute differences multiplied by −1
7 - 6-months backward-looking rolling window, standard deviation

Exceptions:
Greece: No inclusion of inverted term spread due to its paradoxical evolution during the current financial and economic crisis, see also Neely (2012). CMAX is not multiplied by the Price-to-Book ratio which has some extreme outliers at the beginning of 2011.
Ireland: No availability of corporate bond spread.

C   Results from unit root testing

Table 13: Unit root tests

test		test-stat.	5% crit.-val.		test-stat.	5% crit.-val.
ERS DF-GLS	ip_aut	-0.395	-1.942	fci_aut	-3.359	-1.942
ERS point-optimal		0.638	3.258		1.120	3.259
ERS DF-GLS	ip_bel	-3.981	-1.942	fci_bel	-2.566	-1.942
ERS point-optimal		0.114	3.258		2.179	3.259
ERS DF-GLS	ip_fin	-0.865	-1.942	fci_fin	-2.901	-1.942
ERS point-optimal		0.231	3.259		1.564	3.259
ERS DF-GLS	ip_fra	-3.648	-1.942	fci_fra	-3.351	-1.942
ERS point-optimal		0.351	3.259		1.285	3.259
ERS DF-GLS	ip_ger	-5.627	-1.942	fci_ger	-3.958	-1.942
ERS point-optimal		0.352	3.259		0.761	3.259
ERS DF-GLS	ip_gre	-2.132	-1.942	fci_gre	-2.442	-1.942
ERS point-optimal		0.012	3.259		2.480	3.259
ERS DF-GLS	ip_ire	-31.178	-1.942	fci_ire	-0.417	-1.942
ERS point-optimal		0.113	3.259		11.394	3.259
ERS DF-GLS	ip_ita	-3.675	-1.942	fci_ita	-1.986	-1.942
ERS point-optimal		0.628	3.258		3.630	3.259
ERS DF-GLS	ip_nld	-1.054	-1.942	fci_nld	-3.721	-1.942
ERS point-optimal		0.236	3.259		0.934	3.259
ERS DF-GLS	ip_prt	-0.542	-1.942	fci_prt	-1.437	-1.942
ERS point-optimal		0.184	3.259		5.126	3.259
ERS DF-GLS	ip_esp	-0.951	-1.942	fci_esp	-1.188	-1.942
ERS point-optimal		0.638	3.259		6.094	3.259

D   Further Results: Empirical Analysis
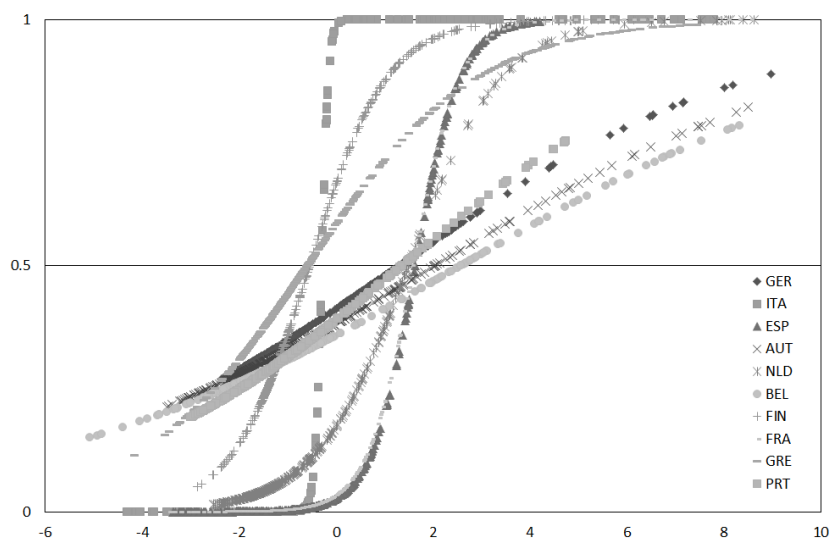
Figure 8: Transition functions for euro area countries, VSTAR model

