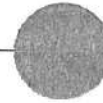




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# Quantifying Systemic Risk

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## Systemic Risks and the Macroeconomy

Gianni De Nicolò and Marcella Lucchetta

### 3.1 Introduction

The recent financial crisis has underscored the need for a deeper understanding of the key drivers of systemic financial risk and its two-way relationship with real activity. We believe that to accomplish these goals, at least two requirements need to be met. First, measures of systemic risk need to be associated with the potential for undesirable welfare consequences, such as extreme adverse real effects. Second, the interplay between real and financial activity needs to be assessed through the implications of some theoretical model, and correspondingly quantified. Importantly, detecting macro-financial linkages through a consistent and tractable framework may make it feasible to design risk monitoring tools implementable in real time. Contributing to accomplishing these goals is the main objective of this chapter.

We design a modeling framework that aims at tracking and quantifying the impact and transmission of structurally identifiable shocks within/between the macroeconomy, financial markets, and intermediaries, as well as their "tail" realizations. In terms of figure 3.1, the proposed framework aims at identifying which sectors of the economy are most affected by a shock at

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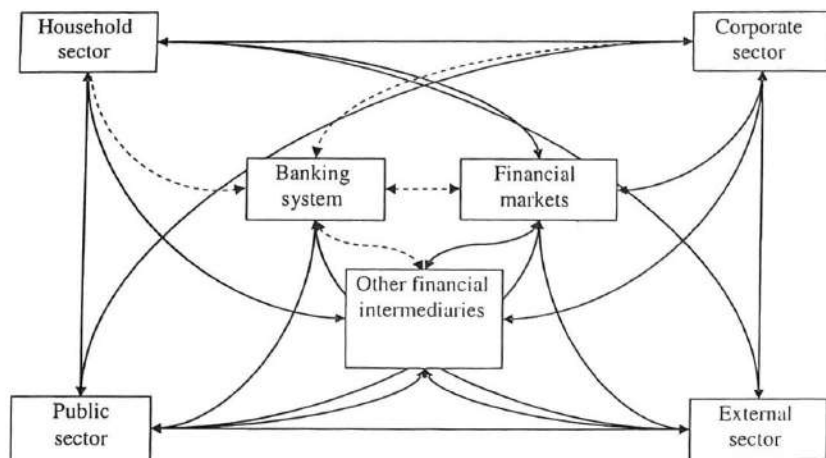


Fig. 3.1 Financial exposures (stocks and flows) between sectors

impact, to gauge size and persistence of shocks' propagation within and between sectors, and forecast their systemic real and financial outcomes.

Ideally, a computable general equilibrium model specified at a suitable level of disaggregation would allow us to identify the sources of shocks as well as the linkages through which they are propagated. In practice, formulating and implementing such a model is a formidable theoretical and computational task. At present, an increasing number of research resources are devoted to develop macroeconomic models with meaningful interaction between financial and real sectors. However, work in this direction is still in its infancy, since workhorse dynamic stochastic general equilibrium (DSGE) models do not yet embed essential financial structure or sectors, being their modeling of financial markets and institutions highly stylized.<sup>1</sup>

As a result, the available modeling technologies are still relatively underdeveloped. Some models analyzing the impact of macroeconomic shocks on segments of the financial sector have been developed recently in some central banks and international organizations. Yet, the feedback effects of financial vulnerabilities on the macroeconomy have been usually left unmodeled, since the output of these models is used mainly for financial supervisory purposes.<sup>2</sup>

Our modeling framework delivers joint forecasts of indicators of systemic

1. However, a rapidly growing literature, briefly reviewed by Walsh (2009), explores the implications of specific financial frictions in the context of extensions of the "financial accelerator" model of Bernanke, Gertler, and Gilchrist (1999), with work by Christiano, Motto, and Rostagno (2010) at the forefront of this effort.

2. See Sorge (2004) for a review of stress testing, and Huang, Zhou, and Zhu (2009a, 2009b) for recent contributions.

real risk and systemic financial risk, as well as stress tests of these indicators as impulse responses to structurally identifiable shocks. This framework is novel in two respects. First, it uses a dynamic factor model with structural identification based on theory. This permits us to extract information on common sources of shocks contained in a large set of time series, and to characterize their economic content. Second, it integrates the dynamic factor model with quantile regressions techniques, which allow us to estimate and forecast the size of tail realizations of systemic risks. We make a distinction between systemic real risk and systemic financial risk based on the notion that real effects are what concerns policymakers most since they are likely to entail welfare consequences. Our systemic real risk indicator is GDP at risk (GDPaR), defined as the worst predicted realization of quarterly growth in real GDP at 5 percent probability over a predetermined forecasting horizon.<sup>3</sup> Our indicator of systemic financial risk (FSaR) is defined as the worst predicted realization of a system-wide financial risk indicator at 5 percent probability over a predetermined forecasting horizon.

The underlying joint dynamics of GDP growth and the system-wide financial risk indicator is modeled through a factor-augmented vector autoregression (FAVAR) model, following variants of the methodology detailed in Stock and Watson (2002, 2005). Estimates of GDPaR and FSaR indicators are obtained through quantile regressions.

Forecasts of GDPaR and FSaR indicators are obtained by inputting the predicted values of factors obtained from the companion factor-augmented VAR into the relevant quantile regressions. Identification of structural shocks is accomplished with an expanded version of the sign restriction methodology introduced by Canova and De Nicolò (2002), where shocks are identified based on standard macroeconomic and banking theory. Stress tests of both systemic risk measures are obtained by inputting impulse responses to shocks identified in the FAVAR model into the relevant quantile regressions.

We implement this framework using a large set of quarterly time series of financial and real activity for the G-7 economies during the 1980Q1 to 2009Q3 period. We obtain two main results. First, we find evidence of out-of-sample forecasting power of the model for tail risk realizations of real activity for several countries. This suggests the usefulness of the model as a risk monitoring tool. Second, in all countries we identify aggregate demand shocks as the main drivers of the real cycle, and bank credit demand shocks are the main drivers of the bank lending cycle. This result is consistent with the hypothesis that shocks to the real economy are the main drivers of both real and financial risks. Importantly, this finding challenges the common

3. In this chapter we focus on real GDP growth, but several other indicators can be considered in our framework. In addition to GDP growth, De Nicolò and Lucchetta (2011) consider unemployment.

wisdom that constraints in the aggregate supply of credit have been a key driver of the sharp downturn in real activity experienced by the G-7 economies in 2008Q4 to 2009Q1.

The remainder of the chapter is composed of four sections. Section 3.2 defines systemic risks and describes indicators consistent with these definitions. Section 3.3 outlines the model setup, estimation and forecasting, and the procedure used to identify structural shocks. Section 3.4 describes the implementation of the modeling framework on data for the G-7 countries and the relevant results. Section 3.5 concludes.

## 3.2 Systemic Risks

### 3.2.1 Definitions

Following Group of Ten (2001) and De Nicolò and Kwast (2002), we adopt the following definitions:

*Systemic financial risk* is the risk that a shock will trigger a loss of economic value or confidence in the financial system.

*Systemic real risk* is the risk that a shock will trigger a significant decline in real activity.

We adopt these definitions for two reasons. First, distinguishing systemic financial risk from systemic real risk allows us to better assess the extent to which a realization of a financial shock is just amplifying a shock in the real sector, or originates in the financial system. Second, financial events that carry significant adverse real effects, such as sharp reductions in output and increases in unemployment, are the ultimate concern of policymakers. The financial shocks following the prick of the dot-com bubble in the United States in 2001, as well as those experienced in several other G-7 countries documented following, appear to have induced no significant real effects. According to our definitions, these shocks may be viewed as realizations of systemic financial risks, but not of systemic real risk.

### 3.2.2 Measurement

To control risk in financial institutions, risk managers track value at risk (VaR). Value at risk measures the worst possible portfolio loss over a given time horizon at a given probability. To control risk in the economy, policymakers may wish to track measures of worst possible real macroeconomic outcomes. One such a measure is GDPaR, defined here as the worst predicted realization of quarterly growth in real GDP at 5 percent probability.

To control risk in the financial system, policy makers may also wish to track measures of worst possible system-wide financial outcomes. One such

a measure is financial system at risk (FSaR), defined as the worst predicted realization of the market-adjusted return of a large portfolios of financial firms at 5 percent probability. Following Campbell, Lo, and MacKinlay (1997), this market-adjusted return is the return of a portfolio of financial firms less the return on the market. We chose this measure for simplicity, treating the portfolio of the financial firms as a composite asset. However, other indicators can be adapted to our framework, such as those based on distance-to-default measures as in De Nicolò, Hayward, and Bathia (2004), those based on CDS spreads, as in Huang, Zhou, and Zhu (2009a, 2009b), as well those based on expected shortfalls constructed on the basis of individual firm returns, such as those in Acharya et al. (2010) and De Nicolò and Lucchetta (2012).

### 3.3 A Dynamic Factor Model of Systemic Risks

Denote real GDP growth with  $GDPG_t$ , and the indicator of system-wide financial risk with  $FS_t$ . The joint dynamics of  $GDPG_t$  and  $FS_t$  is modeled by a version of the dynamic factor model (DFM) detailed in Stock and Watson (2002, 2005).

The model is described by the following equations:

- (1)  $GDPG_t = \lambda^R(L)f_t + \gamma_{11}(L)GDPG_{t-1} + \gamma_{12}(L)FS_{t-1} + u_t^1$
- (2)  $FS_t = \lambda^F(L)f_t + \gamma_{21}(L)GDPG_{t-1} + \gamma_{22}(L)FS_{t-1} + u_t^2$
- (3)  $X_{it} = \lambda_i(L)f_t + \delta_i X_{it-1} + v_{it}$
- (4)  $f_t = \Gamma(L)f_{t-1} + \eta_t$

Equations (1) and (2) describe a VAR in  $GDPG_t$  and  $FS_t$  augmented with a factor structure. The dynamics of a (large) vector of series (predictors)  $X_t$  indexed by  $i \in N$  is represented by the factor model (3), where  $f_t$  is a set of *dynamic* factors.<sup>4</sup> Equation (4) describes the dynamics of these factors through a VAR.

