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FINANCIAL SHOCKS AND THE REAL ECONOMY IN A NONLINEAR WORLD: A SURVEY OF THE THEORETICAL AND EMPIRICAL LITERATURE

by Andrea Silvestrini* and Andrea Zaghini*

Abstract

In this paper we present an overview of theoretical and empirical contributions exploring the inter-linkages between financial factors and real economic activity. We first revisit the main theoretical approaches that allow financial frictions to be embedded into general equilibrium models, and then we survey, from an empirical perspective, the most recent papers focusing on macro-financial linkages, with a particular emphasis on works dealing with parameter time variation and other types of nonlinearities. We conclude by discussing some policy implications and suggesting directions for future research.

JEL Classification: C32, E32, E44, E58.

Keywords: financial shocks, credit, financial crisis, nonlinearity.

Contents

* Bank of Italy, Directorate General for Economics, Statistics and Research.

"*To motivate interest in a paper on financial factors in business fluctuations it used to be necessary to appeal either to the Great Depression or to the experiences of many emerging market economies. This is no longer necessary. Over the past few years the United States and much of the industrialized world have experienced the worst post-war financial crisis, and the global recession that has followed also appears to have been the most severe of this era.*" Gertler and Kiyotaki (2010).

1 Introduction[1]

The most recent empirical evidence supports the view that financial and real fluctuations are closely intertwined, and that financial conditions are important drivers of the economy, contributing significantly to the propagation of economic shocks. Indeed, the severity of the global financial crisis has highlighted the fact that several mechanisms can accentuate business cycle fluctuations. The financial sector has turned out to be inherently procyclical and capable of amplifying macroeconomic volatilities: during the contractionary phases of the business cycle, profitability falls as asset prices decline, credit conditions deteriorate, loan defaults rise, and the provision of credit is tightened, aggravating the downturn. These observations point to the relevance of the linkages and feedbacks that characterise the interaction between financial markets, the credit market, the housing sector, and the real economy.

From a modelling viewpoint, the recent episodes of financial turmoil have clearly shown that macro models based on frictionless financial markets can not reproduce salient features of the business cycle. In particular, those policy models which, in the decade prior to the crisis, implicitly assumed perfectly functioning capital markets, have been unable to capture the procyclicality of the financial system and to predict the persistence and the intensity of the (new) "Great Recession". As a result, in the most recent years, a large theoretical litera-

[1]While assuming scientific responsibility for any errors in the paper, the authors wish to thank Giuseppe Grande, Andrea Mercatanti and Raf Wouters for useful suggestions and discussions. Part of this paper was written while the first author was visiting the National Bank of Belgium, whose hospitality he gratefully acknowledges. The views expressed herein are those of the authors and do not necessarily reflect those of the Bank of Italy.

ture has attempted to incorporate financial features and the banking sector into standard real business cycle models or New Keynesian dynamic stochastic general equilibrium models as in Christiano, Eichenbaum and Evans (2005), and Smets and Wouters (2007).[2]

In parallel, abundant empirical research has analysed and quantitatively assessed the transmission of financial shocks to the macroeconomy, both for the euro area (individual countries and as a whole) and for the US. Further, it has been emphasised that a feature closely related to the intensity of real-financial linkages is the presence of nonlinearities (Hubrich and Tetlow, 2013). Indeed, the recent literature suggests that the transmission of financial shocks to the real economy differs according to the states of the world: output reacts to a greater extent to financial shocks in periods of high stress than in tranquil ones.[3] The financial condition seems to be of negligible importance in "normal" times but it matters greatly in conditions of "stress".

One of the explanations that has been proposed for the failure of many reduced-form vector autoregression (VAR) models to mimic the relationship between financial variables and economic activity during the crisis is the common assumption that coefficients (and the variance-covariance matrix of the model's disturbances) are constant over time. These models are therefore unable to account for the potential time-varying nature of aggregate phenomena in the economy. As a consequence, time-varying parameter and Markov-switching models have recently been proposed to overcome this flaw in the empirical modelling. The common finding of this literature is that not only are the effects of a financial shock contingent on the state of the economy (usually "financial crisis periods" versus "normal times"), but also the consequences of a monetary policy shock are different in time. This has major policy implications, as it implies that the adequate policy response (be it from a macroprudential or a monetary policy perspective) should also be calibrated depending on the state of the economy. Thus, relying on models based on constant parameters might be misleading for the authorities.

With this background in mind, the objective of this paper is to make a survey of the contributions exploring the interaction between financial and real factors, with a particular emphasis

[2]See, among others, Nolan and Thoenissen (2009), Hirakata, Sudo and Ueda (2009), Christiano, Motto and Rostagno (2010, 2014), Meh and Moran (2010), de Walque, Pierrard and Rouabah (2010), Gerali et al. (2010), Gertler and Karadi (2011) and Jermann and Quadrini (2012).

[3]Usually nonlinearities have been modelled allowing for discrete regime switches that affect the volatility of shocks and their dynamic propagation.

on papers that incorporate time variations and other types of nonlinearities into standard constant parameter reduced-form models.

From the theoretical viewpoint, the interest in incorporating financial frictions in business cycle models is not new. In fact, since the early 1980s, several attempts have been made in the academic literature to embed financial frictions into macroeconomic models. Most often, financial frictions have been introduced in order to account for informational asymmetries between lenders and borrowers, and non-convex transaction costs. Thus, in what follows, besides providing an overview of the most recent empirical studies, the paper briefly refers to the leading economic theories that explain how the financial sector can influence the real economy. While revisiting the main theoretical frameworks of frictions within financial markets, it explains in detail, mostly intuitively, the basic mechanisms at the heart of the models.

The rest of this work is organised as follows. Section 2 explains how highly influential theoretical studies have embedded financial frictions into a macroeconomic framework, discussing some conceptual issues related to the external finance premium and collateral constraints. Section 3 reviews the most recent empirical literature on macro-finance linkages, with a special emphasis on the contributions featuring time-varying parameter models and other types of nonlinearities, such as Markov-switching. Section 4 draws conclusions and hints at future research.

2 Financial frictions, the financial accelerator and collateral constraints

An extensive theoretical literature starting from the Modigliani and Miller (1958) framework and featuring credit market imperfections has grown out of Bernanke (1983), Bernanke and Gertler (1989), Kiyotaki and Moore (1997) and Carlstrom and Fuerst (1997).[4] Although early approaches to modelling financial frictions already existed, these papers should be considered seminal contributions in the field. According to Adrian and Shin (2010), the common thread among these works is the focus on fluctuations in the creditworthiness of the non-financial borrower. In fact, fluctuations in borrowers' net worth is the essential ingredient that can contribute

[4]See Gertler and Kiyotaki (2010) for an assessment of this research over the past two decades.