Table 14: Excluded time periods for rolling linearity tests and IRFs

	Excluded time periods due to unstable results
AUT	2008M08 − 2008M12
BEL	1995M01–1998M12, 2008M09 − 2009M02, 2009M06, 2011M08 − 2013M01
ESP	2011M10 − 2013M01
FIN	-
FRA	2008M09 − 2008M11, 2011M11
GER	2008M09 − 2009M01
GRE	1995M01 − 1998M01
ITA	1995M01 − 1995M04, 1995M06, 2011M12, 2012M04, 2012M06
NDL	2008M09 - 2008M11, 2009M04
PRT	2011M08 − 2013M01
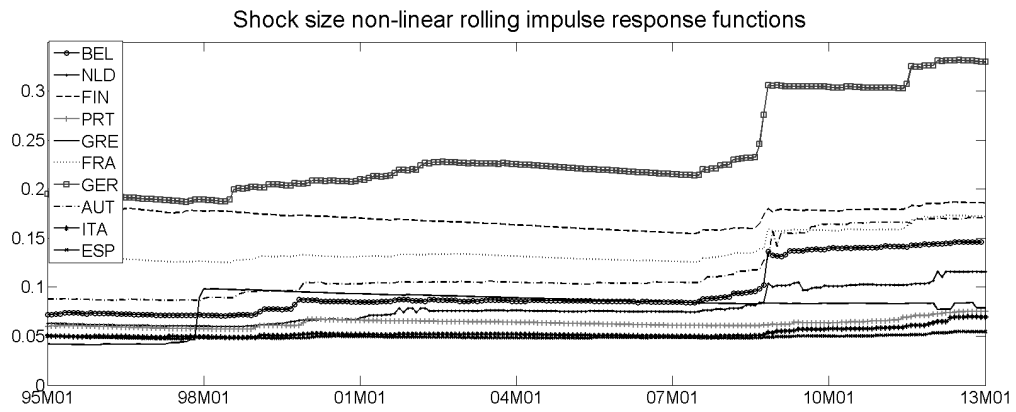
Figure 9: Evolution of initial shock size of the FCI
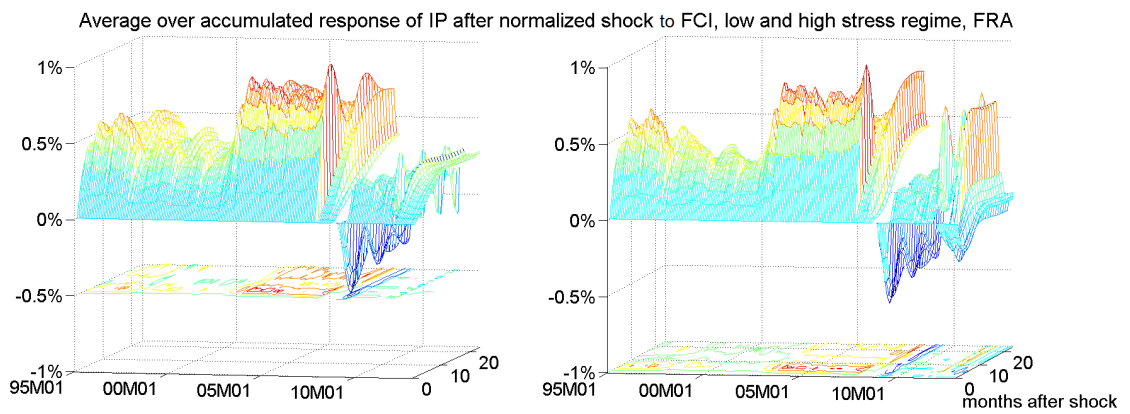
Figure 10: Rolling IRFs of IP, normalized shock, France
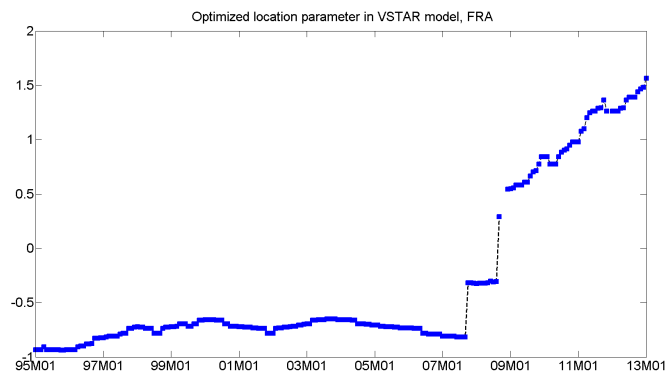
Figure 11: Optimized location parameter VSTAR model, France