As in Stock and Watson (2005), factors and idiosyncratic errors,  $u_t^1$ ,  $u_t^2$ , and  $v_{it}$  are assumed to be uncorrelated at all leads and lags. Assuming finite lags up to  $p$ , and defining the vector of *static* factors with  $F_t \equiv [f_t', f_{t-1}', \dots, f_{t-p}']$ , one obtains the *static form* representation of the DFM:

- (5)  $GDPG_t = \Lambda^R F_t + \gamma_{11}(L)GDPG_{t-1} + \gamma_{12}(L)FS_{t-1} + u_t^1$
- (6)  $FS_t = \Lambda^F F_t + \gamma_{21}(L)GDPG_{t-1} + \gamma_{22}(L)FS_{t-1} + u_t^2$
- (7)  $X_{it} = \Lambda_i' F_t + \delta_i X_{it-1} + v_{it}$
- (8)  $F_t = \Phi(L)F_{t-1} + G\eta_t$

4. Following Stock and Watson (2006), we do not include GDP growth and the FS indicator in the vector  $X_t$  of predictors.



Note that  $\Phi(L)$  includes  $\Gamma(L)$  and 0's, while  $G$  is a matrix of coefficients of dimension  $r \times q$ , where  $r$  is the number of static factors and  $q$  that of dynamic factors. If  $r = q$ , then  $\Phi(L) = \Gamma(L)$  and  $G = I$ ; that is, (8) is equivalent to (4).

Substituting (8) in (5) and (6), we obtain a FAVAR representation of the DFM, akin to that adopted by Bernanke, Boivin, and Eliasch (2005):

$$(9) \quad F_t = \Phi(L)F_{t-1} + G\eta_t$$

$$(10) \quad \text{GDPG}_t = \Lambda^{R'}\Phi(L)F_{t-1} + \gamma_{11}(L)\text{GDPG}_{t-1} + \gamma_{12}(L)\text{FS}_{t-1} + u_t^1$$

$$(11) \quad \text{FS}_t = \Lambda^{F'}\Phi(L)F_{t-1} + \gamma_{21}(L)\text{GDPG}_{t-1} + \gamma_{22}(L)\text{FS}_{t-1} + u_t^2.$$

### 3.3.1 Systemic Risk Measures

Using estimates of the static factors  $F_t$ , the systemic risk indicators GDPaR and FSaR are obtained by estimating the following quantile regressions:

$$(12) \quad \text{GDPG}_t = \alpha_1^q + \Lambda_q^{R'}F_t + \gamma_{11}^q(L)\text{GDPG}_{t-1} + \gamma_{12}^q(L)\text{FS}_{t-1} + u_t^{1q}$$

$$(13) \quad \text{FS}_t = \alpha_2^q + \Lambda_q^{F'}F_t + \gamma_{21}^q(L)\text{GDPG}_{t-1} + \gamma_{22}^q(L)\text{FS}_{t-1} + u_t^{2q}.$$

Denoting the estimated coefficients of (12) and (13) with a "hat," GDPaR<sub>*t*</sub> and FSaR<sub>*t*</sub> are the fitted values of the quantile regressions (12) and (13) with  $q = 0.05$ :

$$(14) \quad \text{GDPaR}_t = \hat{\alpha}_1^q + \hat{\Lambda}_q^{R'}F_t + \hat{\gamma}_{11}^q(L)\text{GDPG}_{t-1} + \hat{\gamma}_{12}^q(L)\text{FS}_{t-1}$$

$$(15) \quad \text{FSaR}_t = \hat{\alpha}_2^q + \hat{\Lambda}_q^{F'}F_t + \hat{\gamma}_{21}^q(L)\text{FS}_{t-1} + \hat{\gamma}_{22}^q(L)\text{GDPG}_{t-1}.$$

### 3.3.2 Measures of Systemic Risk Spillovers

It can be useful and informative to compute measures of systemic risk spillovers from real activity to the financial sector (and vice versa) that are net of the impact of common factors on GDPaR and FSaR measures. These can be obtained by using the CoVar measures introduced by Adrian and Brunnermeier (2008). Estimates of Co(GDPaR<sub>*t*</sub>) and Co(FSaR<sub>*t*</sub>) are given by:

$$(16) \quad \text{Co(GDPaR}_t) = \hat{\alpha}_1^q + \hat{\beta}_1^q F_t + \hat{\gamma}_{11}^q(L)\text{GDPaR}_{t-1} + \hat{\gamma}_{12}^q(L)\text{FSaR}_{t-1}$$

$$(17) \quad \text{Co(FSaR}_t) = \hat{\alpha}_2^q + \hat{\beta}_2^q F_t + \hat{\gamma}_{21}^q(L)\text{GDPaR}_{t-1} + \hat{\gamma}_{22}^q(L)\text{FSaR}_{t-1}.$$

The existence of systemic risk spillovers can be gauged comparing Co(GDPaR<sub>*t*</sub>) with GDPaR<sub>*t*</sub>, and Co(FSaR<sub>*t*</sub>) with FSaR<sub>*t*</sub>. For example, if Co(GDPaR<sub>*t*</sub>) < GDPaR<sub>*t*</sub>, then negative risk spillovers in the real sector arise from negative risk spillovers either in the real sector, or in the financial sector, or both. However, positive risk spillovers cannot be ruled out, since improvements in real activity, or a reduction in system-wide financial risk, can have positive feedback effects on either sectors. This is apparent noting that the differences between the CoVar and the systemic risk measures are given by:

$$(18) \quad \text{Co(GDPaR}_t) - \text{GDPaR}_t = \hat{\gamma}_{11}^q(L)(\text{GDPaR}_{t-1} - \text{GDPG}_{t-1}) + \hat{\gamma}_{12}^q(L)(\text{FSaR}_{t-1} - \text{FS}_{t-1})$$

$$(19) \quad \text{Co(FSaR}_t) - \text{FSaR}_t = \hat{\gamma}_{21}^q(L)(\text{GDPaR}_{t-1} - \text{GDPG}_{t-1}) + \hat{\gamma}_{22}^q(L)(\text{FSaR}_{t-1} - \text{FS}_{t-1}).$$

### 3.4 Estimation and Forecasting

The first estimation step is to compute static factors and choose their number. Since our focus is on forecasts of systemic risk indicators, we adopt the following forecasting criterion to select both number of static factors and lags of the FAVAR (10) and (11).

First, we use principal components to extract all factors with eigenvalues greater than 1, in number  $R$ . Second, we order factors according to their explanatory power of the variance of the data, and construct  $\tilde{F} = \{(F_{t-1}), (F_1, F_{t-2}), \dots, (F_1, F_2, \dots, F_{t-R})\}$ . Lastly, we choose the number of lags  $L$  and the number of static factors  $r \in \tilde{F}$  that maximize  $\text{FPE}(L, r) + \text{AIC}(L, r)$ , where FPE is the Final Prediction Error Criterion and AIC is the Akaike Information Criterion. As detailed following, our forecasting criterion turns out to yield an optimal number of static factors close to the number of dynamic factors obtained by applying the statistical criteria based on Bai and Ng (2002).

In the second estimation step, we use the optimal number of lags  $L^*$  and number of static factors  $r^*$  obtained in the previous step to estimate quantile regressions (12) and (13). Note that these quantile regressions can be viewed as forecasting equations of systemic risk indicators. Using the VAR of static factors described by equation (9), we compute dynamic forecasts of static factors  $k$  quarters ahead. Then, these forecasts are used to obtain recursive forecasts of indicators of systemic risk using estimated coefficients of regressions (12) and (13). In sum, the foregoing procedure yield forecasts of GDPaR, FSaR, Co(GDPaR), and Co(FSaR) indicators  $k$  quarters ahead.<sup>5</sup>

### 3.5 Identification and Stress Tests

We would like to know how systemic risk indicators respond to structural shocks in the economy. To this end, we can use impulse responses to identified structural shocks through the FAVAR. These impulse responses can be viewed as stress tests of systemic risk indicators to these structural shocks.

5. Differing from Stock and Watson (2002), we obtain multistep-forecasts using the FAVAR rather than  $k$ -step projections. Assessing the relative merit of these procedures in terms of their out-of-sample forecasting ability is a worthwhile enterprise in future applications.

At a given date, the size of these responses provides a gauge of the sensitivity of systemic risk indicators to shocks of a given (standardized) size. Between dates, changes in the size of impulse responses of the systemic risk indicators to a given shock can provide a measure of changes in the resilience of an economy to a given shock.

### 3.5.1 Orthogonalization

We can obtain impulse responses of “factors” to their orthogonalized innovations, and translate them into impulse responses of indicators of systemic risk in (14) and (15) via the estimated coefficients of the quantile regressions. Yet, orthogonal innovations extracted from the FAVAR estimation do not have any “economic” interpretation, although they have the useful property of being contemporaneously and serially uncorrelated. Their economic interpretation can be obtained through identification based on some underlying theoretical model, as detailed next.

Under the assumption that the factor VAR of equation (9) is covariance-stationary, we can invert (9) obtaining the moving average (MA) form of the factor VAR:

$$(9a) \quad F_t = A(L)\eta_t,$$

where  $A(L) = (I - \Phi(L)L)^{-1}G$ . Substituting (9a) in (10) and (11), we obtain:

$$(10a) \quad \text{GDPG}_t = \Lambda^R A(L)\eta_t + \gamma_{11}(L)\text{GDPG}_{t-1} + \gamma_{12}(L)\text{FS}_{t-1} + u_t^1$$

$$(11a) \quad \text{FS}_t = \Lambda^F A(L)\eta_t + \gamma_{21}(L)\text{GDPG}_{t-1} + \gamma_{22}(L)\text{FS}_{t-1} + u_t^2.$$

For the sole purpose of identification, we make the simplifying assumption that the dynamic impact of FS on GDPG, and of GDPG on FS, is entirely captured by the dynamics of factors. This amounts to posit  $\gamma_{12}(L) = \gamma_{21}(L) = 0$ , and converts our forecasting model into the standard factor VAR detailed in Stock and Watson (2005). Under this assumption, inverting (10a) and (11a) yields the MA representation of the FAVAR:

$$(10b) \quad \text{GDPG}_t = B^R(L)\eta_t + w_t^1$$

$$(11b) \quad \text{FS}_t = B^F(L)\eta_t + w_t^2,$$

where  $B^R(L) = (1 - \gamma_{11}(L)L)^{-1}\Lambda^R A(L)$ ,  $B^F(L) = (1 - \gamma_{22}(L)L)^{-1}\Lambda^F A(L)$ ,  $w_t^1 = (1 - \gamma_{11}(L)L)^{-1}u_t^1$ , and  $w_t^2 = (1 - \gamma_{22}(L)L)^{-1}u_t^2$ . Likewise, the MA representation of the systemic risk indicators is:

$$(14a) \quad \text{GDPaR}_t = B_q^R(L)\eta_t + v_t^{1q}$$

$$(15a) \quad \text{FSaR}_t = B_q^F(L)\eta_t + v_t^{2q}.$$

where  $B_q^R(L) = (1 - \gamma_{11}^q(L)L)^{-1}\Lambda_q^R A(L)$ ,  $B_q^F(L) = (1 - \gamma_{22}^q(L)L)^{-1}\Lambda_q^F A(L)$ ,  $v_t^{1q} = (1 - \gamma_{11}^q(L)L)^{-1}u_t^{1q}$ , and  $v_t^{2q} = (1 - \gamma_{22}^q(L)L)^{-1}u_t^{2q}$ .