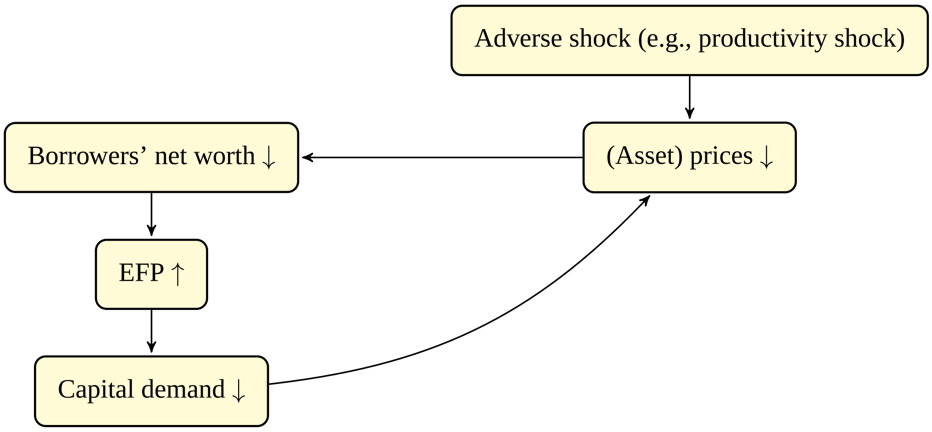
to the amplification and persistence of exogenous shocks to the economy. Yet, while the key concept in Bernanke's and Gertler's framework is the "external finance premium" due to the presence of asymmetry of information between borrowers and lenders, collateral constraints are at the heart of Kiyotaki and Moore (1997).

The external finance premium can be broadly defined as the difference in cost between funds raised externally, by issuing equity or debt, and funds generated internally (retained earnings). It hinges upon the assumption of a "costly state verification" mechanism (Townsend, 1979) – meaning a setup in which verification of the entrepreneur's performance is costly, and lenders incur a monitoring cost – which drives a wedge between the cost faced by a borrower when raising funds externally and the opportunity cost of internal funding. It is through this premium that credit market frictions are endogenised and introduced in otherwise frictionless models.

Other authors have highlighted the contribution of informational asymmetries to business cycle dynamics. Carlstrom and Fuerst (1997) introduce financial frictions into a standard real business cycle model and show how they may affect its properties. To generate frictions, they assume asymmetric information between entrepreneurs and households providing funds and a "costly state verification" mechanism. This idea is strictly related to the original overlapping generations model developed by Bernanke and Gertler (1989), in which asymmetries between borrowers and lenders (informational frictions) generate agency costs that manifest themselves through a premium on external funds with respect to the risk-free rate. Agency costs are inversely related to the borrower's net worth. Countercyclical agency costs are crucial for the propagation of productivity shocks and for generating "accelerator effects on investment" (p. 28).

Consistent with this way of reasoning, many authors have drawn on these insights and developed models incorporating an external finance premium. In a highly influential study, Bernanke, Gertler and Gilchrist (1999) introduce a "financial accelerator" mechanism in a model featuring nominal price rigidities, in which procyclical movements in non-financial borrowers' net worth and countercyclical movements in the cost of external funds relative to internal funds can generate large changes in output from relatively small technology and demand shocks. As already mentioned, this mechanism helps to explain how negligible and temporary shocks can result in large and persistent business cycle fluctuations.

Figure 1: Financial accelerator: the effect of an adverse shock



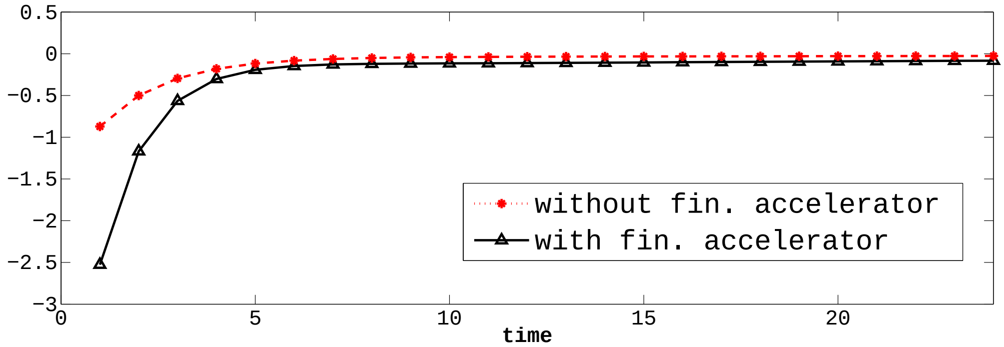
The basic mechanism operates as follows. The external finance premium (EFP) and net worth of non-financial borrowers are negatively related: the reason is that, in principle, the higher the borrower's net worth, the lower are the expected agency costs of financing investment. Thus, since the borrower's net worth is procyclical, when investment, output and asset prices go up, the net worth of borrowers also increases, and leverage falls, endogenously reducing the external finance premium. This in turn increases investment and amplifies the upturn. The reverse happens during recessions. In particular, adverse shocks to the economy lead to a reduction of asset prices and of net worth; leverage and the external finance premium rise: this increases financial frictions, and borrowers are thus forced to invest less (see Figure 1). All this leads to the amplification and propagation of shocks.

The argument can be made slightly more formal by considering a Dynamic New Keynesian model as in Bernanke, Gertler and Gilchrist (1999) and their complete log-linearised form. The same model parameterisation is used here to plot Figure 2, which shows the output response to a contractionary monetary policy shock (one standard deviation) with and without capital market frictions.[5] Without going into too much detail, it is enough to note that when financial frictions are assumed in the model, the initial response of output to a monetary policy shock is

[5]To plot Figure 2, the authors gratefully acknowledge use of a Dynare script made available by Ambrogio Cesa-Bianchi on his webpage.

significantly greater than when financial frictions are not included.[6] This result confirms that in this model setting credit market frictions affect the transmission of monetary policy and that the financial accelerator constitutes a mechanism of amplification of a wide range of (both real and nominal) shocks to the economy.

Figure 2: Output response to a contractionary monetary policy shock (Bernanke, Gertler and Gilchrist, 1999)



Financial frictions and the financial accelerator have also been introduced starting from the "costly state verification" hypothesis and following other approaches, such as assuming collateral constraints in the modelling framework. An outstanding example is given by Kiyotaki and Moore (1997), who highlight the contribution of collateral constraints to business cycle fluctuations through feedback effects. In particular, they develop a real business cycle model in which debt must be fully secured by collateral and lending occurs only when collateralised. Binding credit constraints are determined by the value of collateralised assets.