34
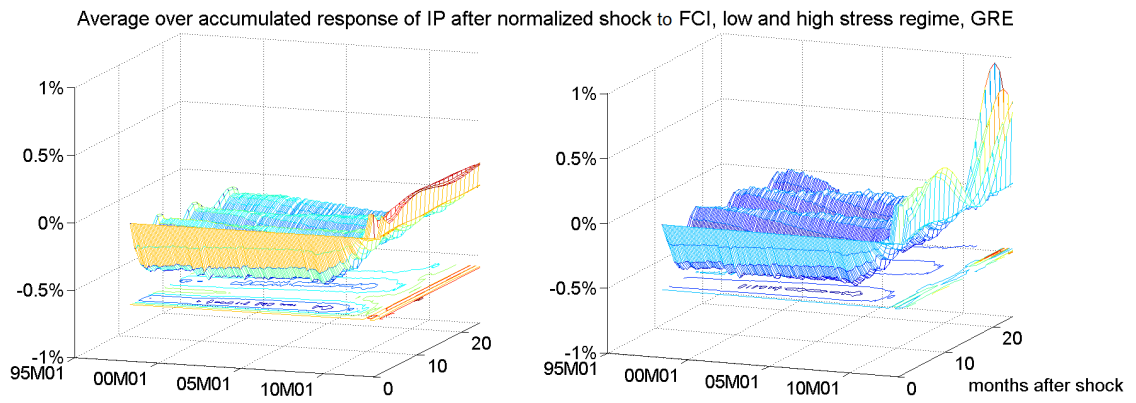
Figure 12: Rolling IRFs of IP, normalized shock, Greece
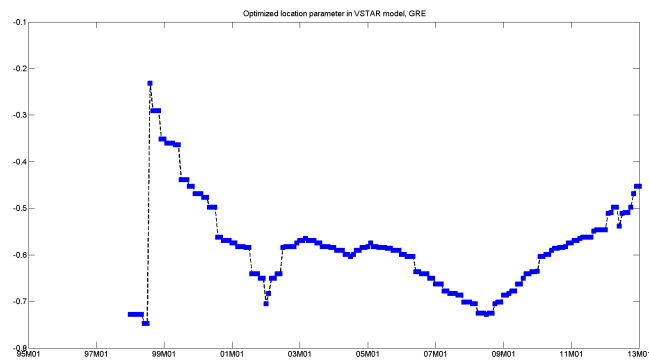
Figure 13: Optimized location parameter VSTAR model, Greece
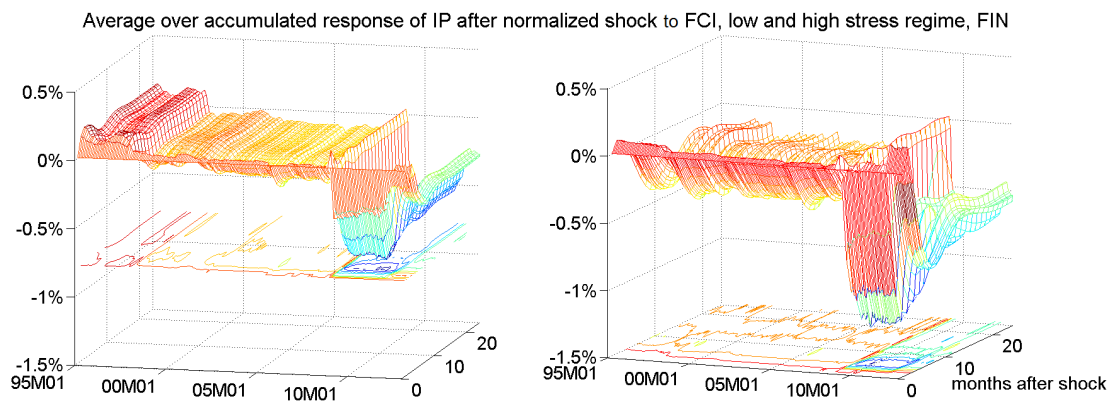
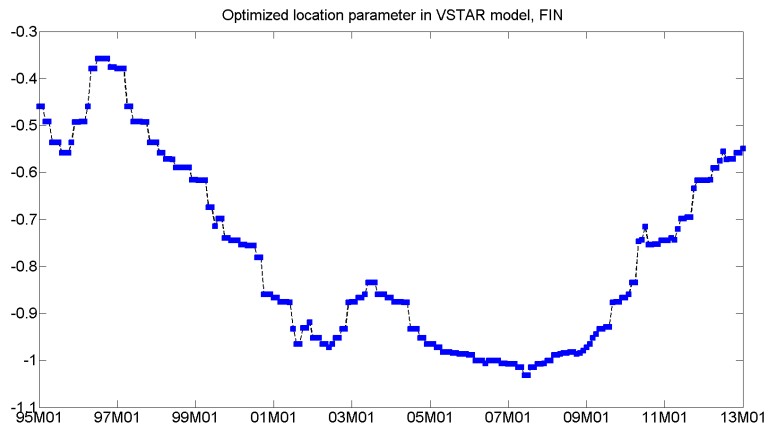Figure 14: Rolling IRFs of IP, normalized shock, Finland