### 3.5.2 Theory-Based Identification

Extending the identification procedure introduced in Canova and De Nicolò (2002), we identify a chosen set of orthogonal innovations as *structural* shocks if they satisfy certain sign restrictions on key variables derived from aggregate dynamic macroeconomic theory and a simple banking model.

Specifically, the theoretical restrictions on the responses of key aggregates to structural shocks implied by an aggregate macroeconomic model are as follows. If a positive *temporary* orthogonal innovation represents a positive transitory aggregate supply shock, then it should generate transitory weakly positive output responses and weakly negative transitory responses in inflation, depending on capacity utilization. On the other hand, if it is a real aggregate demand shock, it should generate weakly positive transitory responses in output and inflation. Canova and De Nicolò (2002) show that these sign restrictions can be derived from a wide class of general equilibrium monetary macroeconomic models with different micro-foundations.

What are the implications of these theoretical responses for the demand and supply of bank credit? To answer this question, we use the implications of textbook partial equilibrium banking models, as, for example, described in chapter 3 of Freixas and Rochet (2008), or the simple model in Boyd, De Nicolò, and Loukoianova (2009). In these models, aggregate shocks can have an impact on both the demand for credit and the supply of funding for intermediaries.

Specifically, the theoretical restrictions on the responses of bank credit growth and changes in loan rates implied by these banking models are as follows. If there is a positive transitory shock to the demand for bank credit (e.g., because of a positive technology shock to firms generating an increase in demand for investment, or an increase in the quality of investment prospects), then we should observe a transitory increase in bank credit growth and an increase in loan rates. We call a shock generating these responses a positive credit demand shock. Conversely, if there is a positive transitory shock to the supply of bank credit (e.g., the supply of bank liabilities increases or banks expand by raising capital), then we should observe a transitory increase in bank credit growth but a decline in loan rates. We call a shock generating these responses a positive credit supply shock. Of course, negative shocks have all the signs of these responses reversed.

Note that real aggregate demand or supply shocks can affect the underlying drivers of the supply and demand for bank credit simultaneously. For example, a negative aggregate demand shock can induce firms and households to decrease their demand for bank credit, shifting the demand for bank credit to the left: this would result in a decline in loan rates *ceteris paribus*. At the same time, the adverse wealth effects of a negative aggregate demand shock may induce investors to reduce their supply of loanable

Table 3.1 Theoretical responses of key variables to positive shocks

<i>Macroeconomic model</i>	<i>Aggregate supply</i>	<i>Aggregate demand</i>
GDP growth	Positive	Positive
Inflation	Negative	Positive
<i>Banking model</i>	<i>Bank credit demand</i>	<i>Bank credit supply</i>
Bank credit growth	Positive	Positive
Change in lending rates	Positive	Negative

funds to banks, or banks could reduce their supply of credit as they may become increasingly capital constrained or risk averse: this would result in a leftward shift in the supply of credit *ceteris paribus*. Which effect dominates on net will be reflected in movements in loan rates and bank credit growth. If negative credit demand shocks dominate, then loan rates and bank credit growth should decline, while the converse would be true if negative credit supply shocks dominate.

Table 3.1 summarizes the responses of GDP growth, inflation, bank lending growth, and changes in loan rates in response to positive structural shocks implied by standard aggregate macroeconomic models and partial equilibrium banking models.

Identification of structural shocks will be conducted by checking whether a subset of orthogonal innovations of the FAVAR produces responses of the four variables considered that match the signs of the responses implied by theory.

### 3.6 Implementation

Our modeling procedure is implemented using quarterly macroeconomic and financial series for the G-7 economies for the period 1980:Q1 to 2009:Q3. All series are taken from Datastream.

For each country, the vector of quarterly series  $X$ , in equation (3) includes about 95 series, which are detailed in the appendix. They can be classified into three main groups. The first group comprises equity markets data, including prices, price/earnings ratios, and dividend yields for the entire market and by sector. The inclusion of all sectors spanning from manufacturing to services allows us to gauge the differential impact of shocks on different sectors of the economy, as well as to capture the impact of specific sectors on systemic risks. The second group includes financial, monetary, and banking variables related to credit conditions, namely, interest rates for different maturities, monetary policy rates, bank prime rates and inter-bank rates, bank lending, and monetary aggregates. The third and last group includes price and quantity indicators of real activity. This set of variables includes net exports, capacity utilization, firms' investment, consumer confidence, unemployment, consumption and saving for firms, government and

household, a consumer price index, industrial production, house prices, and manufacturing orders.

In the remainder of this section, we first report some descriptive statistics, then we detail the results of the forecasting model of systemic risks, and lastly, we carry out a benchmark identification of structural shocks, examining the responses of the systemic risk indicators to these shocks.

#### 3.6.1 Descriptive Statistics

Table 3.2 reports basic statistics for GDP growth (GDPG) and our system-wide indicator of financial risk (FS). Three facts are worth noticing. First, ranges as well as volatilities of GDPG and FS appear to differ markedly across countries, suggesting differential sensitivities of these indicators to underlying shocks. Second, means of FS are generally small and not different from 0 according to simple  $t$ -statistics tests: this is expected, as in the long run the evolution of bank stock returns tracks that of the market. Third, the contemporaneous correlation between GDPG and FS appears relatively small, with no significant correlation for the United States, Canada, Japan, and Italy, and a positive and significant—albeit small—correlation for the United Kingdom, France, and Germany.

As shown in figure 3.2, however, the comovement between GDPG and FS appears to be the most pronounced during recessions and the latest “crisis” period in all countries. This suggests either an increase in the sensitivities of both indicators to common shocks, or a significant increase in risk spillovers between real and financial activity, or a combination of both. Furthermore, in several instances the indicators of systemic financial risk worsen with no

Table 3.2 Descriptive statistics of real GDP growth (GDPG) and the system-wide financial risk indicator (FS)

		Mean	Std. dev.	Min	Max	Correlation
United States	GDPG	1.41	0.84	-1.38	4.57	0.08
	FS	-0.19	8.58	-33.5	38.34	
Canada	GDPG	0.53	1.06	-3.16	3.09	0.16
	FS	-0.31	10.27	-29.09	56.07	
Japan	GDPG	0.53	1.07	-3.43	3.09	0.15
	FS	-0.17	10.19	-29.09	56.07	
United Kingdom	GDPG	0.54	0.71	-2.52	2.17	<b>0.20</b>
	FS	-0.06	8.61	-38.68	19.52	
France	GDPG	0.46	0.51	-1.52	1.48	<b>0.15</b>
	FS	0.46	9.81	-41.3	29.16	
Germany	GDPG	0.32	0.75	-3.6	1.8	<b>0.38</b>
	FS	-0.69	6.85	-34.26	19.66	
Italy	GDPG	0.36	0.67	-2.76	2.19	0.03
	FS	-0.2	7.71	-17.69	29.26	

Note: Bold values indicate an estimate significantly different from zero at a 5 percent confidence level.



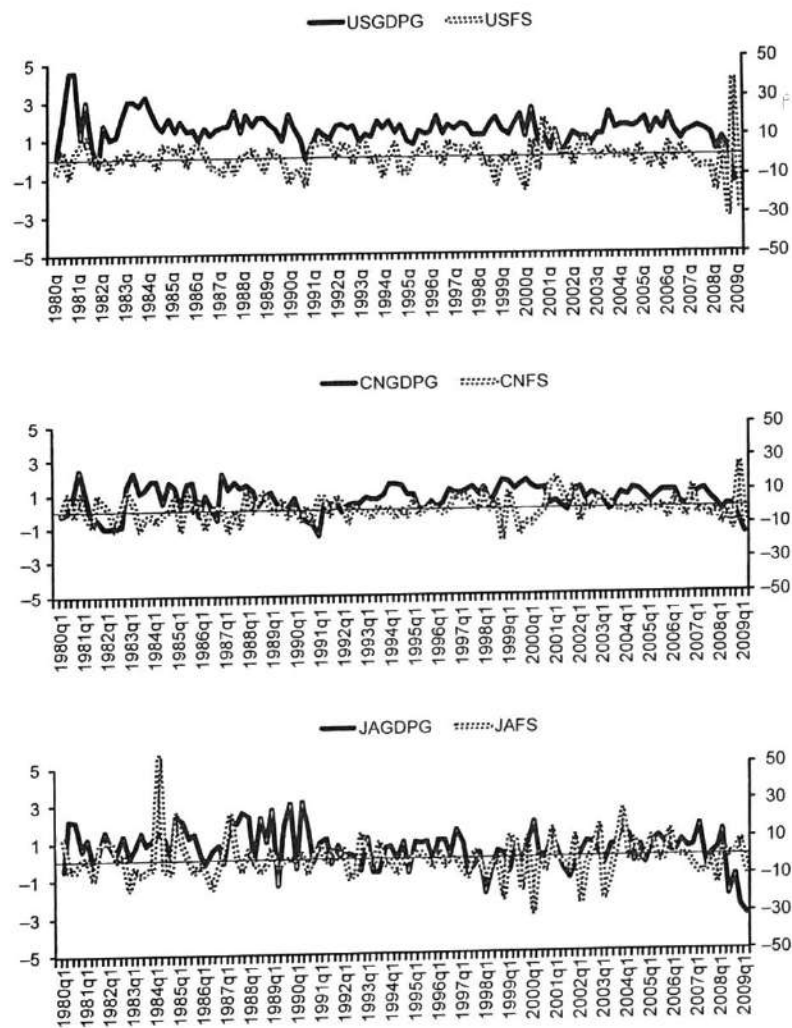


Fig. 3.2 GDP growth and FS indicators

detectable adverse effect on the indicators of systemic real risk, supporting the usefulness of our distinction between the systemic real and financial risks.