Their main finding is that recessions are amplified when, during the economic downturn (e.g. following an unanticipated adverse productivity shock), agents are affected by the depreciation of assets used as collateral (in the economy considered by Kiyotaki and Moore, 1997, there is a single durable asset, land, which serves as collateral). The way the mechanism operates is very intuitive: with collateral requirements, the borrower faces a wealth effect; in a

[6]In order to shut down financial frictions, it is necessary to properly modify equation (4.17) on page 1361 (see also the discussion on page 1363). The interested reader is referred to Fig. 3 on page 1371 on the original paper, where a decline in the nominal interest rate of 25 basis points is considered.

recession, the income from capital falls, capital becomes less valuable as collateral, and this forces firms to reduce their borrowing and to curtail their investment, thereby causing an additional decline in output and a worsening of the recession.

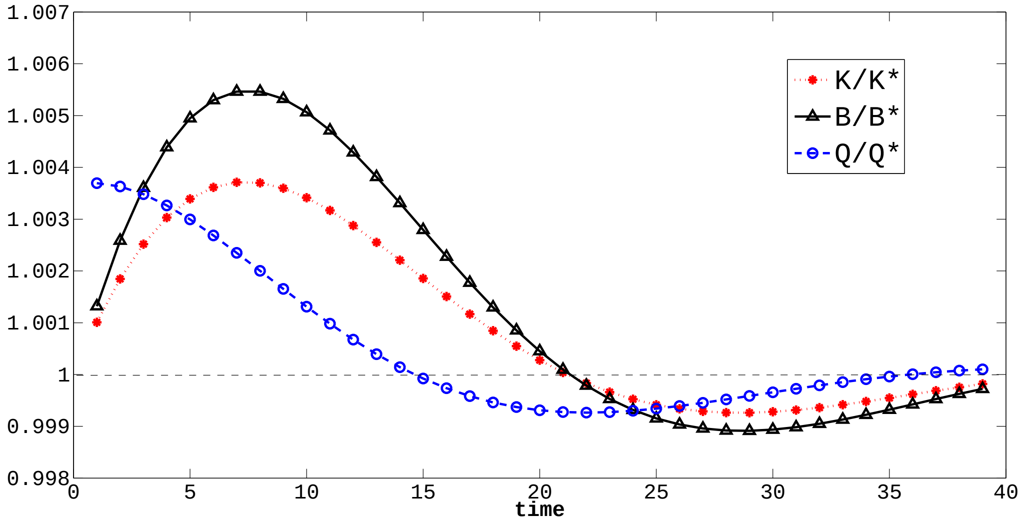
The same propagation is generated by a temporary positive productivity shock, which increases agents' net worth. For illustration, Figure 3 replicates the dynamics of Fig. 3, page 238, in Kiyotaki and Moore (1997).[7] Following a 1 per cent productivity shock, the land price increases by 0.37 per cent, while landholding and debt rise contemporaneously by 0.10 and 0.13 per cent, respectively. There is a large amount of persistence: indeed, it takes almost 40 periods for the system to return to equilibrium after being shocked. Thus, a temporary positive productivity shock can generate relatively large and persistent fluctuations in output, investment and (asset) prices. The causal link works as follows: the greater the value of the collateral, the greater the amount constrained agents can borrow. This capital gain increases borrowing, investment and economic activity.

It is worth noting that, without credit constraints, the same unanticipated temporary productivity shock would not affect contemporaneously either the land price (Q), or landholding (K), and there would not be any changes to prices and production in future periods. This is because, in a standard real business cycle model without credit constraints, prices and production do not depend on changes in borrowers' net worth.

In common with Kiyotaki and Moore (1997), collateral constraints have been assumed by Iacoviello (2005) and Iacoviello and Neri (2010) in modelling the interaction between the real economy and the housing sector. Here again, financial frictions and lower/higher asset values produce real effects. In the same spirit, Adrian and Boyarchenko (2012) develop a theory of financial intermediary leverage cycles in which intermediaries face leverage constraints. The tightness of the constraints may depend on capital regulation, the underlying risk of assets, liquidity, and collateral values. As economic conditions deteriorate, the leverage cycle acts as an amplification mechanism of underlying shocks.

[7]Figure 3 illustrates the response to an unanticipated temporary productivity shock of land price (Q), landholding (K), and debt (B) expressed as ratios to their respective steady-state values (starred variables). Prior to the shock, the system is assumed to be at the steady state. Simulation results are presented assuming the same parameter values as in Kiyotaki and Moore (1997): the interest rate equals $R = 1.01$, the depreciation rate of capital $\lambda = 0.975$; moreover, $\pi = 0.1$, $a = 1$, $\phi = 20$.

Figure 3: Temporary productivity shock and land price (Q), landholding (K), and debt (B) responses (Kiyotaki and Moore, 1997, p. 238)



Recently, the financial accelerator mechanism as in Bernanke, Gertler and Gilchrist (1999) has been explicitly extended to financial intermediaries (and not only applied to non-financial borrowers as in the earlier literature). Notably, Gertler and Kiyotaki (2010) introduce agency problems in a model featuring banks that intermediate funds between households and firms. With financial frictions, the model is able to generate a decline in output following an exogenous shock capable of depressing asset prices that is roughly twice as large as in the frictionless case, and more persistent.

In a similar vein, Gertler and Karadi (2011) develop a monetary dynamic stochastic general equilibrium (DSGE) model with financial intermediaries facing balance sheet constraints: these constraints may limit the ability of firms to obtain funds, and this mechanism produces financial frictions. As in Bernanke, Gertler and Gilchrist (1999), the presence of the financial accelerator mechanism amplifies the effects of shocks relative to the baseline DSGE. In addition, the model is designed to study the welfare effects of an unconventional monetary policy measure: it is assumed that the central bank can borrow funds from households and lend directly to firms, as private intermediaries do. Yet, unlike private intermediaries, the central bank is not "balance sheet" constrained. In normal times, a simple Taylor rule characterises monetary policy. Instead, in a crisis, credit policy is introduced, and the central bank is allowed to target credit spreads. The authors show that expanding central bank credit intermediation in response to an exogenous capital quality shock (a "crisis" situation that mimics some of the features of the most recent one) moderates the contraction and produces welfare gains.