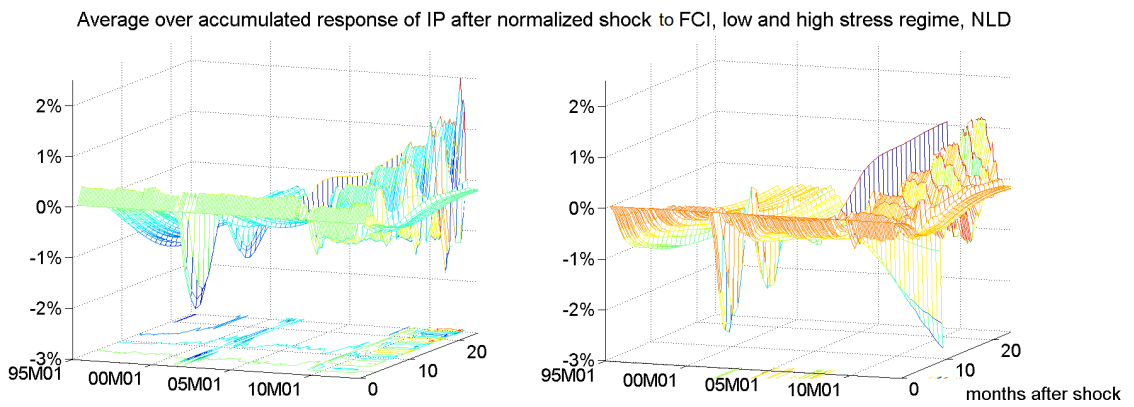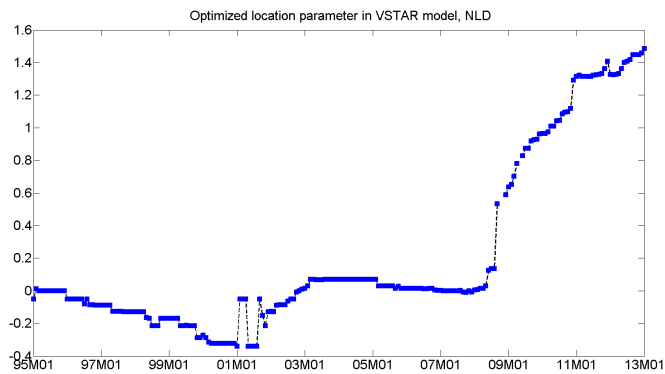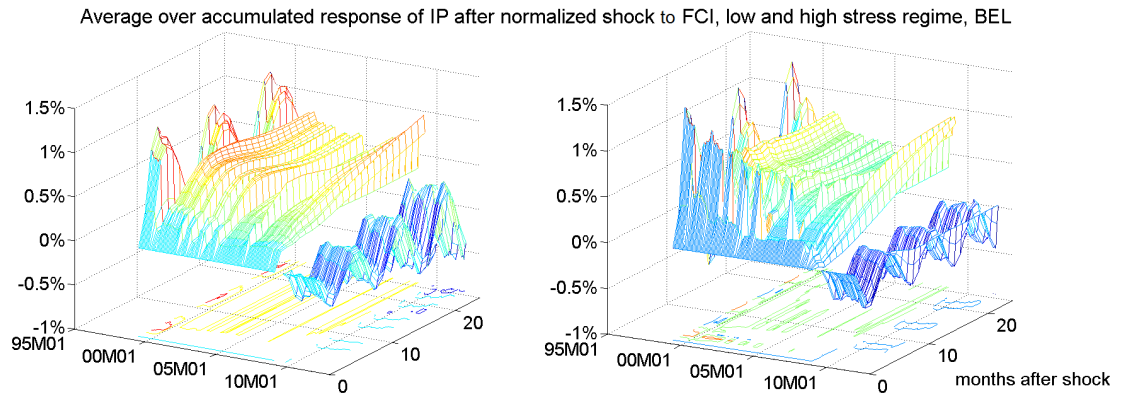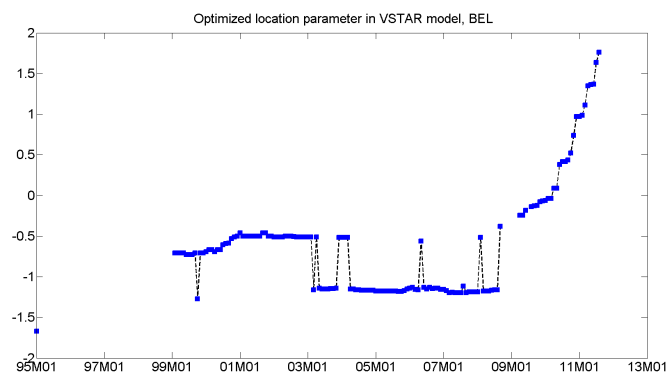