Assessing to what extent movements in real activity and the financial risk indicator are primarily driven by common shocks or primarily by spillovers is especially important during periods of both real and financial instability. Whether the recent crisis has been one in which the sharp contraction in real activity registered at end of 2008 and beginning of 2009 has been caused by

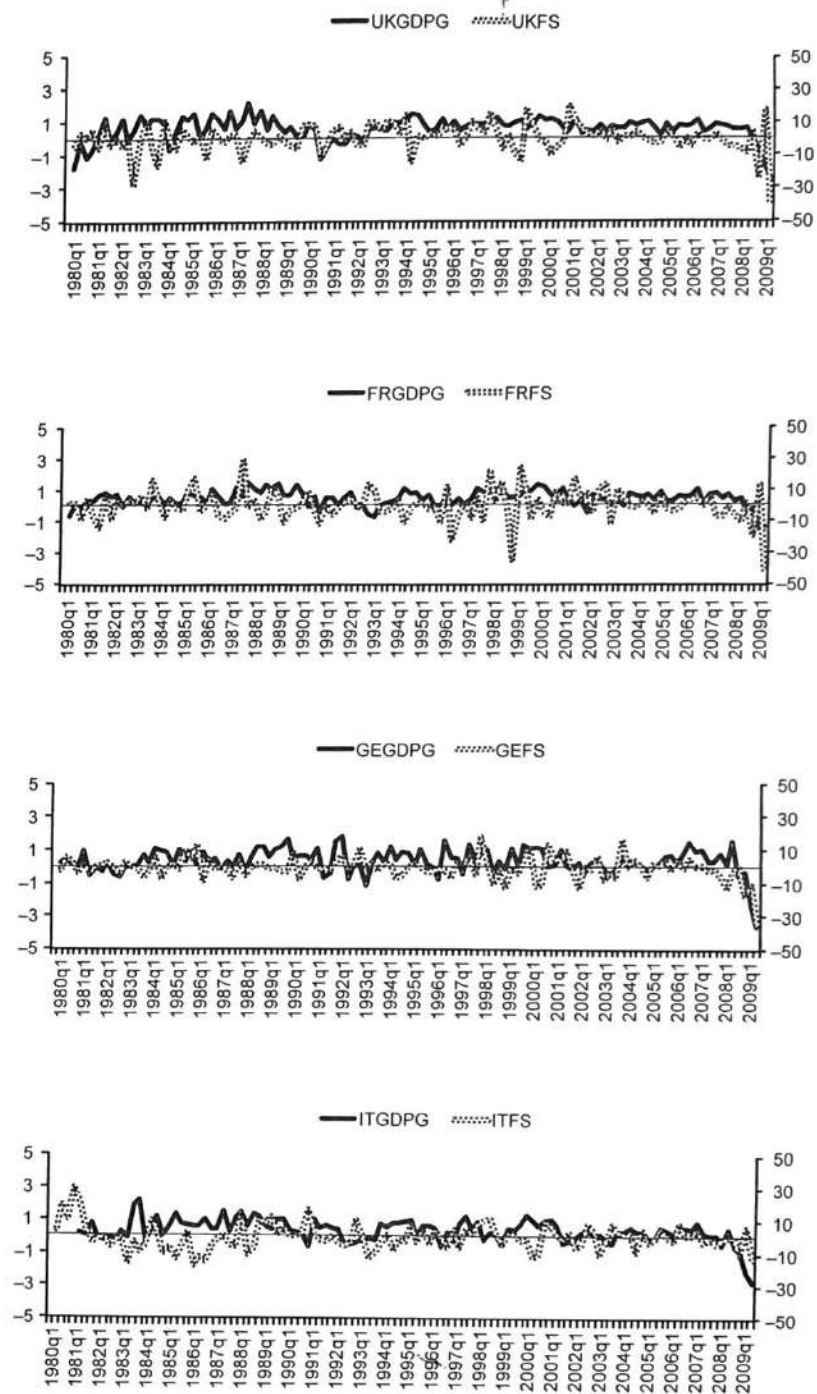


Fig. 3.2 (cont.)



sharp declines in the aggregate supply of bank credit, or alternatively, sharp declines in real activity are the main drivers of the reduction in the demand for bank credit, is still an open issue. Indeed, the conventional wisdom has been one in which the credit crunch has prompted banking systems to curtail lending, and banks' increasingly binding capital constraints have forced banks to de-leverage, with the attendant contraction of their asset size and further constraints in their lending capacity. Yet, bank loan growth in the United States and the Euro area, for example, has been buoyant since the start of the crisis, although it has decelerated since September 2008. This may suggest that the contraction in bank lending growth reflects primarily the sharp decline in the demand for credit resulting from the severe contraction in consumption growth and investment.<sup>6</sup>

Identification is essential to address these issues, and this is exactly what we do. Capturing the main drivers of the demand and supply of credit, and assessing whether shifts in the demand or supply of bank credit dominate on net requires identification of structural shocks.

### 3.6.2 Estimation and Forecasting

We estimated static factors and autoregressive coefficients of each variable by principal components according to the iterative procedure described in Stock and Watson (2005), and chose their number and the lags of equations (12) and (13) according to the forecasting criterion described previously. Notably, for all data sets of the seven countries our forecasting criterion selected the same number of static factors and lags: five factors and one lag. As a cross-check, we also estimated the number of static factors chosen according to the Bai and Ng's  $IC_{p1}$  and  $IC_{p2}$  criteria, obtaining eleven static factors for the United States—consistent with Stock and Watson (2005) results—and between nine and twelve static factors for the other countries. We also estimated the number of dynamic factors as principal components of the residuals of each variable in equations (10) and (11), obtaining six dynamic factors for the United States, and between four and six dynamic factors for the other countries. In light of these results, and because our focus is on forecasting and on identification with restrictions dictated by theory, we acted conservatively by treating the five estimated static factors equal to the number of dynamic factors, essentially assuming  $F_t = f_t$ , so that in equation (8)  $G = I$ .

We used these five estimated factors as independent variables of quantile regressions (14) and (15) specified with one lag. The resulting GDPaR and FSaR estimates were also used to compute CoVar measures (16) and (17).

As detailed in the previous section, forecasts of GDPaR and FSaR eight

6. For the United States, Chari, Christiano, and Kehoe (2008) made assertions at variance with the common wisdom, which were countered by Cohen-Cole et al. (2008) and Ivashina and Sharfstein (2008), to whom the former authors further replied.

quarters ahead were obtained projecting forward the factors through the VAR of equation (8) and using the estimated quantile coefficients to project forward GDPaR and FSaR values. Forecasts were undertaken with all data available as of September 25, 2009, that is, at end of 2009Q3. Note, however, that at that time actual real GDP was available only up to 2009Q2, so that the first effective forecast date for GDPaR is 2009Q3 and the estimated 2009Q3 GDP growth is a "nowcast."

Figure 3.3 reports estimated GDPaR and FSaR series, together with their forecasts eight quarters ahead of 2009Q3. Table 3.3 reports basic descriptive statistics of the systemic risk indicators, as well as the difference between CoVar and at-risk measures. As noted, the latter measure is useful to gauge risk spillovers in excess of those implied by the dependence of both measures on common factors.

We point out two main findings. First, means of FSaR estimates are very similar across countries, but their standard deviations vary significantly across countries. The converse is true for GDPaR, whose measures exhibit marked cross-country variations, while their standard deviations do not

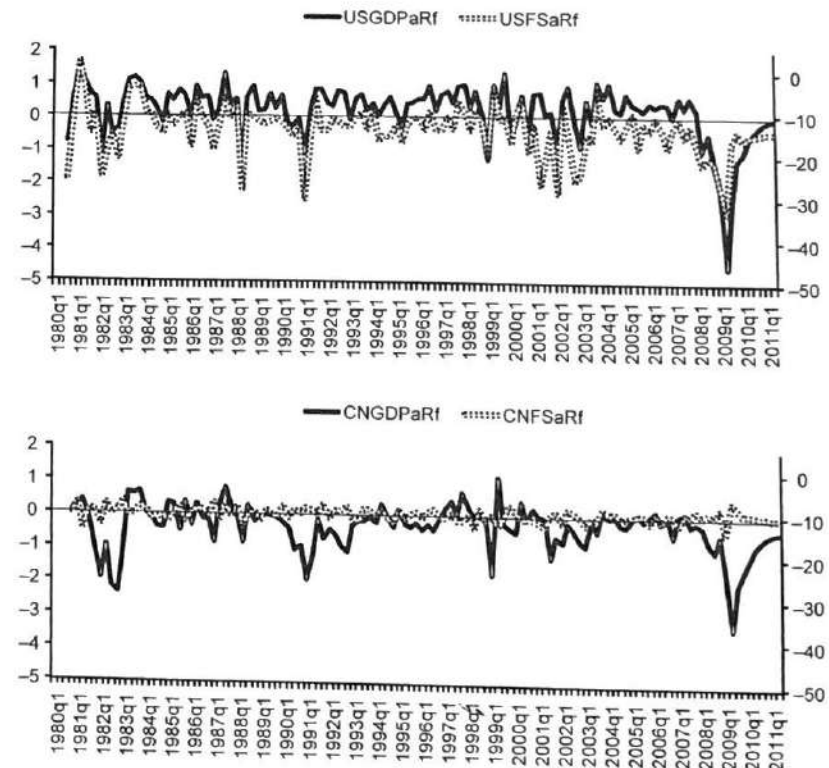


Fig. 3.3 GDPaR and FSaR estimates and forecasts (2009q3–2011a2)