Lastly, two general remarks should be made in respect of financial frictions and macroeconomic models. First, although they been introduced in a standard New-Keynesian setting (see, e.g., Christiano, Trabandt and Walentin, 2011), financial frictions have also been rationalised – with very different implications (i.e., investment wedges can account for only a small fraction of real fluctuations) – in the framework of canonical real business cycle models with wedges (e.g., "equivalence result" in Chari, Kehoe and McGrattan, 2007).[8]

Second, all the contributions surveyed so far deal essentially with linear dynamics. Technically, they all log-linearise the model in the neighbourhood of the steady state and examine to what extent financial frictions amplify exogenous shocks, by looking at impulse response functions. It should be stressed, however, that in recent years a bunch of theoretical papers have explicitly introduced nonlinearities in conjunction with financial frictions in otherwise standard dynamic stochastic general equilibrium models. In a nonlinear framework, it is necessary to solve for the full dynamics of the model by resorting to more complicated solution methods (e.g. higher-order approximations).

Among the works we are aware of, Brunnermeier and Sannikov (2012) build a continuous time model in order to study the full equilibrium dynamics (not only around the steady state) of an economy with financial frictions. The model features a financial system subject to instability due to nonlinear effects, which are asymmetric and only occur during downturns. In tranquil times, the system is characterised by relative stability and low volatility, with low amplification effects. During crisis episodes instead, when the economy is hit by large shocks and it moves away from the steady state, borrowers reduce their positions, and this lowers asset prices and generates amplification loops. Interestingly, in "normal" times, when the aggregate exogenous risk is low, borrowers assume higher leverage (risk-taking is endogenous) and, paradoxically, this makes the system more prone to systemic volatility (higher endogenous systemic risk).

Focusing instead on emerging countries, Mendoza (2010) develops a nonlinear business

[8] In business cycle accounting, investment wedges can be broadly defined as shocks that enter the intertemporal Euler equation and that perturb the economy's long-run equilibrium path.

cycle model featuring a collateral constraint that imposes a ceiling on the leverage ratio. This constraint is occasionally binding, in that it binds only when the leverage ratio is sufficiently high (making the model nonlinear). In particular, when the collateral constraint binds, the cost of borrowing rises. When this situation arises, agents are forced to liquidate assets, and this reduces the value of collaterals, further tightening the constraint. Output falls as access to capital financing is also reduced.

In a similar context, Dewachter and Wouters (2012) incorporate a nonlinear propagation effect of capital-constrained financial intermediaries in a dynamic stochastic general equilibrium model with nominal and real frictions. This capital constraint, which is occasionally-binding as in Mendoza (2010) and becomes more stringent during economic downturns, adds to the model an endogenous risk channel to the transmission mechanism of standard productivity shocks. It also increases the macroeconomic volatility, particularly in periods of high financial stress. When the capital constraints are stringent, intermediaries apply higher premia in evaluating assets. This depresses asset prices. Investment is therefore reduced, leading to a contraction of output. Interestingly, the proposed framework is able to reproduce procyclicality of asset prices and leverage.

The present Section, which has briefly revisited the leading economic theories on financial frictions and nonlinearities in dynamic general equilibrium models, is complemented, next, by an overview of the most recent empirical works examining the interaction between financial conditions and real economic activity.

3 The empirical literature on macro-financial linkages

In recent years, a large empirical literature has analysed the impact of financial factors on economic activity. A wide range of approaches and models have been proposed, such as simple autoregressive distributed lag models with exogenous financial indicators, structural vector autoregression (VAR), and fully specified dynamic stochastic general equilibrium models.

The main goal of this Section is to present, from an empirical perspective, a selective review of the most recent papers that deal with the interactions between financial and real factors. The focus hereafter will be on works that adopt a modelling framework based on standard reduced-form VARs, while the fast growing literature on financial frictions in DSGE models will not be covered, as this topic requires separate attention, beyond the scope of the paper.[9]

Two related approaches are reviewed. Subsection 3.1 considers the recent work that estimates the contribution of identified financial shocks to real fluctuations in the context of constant parameter reduced-form models, while Subsection 3.2 gives an overview of the latest papers that incorporate time variation and other types of nonlinearities – such as Markov-switching dynamics – into otherwise standard empirical macroeconomic models.

3.1 Constant parameter reduced-form models

The interaction between financial market conditions and the real economy has been a hotly debated research topic since the outbreak of the financial crisis. Within a reduced-form approach and assuming that parameters are constant over time, a stream of the empirical literature has proposed "augmenting" standard VAR models to incorporate financial variables such as credit and asset prices.

Although this literature has considered several different approaches to shock identification and selection of the relevant financial variables, a common result worth stressing is that financial factors do interact with real variables and that financial shocks have an impact on real economic activity, as predicted, for instance, by the accelerator mechanism. To the best of our knowledge, the most recent studies that provide for the broader cross-country perspective are those of Ciccarelli, Maddaloni and Peydro (2010), Gilchrist and Zakrajšek (2012), Guarda and Jeanfils (2012), Fornari and Stracca (2012), and Aksoy and Basso (2013). Table 1 provides an overview.

Among the early contributions of the macro-finance literature we find Ciccarelli, Maddaloni and Peydro (2010) who, using quarterly data up to 2009:Q4 for the US and 12 euro area countries, study the linkages between credit and the business cycle by embedding into VAR models information based on the answers to the Bank Lending Survey (BLS) for the euro area and on the Senior Loan Officer (SLO) Survey for the US. They argue that survey information is crucial as it can help identify shocks to loan supply and to loan demand, which are in general unob-

[9] The interested reader is referred to Gerke et al. (2013) for a recent survey and a model comparison exercise of DSGE models featuring a financial accelerator mechanism and/or collateral constraints used in the European System of Central Banks.

Table 1: Macro-financial linkages: A summary of the empirical literature using constant parameter reduced-form VAR models