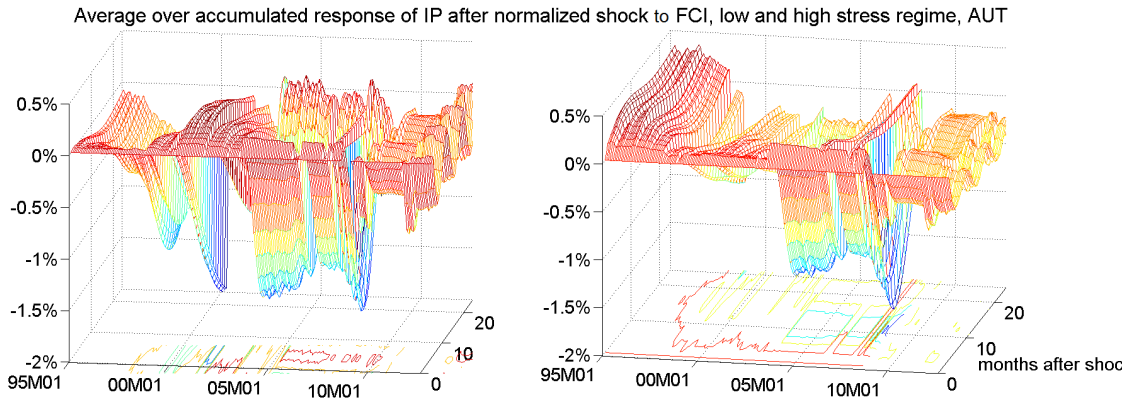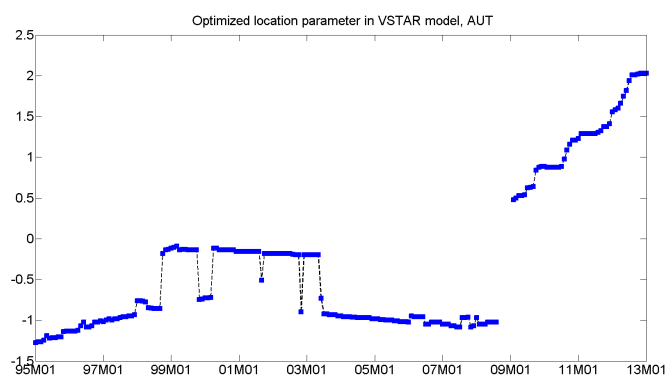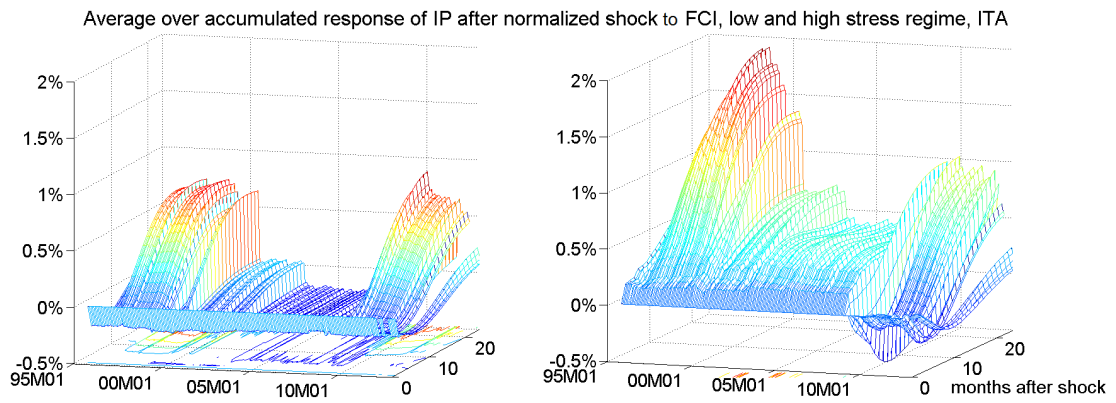Figure 15: Optimized location parameter VSTAR model, Finland