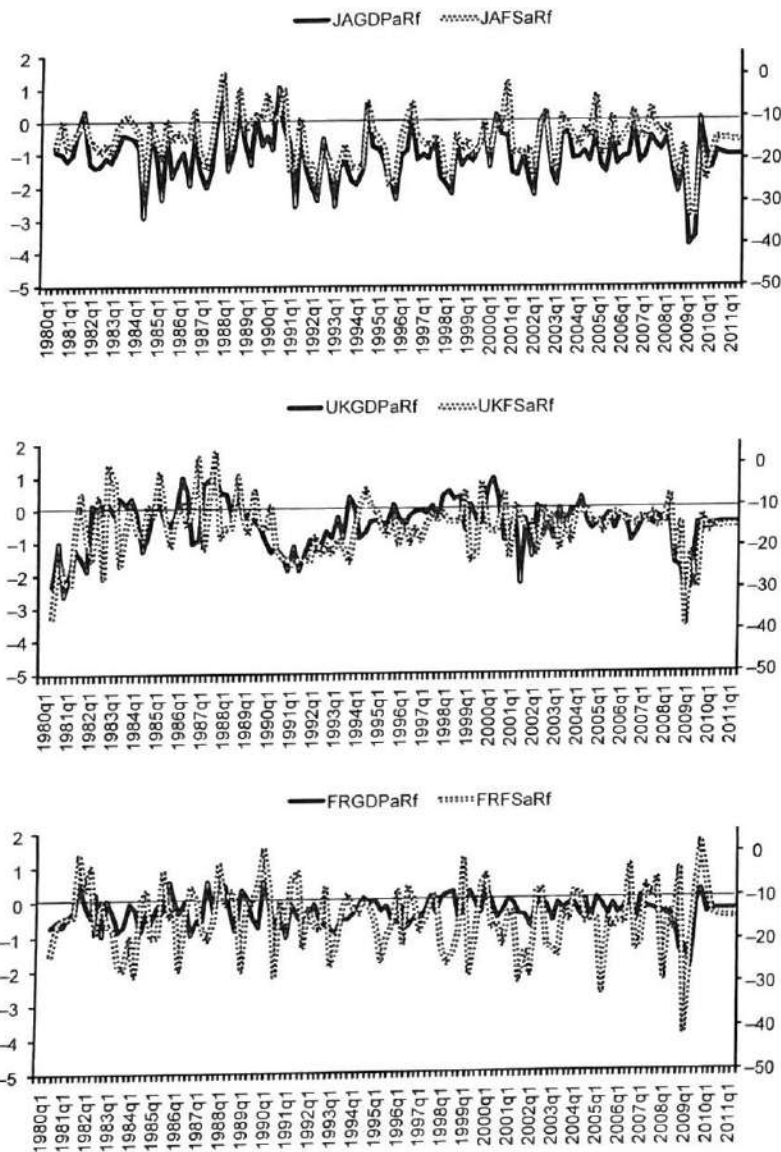


Fig. 3.3 (cont.)

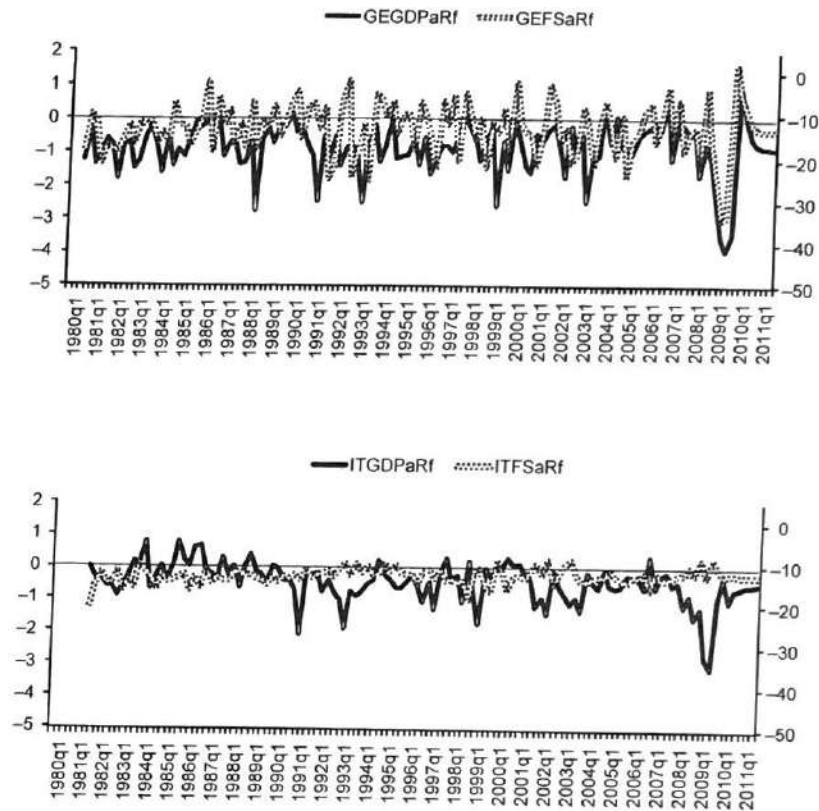


Fig. 3.3 (cont.)

appear to vary markedly. Second, risk spillovers are present for GDPaR measures, as table 3.3 exhibits negative values for all countries, while spillovers for FSaR measures are on average small and not significantly different from zero. Overall, common factors appear to be the dominant drivers of systemic risk indicators, whereas risk spillovers (net of common factors) seem relatively small in all countries.

Turning to GDPaR and FSaR forecasts, figure 3.3 indicates for all countries a V-shaped pattern of systemic risk indicators, with forecasts pointing at a return of these systemic risk indicators to their historical mean by mid-2010. This means that the model predicts a significant decline in the size of real and financial losses associated with tail risk events.

One intuitive—albeit informal—way of judging the forecasting ability of the model is to assess whether out-of-sample forecasts of the systemic risk indicator GDPaR move in the same direction of subsequent actual values of GDP growth. A full formal evaluation of the forecasting performance

Table 3.3 Descriptive statistics of systemic risk indicators

		Mean	Std. dev.	Min	Max
United States	GDPaR	0.24	0.81	-4.51	1.46
	FSaR	-13.6	5.95	-33.5	2.32
	dcoGDPaR	-0.73	0.56	-3.43	0.6
	dcoFSaR	-2.97	2.78	-13.98	3.63
Canada	GDPaR	-0.46	0.59	-2.74	1.16
	FSaR	-10.35	3.17	-18.78	2.75
	dcoGDPaR	-0.34	0.29	-1.45	0.33
	dcoFSaR	2.08	1.03	-0.41	5.46
Japan	GDPaR	-0.99	0.8	-3.67	1.17
	FSaR	-15.47	6.12	-33.63	1.06
	dcoGDPaR	0.08	0.24	-0.61	1.06
	dcoFSaR	1.32	4.03	-10.44	18.04
United Kingdom	GDPaR	-0.46	0.77	-2.61	0.97
	FSaR	-15.16	6.81	-38.68	3.18
	dcoGDPaR	0.13	0.39	-1.1	1.17
	dcoFSaR	-2.92	4.46	-15.93	8.01
France	GDPaR	-0.31	0.42	-1.94	0.67
	FSaR	-14.94	7.65	-41.3	2.26
	dcoGDPaR	-0.52	0.31	-1.42	0.07
	dcoFSaR	3.46	8.37	-20.79	32.87
Germany	GDPaR	-0.88	0.78	-3.95	0.89
	FSaR	-13.2	6.3	-34.26	1.87
	dcoGDPaR	-0.62	0.35	-2.07	0.03
	dcoFSaR	-12.62	8.92	-45.29	1.6
Italy	GDPaR	-0.46	0.62	-3.1	0.8
	FSaR	-12.83	1.96	-20.64	-8.62
	dcoGDPaR	-0.15	0.35	-1.17	0.72
	dcoFSaR	0.11	1.06	-2.83	2.79

Notes: GDPaR is GDP at risk; FSaR is the financial-system at risk indicator; dcoGDPaR =  $\text{co}(\text{GdPaR}) - \text{GDPaR}$ , where  $\text{co}(\text{GdPaR})$  is the CoVaR version of the systemic real risk indicator; dcoFSaR =  $\text{co}(\text{FSaR}) - \text{FSaR}$ , where  $\text{co}(\text{FSaR})$  is the CoVaR version of the systemic financial risk indicator.

of the model is outside the scope of this chapter. However, here we report perhaps the most demanding assessment of the model's forecasting ability. Namely, we assess if the model signals a decline in GDPaR prior to one of the largest historical declines in real activity: that experienced in 2008Q4 to 2009Q1 in all G-7 countries.