REFERENCE	**COUNTRIES**	**MODEL**	**MAIN VARIABLES**	**SAMPLE**
Ciccarelli, Maddaloni and Peydro (2010)	Euro area (12 countries) and US	standard VAR (US) panel VAR (Euro area); recursive identification	growth rate of real GDP, growth rate of GDP deflator, EONIA (Euro area), Fed Funds Rate (US), lending from BLS (Euro area), and from SLO Survey (US)	2002:Q4–2009:Q4 (Euro area) 1992:Q3–2009:Q4 (US)
Gilchrist and Zakrajšek (2012) (*American Economic Review*, 2012)	US	standard VAR; recursive identification	log-diff. of real consumption log-diff. of real investment log-diff. of real GDP log-diff. of GDP price defl. quarterly average of EBP quarterly average of excess stock mkt. return ten-year Treasury yield Fed Funds Rate	1973:Q1–2010:Q3
Guarda and Jeanfils (2012)	19 adv. countries (Euro area, US, UK, Japan, Australia, New Zealand, Switz., Denmark)	standard VAR (for each country separately); recursive identification	real GDP, CPI, consumption, gross capital formation, short and long-term interest rate, real stock prices, real house prices, term spread, loans-to-GDP ratio, and loans-to-deposits ratio	1980:Q1–2010:Q4
Aksoy and Basso (*The Economic Journal*, 2013)	US	standard VAR; recursive identification	GDP, interest rate, private investment, term spread, prices, bank profits, Michigan Ind. Cons. Exp.	1970:Q1–2007:Q2
Fornari and Stracca (*Economic Policy*, 2012)	21 adv. countries (Euro area, US, UK, Japan, Australia, New Zealand, Switzerland, Denmark, Norway, Sweden)	standard VAR (for each country separately); identification with sign restrictions	real GDP, GDP deflator, CPI, non-residential investment, 3-month interest rate, trade openness, credit to private sector, credit to deposits ratio, stock market capitalisation, relative share price fin. sector, financial openness, expected default frequency, banking crisis dummies	1985:Q1–2011:Q2

servable. In addition to financial variables, the authors include in the VAR model GDP, prices and monetary policy interest rates. Results show that the impact of a monetary policy shock on GDP is significantly stronger if the credit channel is accounted for. For firms, the impact through the (supply) bank lending channel is greater than through the demand and firm balance sheet channels. By contrast, for household loans, the demand channel exerts the strongest influence.

In a standard VAR framework and working with US data from 1973:Q1 until 2010:Q3, Gilchrist and Zakrajšek (2012) examine the macroeconomic consequences of shocks to the Excess Bond Premium, which is basically an indicator of credit supply conditions. These authors use market prices of individual corporate bonds to construct a micro-level credit spread index that is then decomposed into a time-varying default premium (linked to the probability of default and hence reflecting default risk) and a residual component, which they term "Excess Bond Premium" (EBP), linked to the balance sheet and capital conditions of financial intermediaries. A key finding of their analysis is that corporate bond credit spreads have a high predictive content for economic activity, which is entirely due to movements in the EBP.[10]

In order to study the macroeconomic implications of these findings, Gilchrist and Zakrajšek (2012) use a medium scale constant coefficient VAR model that includes the growth rate of real consumption, the growth rate of real investment, the growth rate of real GDP, inflation, the quarterly average of the EBP, the quarterly average of the excess stock market return, the ten-year Treasury yield and the Federal Funds Rate:

[10]The fact that credit spreads are useful predictors of a large set of macroeconomic indicators is confirmed by Faust et al. (2013), using a Bayesian model averaging approach. Gains in forecast accuracy appear to be remarkable, especially in recessionary periods.

$$A(L)\begin{bmatrix} CONS_t \\ INV_t \\ Y_t \\ \pi_t \\ \boxed{EBP_t} \\ STMKT_t \\ TREA_t \\ R_t \end{bmatrix} = \begin{bmatrix} u_t^{CONS} \\ u_t^{INV} \\ u_t^{Y} \\ u_t^{\pi} \\ \boxed{u_t^{EBP}} \\ u_t^{STMKT} \\ u_t^{TREA} \\ u_t^{R} \end{bmatrix}, \tag{1}$$

where $A(L)$ in (1) is a matrix of polynomials in the lag operator L and u_t is a vector of residuals whose variance-covariance matrix $var(u_t) = \Lambda$ is unrestricted. They apply a recursive (Cholesky) ordering identification scheme. The recursive identification scheme requires orthogonalising the u_t residuals such that: $BB' = \Lambda$, $Bz_t = u_t$, where z_t are orthogonal disturbances and B is a lower triangular matrix:

$$B = \begin{bmatrix} 1 & 0 & 0 & 0 & \boxed{0} & 0 & 0 & 0 \\ b_{2,1} & 1 & 0 & 0 & \boxed{0} & 0 & 0 & 0 \\ b_{3,1} & b_{3,2} & 1 & 0 & \boxed{0} & 0 & 0 & 0 \\ b_{4,1} & b_{4,2} & b_{4,3} & 1 & \boxed{0} & 0 & 0 & 0 \\ b_{5,1} & b_{5,2} & b_{5,3} & b_{5,4} & \boxed{1} & 0 & 0 & 0 \\ b_{6,1} & b_{6,2} & b_{6,3} & b_{6,4} & \boxed{b_{6,5}} & 1 & 0 & 0 \\ b_{7,1} & b_{7,2} & b_{7,3} & b_{7,4} & \boxed{b_{7,5}} & b_{7,6} & 1 & 0 \\ b_{8,1} & b_{8,2} & b_{8,3} & b_{8,4} & \boxed{b_{8,5}} & b_{8,6} & b_{8,7} & 1 \end{bmatrix}. \tag{2}$$

According to the identification scheme in (2), a shock to the Excess Bond Premium (EBP_t) affects consumption, investment, GDP and inflation with one lag, while stock prices, the ten-year Treasury yield and the Federal Funds Rate react contemporaneously to such a financial disturbance.

Results show that shocks to the EBP, i.e. z_t^{EBP}, cause significant declines in real economic activity, a decline in nominal interest rates, a sharp fall in equity valuations (and a decline in bank lending). Results are robust to a different identification scheme in which the EBP is ordered last in the VAR, after stock prices, the ten-year Treasury yield, and the Federal Funds

Rate. It turns out that, being contemporaneously uncorrelated with the other variables, the ordering of EBP in the VAR is not relevant for identifying the financial shock. In a variance decomposition analysis, a positive shock to the EBP accounts for more than 10 per cent of GDP fluctuations and 25 per cent of the variation in investment, a proportion that exceeds the variation usually explained by monetary policy shocks.

In order to identify shocks to the financial sector, other authors have proposed integrating standard VAR models with credit, property and equity prices. For example, Guarda and Jeanfils (2012) suggest quantifying the contribution of financial shocks to the real economy by augmenting a structural VAR model with five different financial indicators: stock and house prices, the term spread, the ratio of private sector credit to GDP, and the loan to deposit ratio. Asset price variables are included to account for the financial accelerator effect; credit variables, in order to capture bank lending channel effects. The analysis is conducted on a large set of industrial countries (including Canada, Japan and the US). Three different measures of economic activity are used: GDP, private consumption and investment. Data range from 1980:Q1 to 2010:Q4. Estimation is conducted separately country-by-country. A recursive (Cholesky) identification scheme is applied to identify structural shocks.