Figure 16: Rolling IRFs of IP, normalized shock, Netherlands

Figure 17: Optimized location parameter VSTAR model, Netherlands

Average over accumulated response of IP after normalized shock to FCI, low and high stress regime, BEL

Figure 18: Rolling IRFs of IP, normalized shock, Belgium

Optimized location parameter in VSTAR model, BEL

Figure 19: Optimized location parameter VSTAR model, Belgium

Average over accumulated response of IP after normalized shock to FCI, low and high stress regime, AUT

Figure 20: Rolling IRFs of IP, normalized shock, Austria

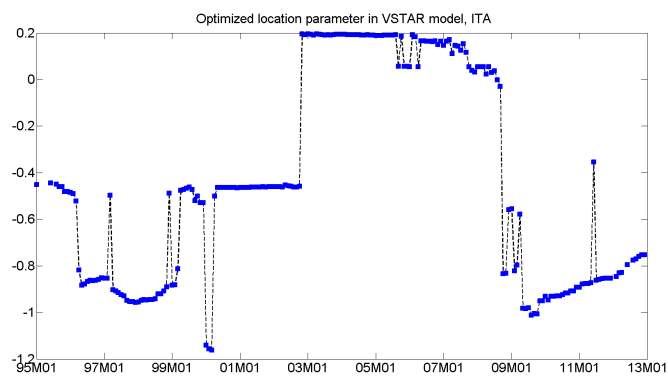Optimized location parameter in VSTAR model, AUT

Figure 21: Optimized location parameter VSTAR model, Austria

Figure 22: Rolling IRFs of IP, normalized shock, Italy

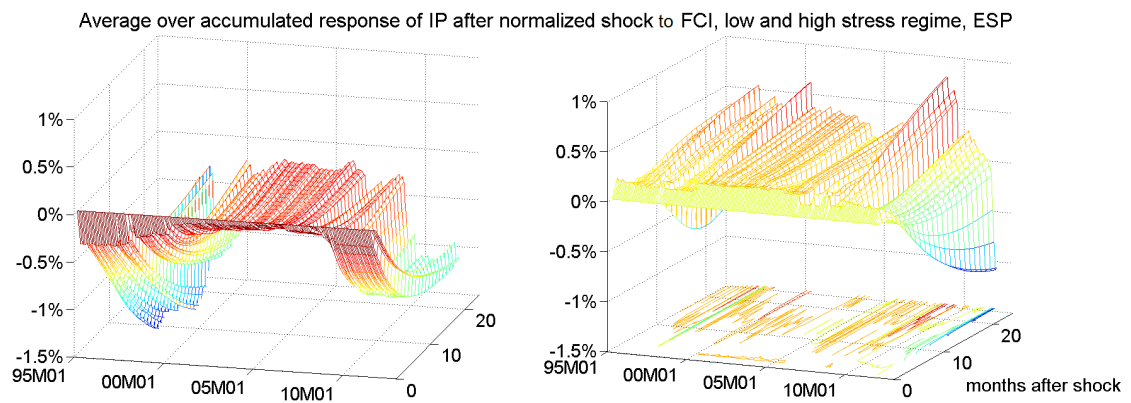Figure 23: Optimized location parameter VSTAR model, Italy

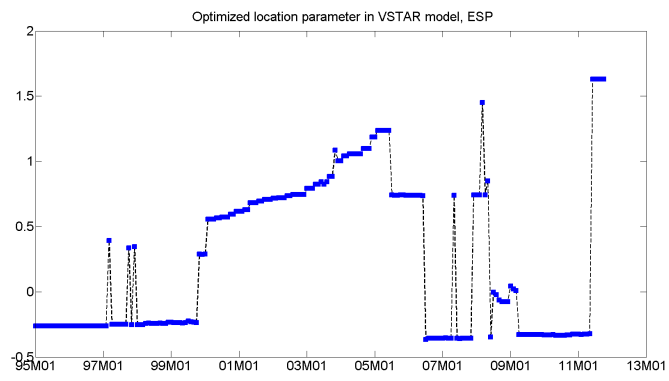Figure 24: Rolling IRFs of IP, normalized shock, Spain

Figure 25: Optimized location parameter VSTAR model, Spain

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