Figure 3.4 reports the results of this comparison: the blue line is the out-of-sample GDPaR forecasts made in 2008Q3, while the red line is actual GDP growth. Predicted changes in GDPaR and actual GDP growth go in the same direction for at least one quarter ahead within a three quarters' horizon (up to 2009Q1) in all countries. Although informal, we view this evidence as notable. The out-of-sample consistency of GDPaR forecasts with the future evolution of actual GDP growth for the most unpredictable

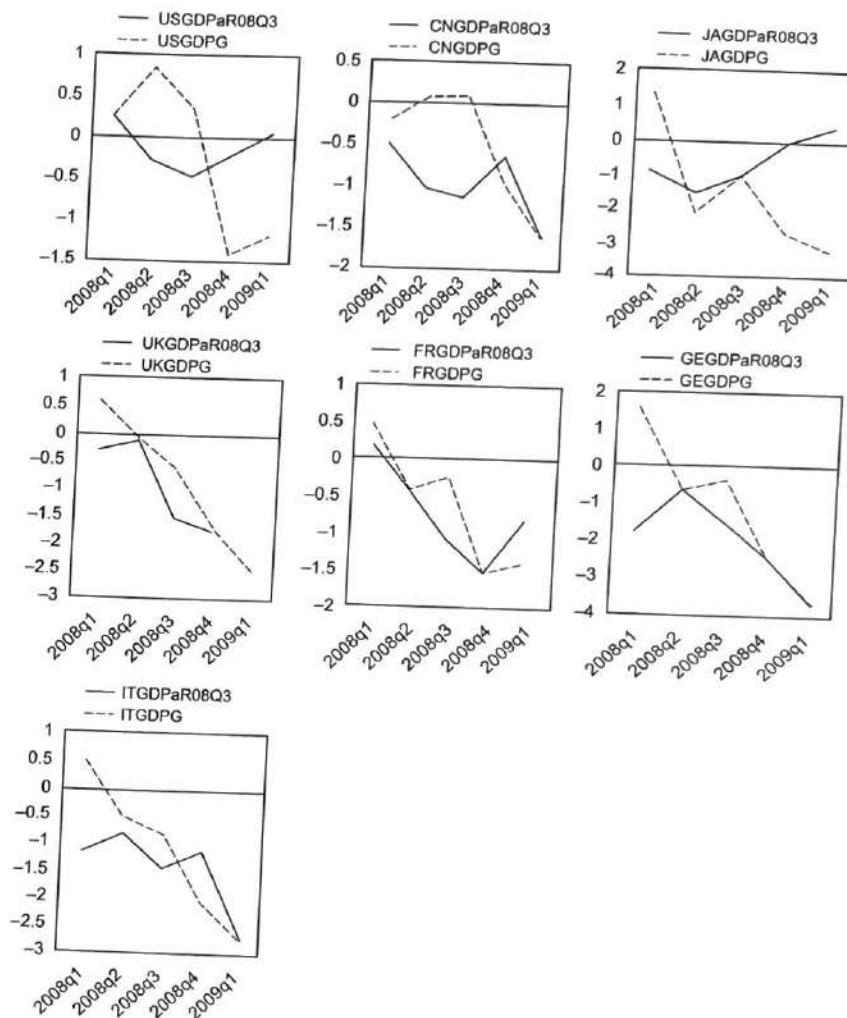


Fig. 3.4 GDPaR out-of-sample forecasts and actual GDP growth (2008q3–2009q1)

event in decades suggests the potential usefulness of our model as a real-time risk-monitoring tool.

### 3.6.3 Identification of Structural Shocks

We implemented the identification procedure outlined previously by following three steps. First, we selected an orthogonal decomposition of the MA representation (9a). Second, we computed impulse responses of FAVARs for GDP growth, inflation, bank lending growth, and first differ-

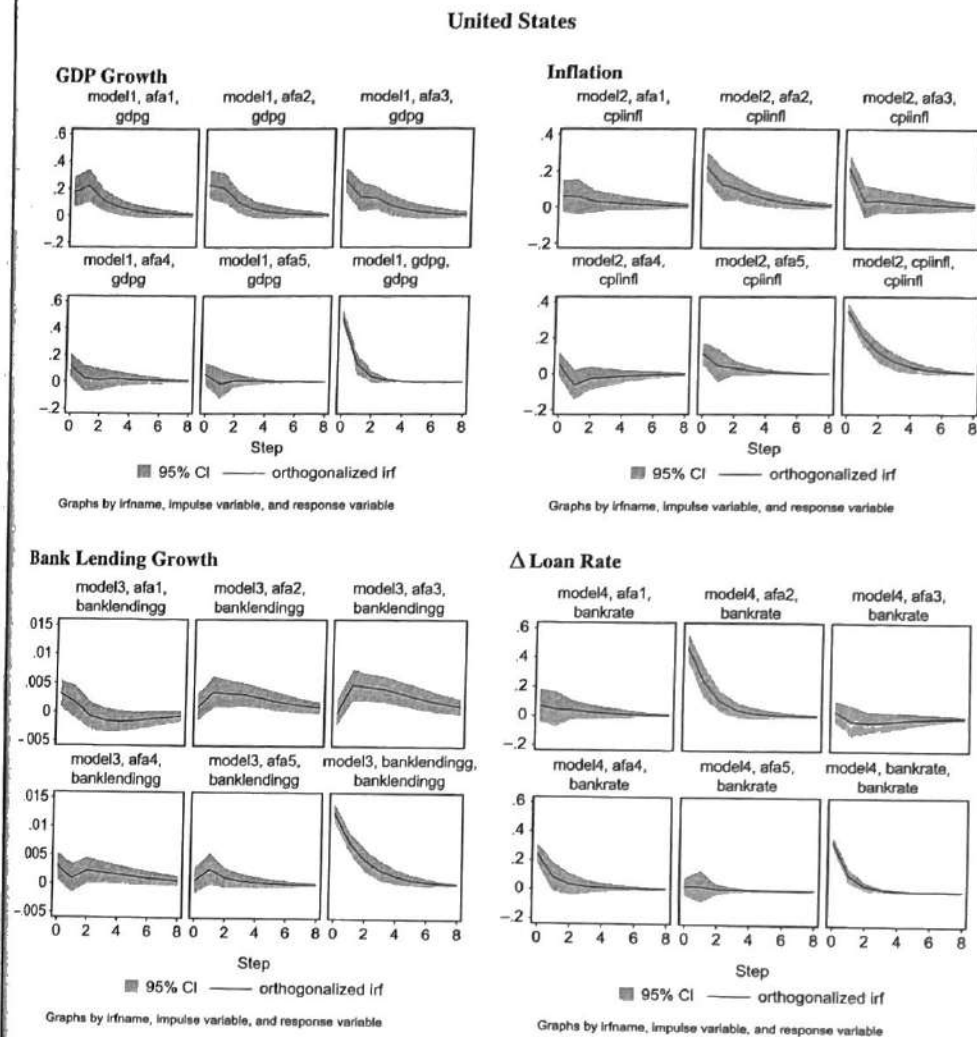
ences in loan rates for each country. Third, we checked whether the joint signs of the responses of these variables conformed to the signs predicted for different shocks by the basic macro and banking models summarized in table 3.1.

As a benchmark orthogonalization, we chose a Choleski decomposition with factors ordered according to their explanatory power of the common variations in the data, with factor 1 ordered first, factor 2 second, and so on, and with GDPG, inflation, bank lending growth, and first differences in loan rates ordered last in each FAVAR equation. The simple assumption underlying this choice is that the casual ordering implied by this decomposition reflects the relative importance of factors in explaining variations in the data, and each idiosyncratic component of the observable variables does not affect any of the factors at impact.

To check robustness, however, we examined alternative decompositions with inverted ordering of the variables, obtaining similar signs of the responses of each of the observable variables to shock to orthogonalized innovations. We also examined the covariance matrix of innovations of the VAR of each country, and such matrices appeared approximately diagonal in all cases, indicating that the ordering of variables in the VAR was not likely to change results under the casual ordering selected. Furthermore, the approximate diagonality of these covariance matrices also suggests that our results may be robust to alternative orthogonal decompositions—not necessarily recursive—that can be extracted applying the systematic statistical search implemented by Canova and De Nicolò (2002).

Figure 3.5 reports impulse responses of GDP growth, inflation, bank lending growth, and changes in lending rates for each of the G-7 countries. Strikingly, the response of all variables to all shocks at impact or for at least up to two quarters after impact is either strictly positive (in most cases) or nonnegative (in few cases).<sup>7</sup> Hence, according to table 3.1, *under the assumed benchmark orthogonalization, all structural shocks in these economies can be identified as aggregate demand shocks associated with bank credit demand shocks.* The finding of aggregate demand shock as the predominant drivers of real cycles in the G-7 economies is matching the findings by Canova and De Nicolò (2003), who used only a small dimension VAR for the G-7 countries, but implemented a full search for shocks interpretable according to aggregate macroeconomic theory in the entire space of nonrecursive orthogonalizations of the VAR of each country. This finding is also consistent with recent work by Arouba and Diebold (2010), who find demand shocks as the dominant source of aggregate fluctuations in the United States.

The finding that aggregate bank demand shocks are the predominant drivers of cycles in bank credit growth is consistent with their being prompted

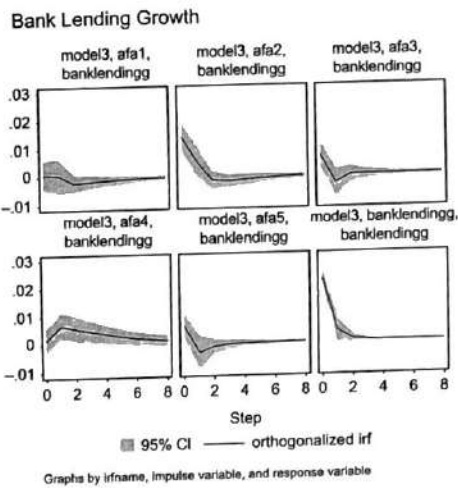
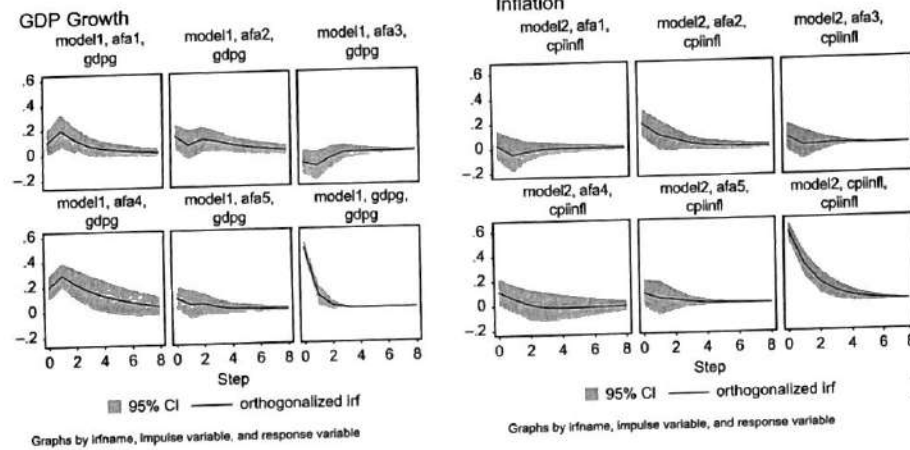


**Fig. 3.5** Impulse responses of GDP growth, inflation, bank lending growth, and change in lending rate to shocks to factors and own shock

7. The only exception is the shock associated with the third factor for Canada, whose responses do not satisfy any of the sign restrictions in table 3.1, and thus the results are unidentified.