The authors obtain several interesting findings. First, the forecast error variance decomposition suggests that the impact of financial variables on real economic activity is heterogeneous across countries (for GDP, the contribution of the five financial shocks is higher in the euro area for Germany, Spain, the Netherlands and Finland, and for Australia, Denmark and Sweden in the rest of the world). Second, the combined contribution from the five financial shocks accounts for 33% of GDP variance over the 3-year horizon, on average across countries. Third, comparing GDP, consumption and investment, the combined impact of financial shocks on real variables is similar, although it is higher for investment than for consumption. Fourth, among the five financial variables considered, shocks to asset prices (real house prices and real stock prices) are the most important source of real fluctuations. The leverage indicators (loans-to-GDP or loans-to-deposits ratios) and the term spread also play a role, although a less important one.

The effects on macro variables of shocks in the banks' profitability and related fluctuations in the term spread are also analysed in a recent work by Aksoy and Basso (2013). Their paper is an attempt to assess the link between changes in banking profitability, resulting movements in the term spreads and key real variables. They lay out a DSGE model in which the endogenous movements in term spreads are linked to the fluctuations in the profitability of banks' portfolios (i.e. during a recession, profitability is low, spreads are high, and it is costly to pay funding costs to increase long-term earnings). In turn, endogenous movements in term spreads feed back to the macroeconomy through investment decisions.

At the same time, they complement their theoretical analysis with empirical evidence by looking at the responses of the main economic variables to anticipated innovations (news) in bank profitability. In particular, they estimate a VAR model for the US with data from 1970:Q1 to 2007:Q2. The VAR features GDP, short-term interest rate, prices, private investment, the term spread, an indicator that reflects news about the future evolution of economic activity, and a measure of bank profits. This latter variable is ordered first in the VAR. A Cholesky decomposition of the innovations is employed. Results indicate that, also in the US, changes in the profitability of banks – which can be assimilated to a financial shock – make a large contribution to real fluctuations: indeed, the analysis based on the forecast error variance decomposition shows that, over a twenty quarter horizon, the bank profitability shock accounts for around 17 per cent of variations in real GDP and 23 per cent of variations in investment. This evidence is approximately in line with that reported by Guarda and Jeanfils (2012) on the euro area.

Finally, Fornari and Stracca (2012), using a sample of 21 advanced economies over the period from 1985:Q1 to 2011:Q2, take a partially different approach with respect to the studies previously surveyed. Basically, in their VAR model, they apply sign restrictions in order to identify structural shocks instead of a triangular ordering.[11] Very recently, a similar route has been pursued by Furlanetto, Ravazzolo and Sarferaz (2014), who assess the magnitude of financial shocks to explain business cycle fluctuations in the US. They use a standard constant coefficient VAR model and impose a minimum set of sign restrictions grounded in economic theory.

An issue that is often debated when applying sign restrictions is whether the set of assumed restrictions imposed on impulse responses might be derived by common economic reasoning or should rather be consistent with the implications of fully-fledged DSGE models. In this

[11] See Rubio-Ramírez, Waggoner and Zha (2010), and Fry and Pagan (2011) for general treatments of the identification scheme based on sign restrictions.

respect, Fornari and Stracca (2012) point out that, besides stemming from intuition, the sign restrictions they impose to identify financial shocks are consistent with the stylised DSGE model developed by Hirakata, Sudo and Ueda (2009), which features financial frictions. Specifically, Hirakata, Sudo and Ueda (2009) argue that a positive financial shock is akin to a transfer of net worth from the non-financial to the financial sector, and this redistribution of net worth between sectors matters for investment. As explained by the authors, this definition of financial shock is similar to the one put forward by Hall (2010), according to whom "*A positive financial shock is akin to a selective fall in taxation of financial intermediation, which makes financial intermediation less costly and more efficient*." As a result, those institutions offering financial intermediation services become more profitable, and more credit is extended.

In Fornari and Stracca (2012), each VAR model estimated country-by-country has domestic variables such as GDP, prices, investment, a short-term interest rate, composite share price indexes of financial and non-financial sectors and credit extended to the private sector. For each country, foreign variables are also included, as exogenous. The impulse response analysis shows that the identified financial shocks have non-negligible influence on macro variables; interestingly, investment seems to react more than real GDP.

Even though Fornari and Stracca (2012) adopt a standard linear econometric framework, they nonetheless try to assess whether their results are disproportionately driven by the global financial crisis. In order to test this conjecture, they estimate the VAR models excluding the period of the global financial crisis (2007:Q3-2011:Q2), obtaining similar results to their baseline estimation. The authors conclude that financial shocks also play a role in "normal" circumstances, not only in times of crisis.[12]

However, the most recent empirical evidence based on the worldwide financial crisis suggests that describing quantitative relationships between the financial and the real sectors requires a nonlinear framework. We explore this issue further in the remaining part of this paper. In particular, the following subsection covers the latest contributions that, in the same class

[12]Given the procedure implemented, this result is largely expected. In fact only 16 observations are left out of the full sample composed of more than 100 data, and therefore constitute only prima facie evidence in favour of their statement. However, the sub-sampling approach is broadly used in the empirical literature. For instance, many of the studies investigating the reasons for the "Great Moderation" compare the results from the same model estimated in two distinct periods before and after the alleged break in 1984 (Lubik and Schorfheide, 2004; Boivin and Giannoni, 2006; De Blas, 2009; Bencivelli and Zaghini, 2012).

of reduced-form models, allow for nonlinearities associated with time-varying parameters and Markov-Switching dynamics.

3.2 Nonlinearities in reduced-form models

As we know, in linear time series models the temporal dependence between random variables in the model is determined by their (auto)covariance structure, which is assumed to be constant over time.[13] By contrast, in nonlinear time series models this dependence takes a more general functional form and can even change over time.[14]

Within nonlinear time series models, a relevant distinction is the one between threshold and Markov-switching models. In threshold models, a single observable time series determines the prevailing regime of the whole system. In Markov-switching models, instead, the regime of the system is governed by an unobservable Markov process. This general definition applies both to univariate and multivariate models, such as VARs.[15]

Nonlinearities have been introduced in the modelling framework through several approaches. The first univariate threshold specification dates back to Tong (1978). In a multivariate context, threshold VAR models have been often used in economics as a tool for studying how the dynamics of relevant variables changes across regimes. Consistently, a key feature of threshold VARs is that they allow for different sets of model parameters over time, each corresponding to a different regime. Which regime applies to a given point in time depends on whether a threshold variable exceeds a given threshold value; further, the observable threshold variable can itself be included in the system or it can be exogenous.

One of the first studies that formalise and implement the threshold VAR model is Tsay (1998), who addresses both model building and testing issues. In particular, the author shows how selecting and estimating a threshold VAR model and how testing formally for the presence of threshold effects. The procedure is applied, for illustrative purposes, to study arbitrage in security markets and to model US monthly interest rates.