Canada



Japan

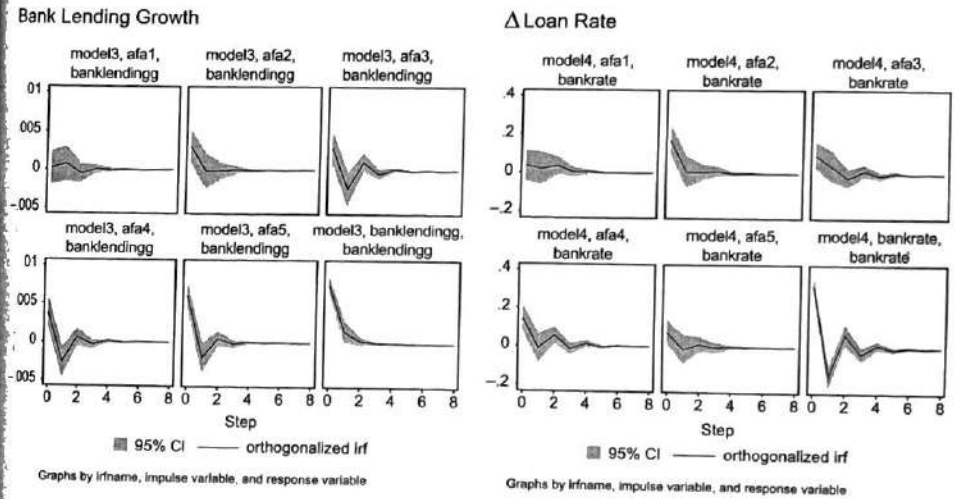
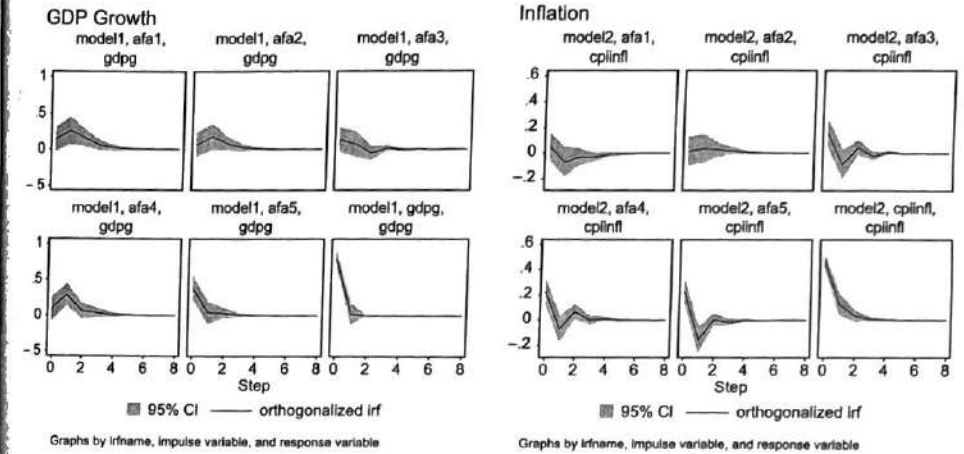
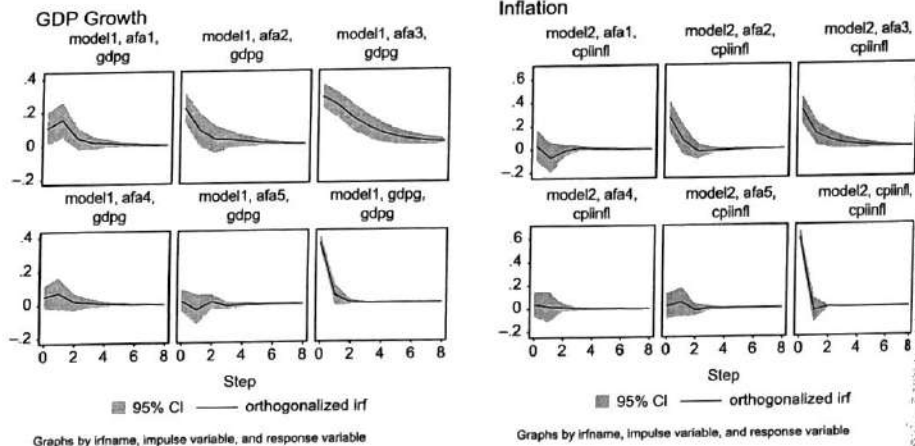


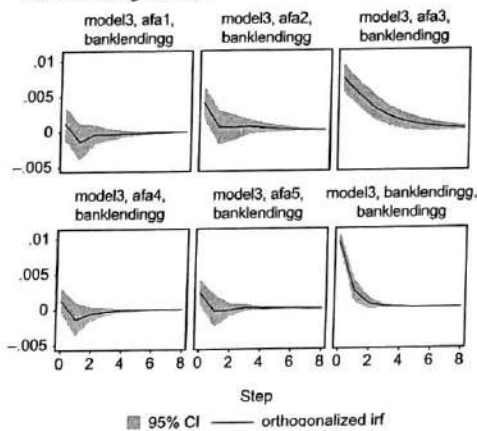
Fig. 3.5 (cont.)

Fig. 3.5 (cont.)

United Kingdom



Bank Lending Growth



$\Delta$  Loan Rate

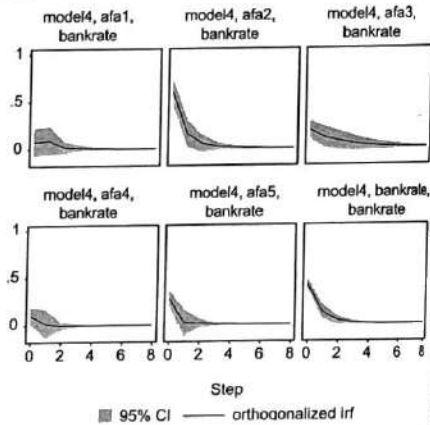
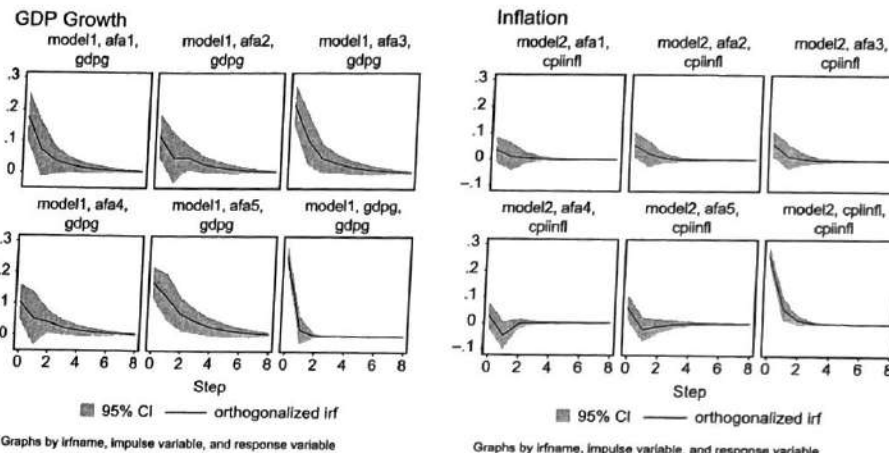
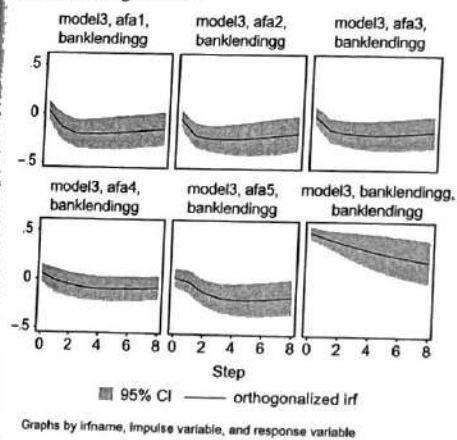


Fig. 3.5 (cont.)

France



Bank Lending Growth



$\Delta$  Loan Rate

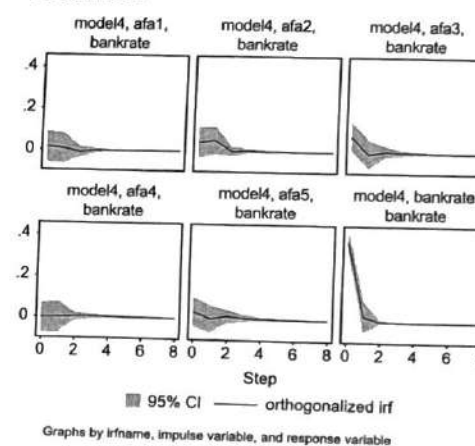


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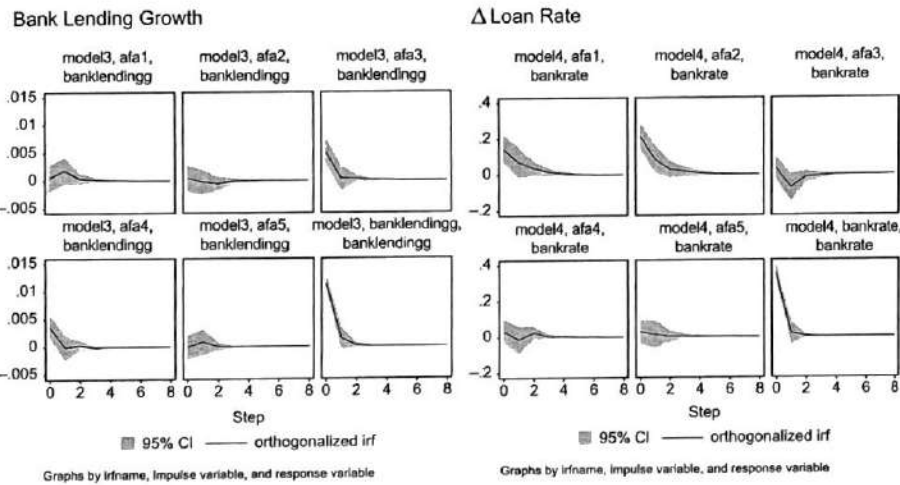
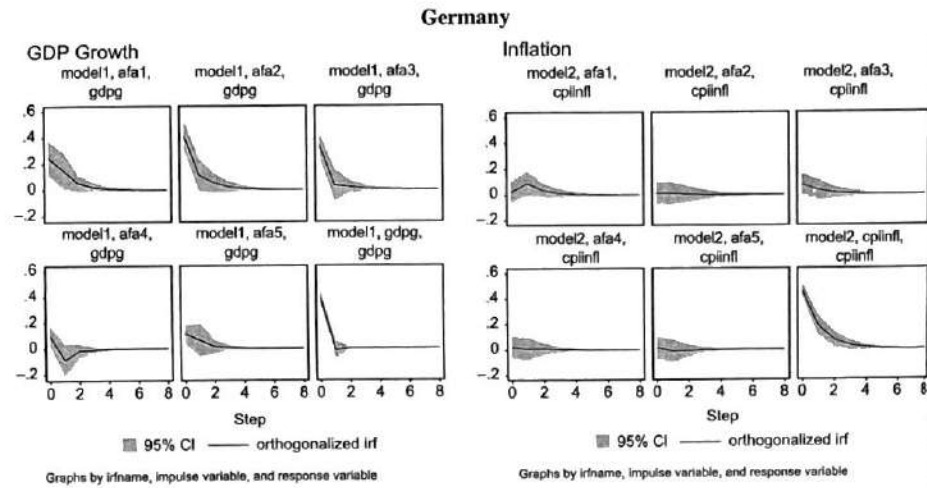


Fig. 3.5 (cont.)