[13]For instance, for a univariate first order autoregression model, the autoregressive coefficient controls the whole autocorrelation pattern between observations.

[14]For a general treatment of nonlinear time series models, the interested reader is referred to Teräsvirta, Tjøstheim and Granger (2010).

[15]For a recent survey of nonlinear vector time series models see Hubrich and Teräsvirta (2013).

Threshold VAR models have also been applied in macroeconomics to examine whether there are any nonlinearities in the relationship between credit and economic activity (Balke, 2000; Calza and Sousa, 2006). Table 2 contains a summary of this specific literature. Balke (2000), using US data, estimates a two-regime threshold VAR model where the regime depends on conditions in the credit market. An indicator of credit conditions is included in a standard three-variable VAR featuring output growth, inflation, and a short-term interest rate. Impulse response analysis is conducted to obtain some insight on the magnitude of the role played by credit in the nonlinear propagation of shocks to economic activity. Nonlinear impulse response analysis – which allows for regime switching throughout the duration of the response – suggests that the identified shocks have a larger effect on output growth in a tight credit regime than in normal times, and that contractionary monetary policy shocks have a larger effect than expansionary monetary policy shocks.

Unlike Balke (2000), Calza and Sousa (2006) focus on the euro area and adopt the same methodological approach to test empirically whether output and inflation respond asymmetrically to credit shocks. Overall, using data from 1981:Q2 to 2002:Q3, they find evidence of threshold effects. Interestingly, also in the light of the most recent credit developments in the euro area, the threshold critical value for the quarter-on-quarter growth of real loans is estimated at 0.78 per cent. According to this estimate, the euro-area economy would currently be in a regime of low credit growth. The estimated conditional linear impulse responses provide evidence of asymmetric reactions of output and inflation to credit shocks over the lending cycle. Turning to nonlinear impulse responses, like Balke (2000), Calza and Sousa (2006) find that when credit conditions are tighter output effects seem to be more pronounced.

In addition to threshold VARs, another approach that has been suggested in recent years to account for nonlinearities is time-varying parameter VAR models. These models have been introduced in macroeconometrics to account for (gradual) structural shifts in the economy. In fact, several authors have argued, time-invariant coefficients and volatilities may turn out to be a restrictive assumption in capturing the evolution of economic time series.

The most prominent contributions in this area are probably those of Cogley and Sargent (2005) and Primiceri (2005), which do not deal with macro-financial linkages, however. Cogley and Sargent (2005) set up a VAR with time-varying coefficients and stochastic volatilities and find that in the United States the monetary policy equation (the FED reaction function) has

Table 2: Macro-financial linkages: A summary of the empirical literature using reduced-form VAR models with nonlinearities

REFERENCE	COUNTRIES	MODEL	MAIN VARIABLES	SAMPLE
Balke (*RES*, 2000)	US	threshold VAR	GDP growth, inflation, Fed fund rate, and credit conditions	1960:Q1–1997:Q3
Calza and Sousa (*SNDE*, 2006)	Euro area	threshold VAR	growth rate of real GDP, inflation, lending rate, loans to the private sector	1981:Q2–2002:Q3
Ciccarelli, Ortega and Valderrama (2012)	G7 and other European economies	time-varying panel VAR	growth rates of GDP, consumption, and fixed capital formation, stock and house prices, term spread (10 year-3 month rates), credit to the private sector, loans to deposit ratio	1980:Q1–2011:Q4
Prieto, Eickmeier and Marcellino (2013)	US	time-varying VAR	GDP growth GDP deflator House price inflation Corporate bond spread Stock price inflation Fed fund rate	1958:Q1–2012:Q2
Kaufmann and Valderrama (*Manchester School*, 2010)	Euro area and US	Markov-switching VAR	GDP, short-term interest rate, HICP inflation (Euro area), and CPI inflation (US), loan aggregates, equity prices	1980:Q1–2004:Q2
Hartmann et al. (2013)	Euro area	Markov-switching VAR	industrial production growth, inflation, short-term interest rate, loan growth, Composite Indicator Systemic Stress	1987:01–2010:12 (monthly freq.)

changed in the post-war period, and that the persistence of inflation has drifted over time. In a similar fashion, Primiceri (2005) estimates a VAR model with time-varying coefficients and time-varying variance-covariance matrix of the model's innovations and finds evidence of time variation in US monetary policy, with higher volatility of monetary policy shocks in the 1970s and in the first half of the 1980s.

There are still very few papers employing time-varying parameter VAR models to examine the linkages between real economic variables and financial variables (Table 2). One of the first attempts is by Ciccarelli, Ortega and Valderrama (2012), who build a time-varying panel VAR model with real and financial variables (stocks, real estate and bank leverage) for a set of major European economies plus the US, Canada and Japan. A panel framework with time-varying parameters enables them to examine the cross-country interdependence and the time evolution of real-financial linkages, accounting simultaneously for spill-overs and heterogeneity.

The model is estimated with Bayesian methods as in Canova, Ciccarelli and Ortega (2007), and in Canova and Ciccarelli (2009), over the period 1980:Q1-2011:Q4. Bayesian inference is used because, in the time-varying parameter VAR setup, maximum likelihood estimation is often unfeasible as there are too many parameters to estimate, especially in high-dimensional models. Thus, to circumvent the computational burden imposed by maximum likelihood estimation, the macroeconometric literature has often resorted to Bayesian inference, which enables large dimensional parameter spaces to be estimated.

Estimation results point to a statistically significant common component for all countries, especially during the 2008-09 recession. Yet, country-specific factors are also relevant, due to the presence of a heterogeneous pattern in the relationship between the financial sector and the real economy. At the same time, the authors report evidence of significant spillovers, meaning that a shock to a variable in a given country seems to affect all the other countries. Allowing for time variation in the panel VAR helps in identifying important asymmetries in the shape and the dynamics of international cycles: as a consequence, otherwise linear models run the risk of missing important features of the data.

Recently, Prieto, Eickmeier and Marcellino (2013) incorporate key financial variables (credit spread, house and stock prices) in a time-varying parameter VAR model for the US. The model is estimated over the period 1958:Q1-2012:Q2 with Bayesian methods. A recursive (Cholesky) identification scheme is used. The following ordering is chosen: GDP, inflation, house prices, a BAA-AAA corporate bond spread, stock market, Fed Funds rate. In terms of equation (2), the recursive identification scheme requires:

$$B = \begin{bmatrix} 1 & 0 & 0 & \boxed{0} & 0 & 0 \\ b_{2,1} & 1 & 0 & \boxed{0} & 0 & 0 \\ b_{3,1} & b_{3,2} & 1 & \boxed{0} & 0 & 0 \\ b_{4,1} & b_{4,2} & b_{4,3} & \boxed{1} & 0 & 0 \\ b_{5,1} & b_{5,2} & b_{5,3} & \boxed{b_{5,4}} & 1 & 0 \\ b_{6,1} & b_{6,2} & b_{6,3} & \boxed{b_{6,4}} & b_{6,5} & 1 \end{bmatrix},$$

i.e., delayed effects of the financial shock on the variables located before the corporate bond spread (GDP, inflation and house prices).

Among their main findings, Prieto, Eickmeier and Marcellino (2013) report that during the global financial crisis the explanatory power of financial shocks for GDP growth has risen to 50 per cent, compared with 20 per cent in normal times. In addition, house price shocks are found to be very important in explaining the “Great Recession”, accounting for about 2/3 of the overall contribution of the financial sector to GDP growth. The size of house price and credit spread shocks has been larger and the transmission to growth stronger than in the early 2000s. Finally, the housing sector affects the macroeconomy asymmetrically. In fact, negative shocks tend to be more important for the economy than positive shocks.

Within the class of reduced-form nonlinear models, Markov-switching models have also been used to account for parameter instability over time (Table 2). In the last decade, the univariate framework originally proposed by Hamilton (1989) has been extended to multiple-equation models (see Sims and Zha, 2006, and Sims, Waggoner, and Zha, 2008, who outline how to conduct inference with Markov-switching VAR models). Unlike time-varying VARs or other time-varying models proposed in the literature, in Markov-switching VAR models parameters switch according to an unobservable state indicator that follows a Markov process. Being unobservable, the state is estimated jointly with the other model parameters. The state estimate determines different regimes of the economy.

In this framework, Kaufmann and Valderrama (2010) use a Markov-switching VAR model to study the role of credit and asset prices in the transmission mechanism of shocks to the real economy. By comparing the euro area to the US, the authors intend to gauge whether credit and asset prices exert a different role in the transmission mechanism in economies with, respectively, a bank-based and a market-based financial system. A five-variable system including GDP, prices, short-term interest rate, credit, and asset prices is estimated using quarterly data ranging from 1980:Q1 to 2004:Q2: thus, the period of the financial crisis is not covered in the analysis.

Focusing on the euro area, the empirical evidence suggests that the two uncovered regimes can be associated with business cycle conditions (i.e. expansion versus recession). The recession is characterised by low credit growth, which is mainly driven by supply restrictions, while the role of demand is stronger in the expansion. An interesting result is that credit conditions do not seem to have an amplifying effect on the business cycle in the supply-driven lending regime. By contrast, credit has a procyclical effect on the real economy during the demand-driven lending regime. Differences between euro-area and US financial systems are confirmed by the analysis:[16] on the one hand, asset prices contribute more to GDP forecast error variance in the US than in the euro area; on the other hand, lending explains a larger fraction of output volatility in the euro area than in the US.

These issues are closely related to a very recent research undertaken by Hartmann et al. (2013).[17] These authors estimate a Markov-switching VAR model for the euro area, employing a sample running from January 1987 to December 2010 (monthly data are used). They argue that the Markov-switching VAR model provides a rigorous statistical framework to examine nonlinearities and makes it possible to compare how financial variables affect the real economy in regimes of "low" and "high" financial stress.

Five variables are included in the system, in this order: industrial production, consumer price inflation, short-term interest rate, bank loans, and a composite indicator of systemic stress for the euro area. The structural model is identified through a Cholesky decomposition of the innovations. A sensitivity analysis reveals that marginal changes in the variable ordering (e.g., placing loans before the short-term interest rate) do not seem to affect the results. The model is estimated with Bayesian methods (following the procedure outlined in Sims, Waggoner and

[16] For an econometric analysis of the convergence of financial systems the interested reader is referred to Bruno, De Bonis and Silvestrini (2012).

[17] For a short summary of the findings reported by Hartmann et al. (2013), see Section 7 in Hubrich et al. (2013).

Zha, 2008).

Estimation results provide strong evidence against the constant-parameter VAR specification: in particular, the log marginal data density favours a specification with three volatility regimes and two independent coefficient regimes, making six different regimes in all. The effect of nonlinearities in the transmission of the financial stress shock to the real economy is analysed on the basis of regime-dependent impulse response functions. The focus is on the impulse response functions constructed from a shock to the financial stress indicator (or to loan growth). Results reveal that there is a large amplification effect during periods of severe systemic stress: namely, in times of crisis a positive shock to the systemic stress indicator generates a pronounced contraction of industrial production. By contrast, in normal times, the effect is negligible. Further, bank lending seems to play a role in amplifying the transmission of financial stress to the real economy. As a consequence, the authors conclude that in order to analyse macro-financial linkages it is crucial to take nonlinearities into account in the model specification.

4 Conclusions

This paper presents an up-to-date overview of theoretical and empirical contributions dealing with the inter-linkages between financial conditions and real variables, focusing on the transmission mechanism of financial shocks to the economy.

First, it revisits the main theoretical frameworks that allow frictions to be embedded into general equilibrium models, explaining intuitively how the financial accelerator mechanism (Bernanke, Gertler and Gilchrist, 1999) and collateral constraints (Kiyotaki and Moore, 1997) are able to amplify the impact of financial shocks on the real economy.

Then, it surveys the most recent empirical papers on macro-financial linkages. In the framework of constant parameter reduced-form models, several different approaches to shock identification and selection of the relevant financial variables have been adopted in the literature. A relevant common finding is that financial and real variables interact through the business cycle according to a pattern consistent with the predictions of the theoretical literature. In addition, some authors suggest that the contribution of financial shocks to the GDP volatility is sizeable even compared with the evidence on the contribution of monetary policy shocks usually reported in the literature.

In the light of the worldwide financial crisis, particular emphasis is also given to those works that incorporate time variation and other types of nonlinearities – such as Markov switching – into standard constant parameter reduced-form models.

In short, the main policy conclusion we draw from this literature is that deriving implications on the basis of constant-parameter models may provide misleading guidance or even wrong indications, especially during episodes of severe financial and economic distress or when the functioning of financial markets is impaired. Rather, the response to exogenous shocks must be calibrated according to the state of the economy and the intensity of the shock.

In terms of future research, a possible strand of investigation should aim to improve this very promising econometric framework in order to deepen our understanding of several relevant features of macro-financial linkages, such as heterogeneity and cross-country spill-overs, especially from the financial stability and monetary policy perspectives.

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