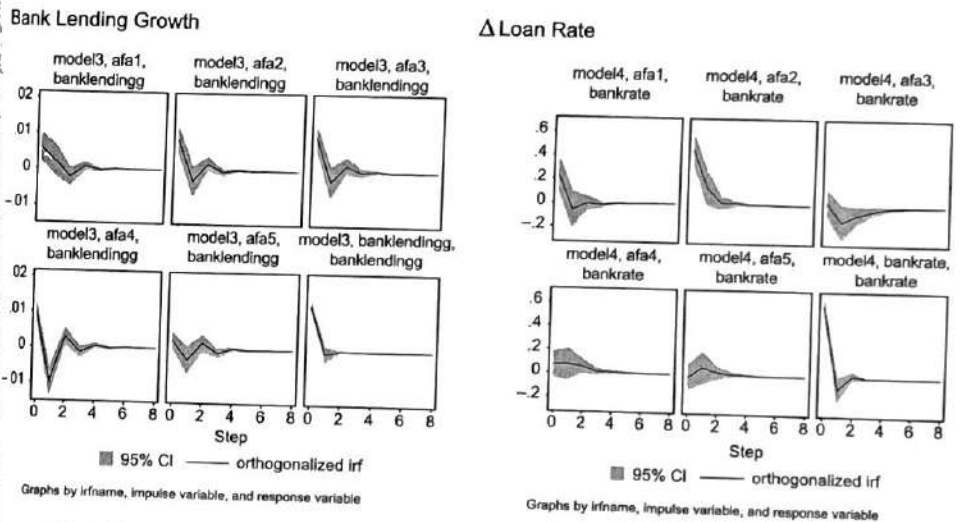
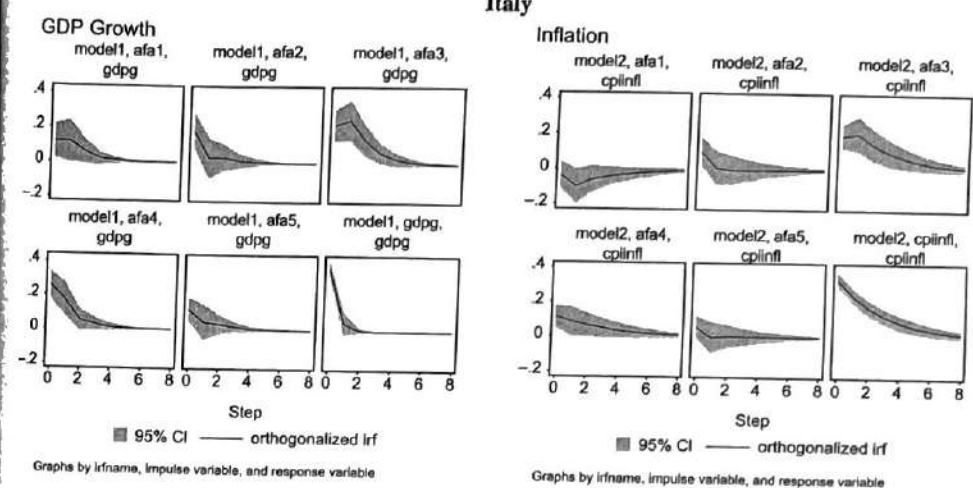


Fig. 3.5 (cont.)

by aggregate demand shocks. This result also supports the conjecture that slowdowns in aggregate bank credit growth are primarily the result of downturns in real activity, as they reflect declines in the aggregate demand for bank credit by households and firms, rather than a reduction in the aggregate supply of bank credit. Recent evidence by Berrospide and Edge (2010) and Kahle and Stulz (2010) for the United States is also consistent with our results.

Notably, the five identified aggregate demand and bank credit demand shocks are not all the same, as they have a differential impact on GDP growth, inflation, bank lending growth, and changes in loan rates within as well as between countries. This suggests that the sectors of the economy where they originate are different. As shown in table 3.4, the variance decompositions of the four variables VAR in each country show that the variance explained by each shock varies across both variables and countries, with most shocks resulting relevant in each country.<sup>8</sup>

Similar results are obtained when we look at the impulse responses and variance decompositions of GDPaR and FSaR measures. As shown in figure 3.6, the sign of the impact of each shock on GDPaR is essentially the same in each country, although magnitude and persistence of these shocks widely differ. As shown in table 3.5, the relevant variance decompositions indicate the importance of each of the identified shocks for the systemic risk indicators in each country.

In sum, all identified structural shocks are aggregate demand shocks associated with bank credit demand shocks, this identification is the same for all countries considered, and it appears robust to alternative orthogonalizations of the innovations in the FAVAR.

### 3.7 Conclusion

This chapter has developed a modeling framework that delivers forecasts of indicators of systemic real and financial risks that can be updated in real time. In addition, the proposed identification procedure allows gauging the sensitivity of these indicators to structural shocks identified by theory, giving economic content to stress tests. The implementation of such framework appears promising as a risk-monitoring tool.

We view this framework as a first building block for an analysis of the determinants of systemic risks. As it can be inferred from our discussion, refinements and extensions of our framework are plenty, since we have exploited the rich information provided by the factor model only in a limited way.

There remain deeper questions that need yet to be answered: Where do

8. The results echo the findings of an increased impact of sectoral shocks on aggregate industrial production indexes documented recently by Foerster, Sarte, and Watson (2008).

Table 3.4 Variance decomposition of GDP growth, inflation, bank lending growth, and changes in loan rates to identified aggregate demand and bank credit demand shocks

	Shock 1	Shock 2	Shock 3	Shock 4	Shock 5	Shock sum	Idiosyncratic
United States							
GDP growth	<b>0.17</b>	<b>0.18</b>	<b>0.19</b>	0.03	0.01	0.58	0.42
Inflation	0.03	<b>0.24</b>	<b>0.14</b>	0.02	0.05	0.48	0.52
Bank credit growth	0.05	<b>0.11</b>	<b>0.20</b>	0.06	0.02	0.44	0.56
Loan rate	0.02	<b>0.58</b>	0.01	<b>0.14</b>	0.00	0.75	0.25
Canada							
GDP growth	<b>0.12</b>	0.09	0.09	<b>0.30</b>	0.01	0.61	0.39
Inflation	0.01	0.08	0.00	0.03	0.02	0.14	0.86
Bank credit growth	0.01	<b>0.21</b>	0.06	<b>0.13</b>	0.05	0.46	0.54
Loan rate	0.07	0.10	0.02	<b>0.22</b>	0.03	0.44	0.56
Japan							
GDP growth	<b>0.10</b>	0.03	0.01	0.09	<b>0.11</b>	0.34	0.66
Inflation	0.03	0.02	0.04	<b>0.15</b>	<b>0.23</b>	0.47	0.53
Bank credit growth	0.02	0.01	0.05	<b>0.17</b>	<b>0.29</b>	0.54	0.46
Loan rate	0.02	<b>0.14</b>	<b>0.08</b>	<b>0.10</b>	0.01	0.35	0.65
United Kingdom							
GDP growth	0.09	<b>0.14</b>	<b>0.42</b>	0.02	0.00	0.67	0.33
Inflation	0.01	<b>0.14</b>	<b>0.22</b>	0.00	0.01	0.38	0.62
Bank credit growth	0.02	0.08	<b>0.44</b>	0.02	0.03	0.59	0.41
Loan rate	0.02	<b>0.53</b>	0.08	0.01	0.10	0.74	0.26
France							
GDP growth	0.15	0.07	<b>0.25</b>	0.06	<b>0.20</b>	0.73	0.27
Inflation	0.01	0.04	0.05	0.04	0.05	0.19	0.81
Bank credit growth	<b>0.11</b>	<b>0.17</b>	<b>0.10</b>	0.02	0.08	0.48	0.52
Loan rate	0.00	0.03	0.04	0.00	0.01	0.08	0.92
German							
GDP growth	<b>0.15</b>	<b>0.33</b>	<b>0.20</b>	0.03	0.03	0.74	0.26
Inflation	0.04	0.00	0.03	0.00	0.00	0.07	0.93
Bank credit growth	0.02	0.00	<b>0.15</b>	0.08	0.00	0.25	0.75
Loan rate	<b>0.13</b>	<b>0.25</b>	0.03	0.01	0.00	0.42	0.58
Italy							
GDP growth	0.07	0.08	<b>0.30</b>	<b>0.22</b>	0.04	0.71	0.29
Inflation	0.05	0.02	<b>0.29</b>	0.07	0.01	0.44	0.56
Bank credit growth	0.07	<b>0.14</b>	<b>0.17</b>	<b>0.33</b>	0.03	0.74	0.26
Loan rate	0.08	<b>0.33</b>	0.04	0.02	0.01	0.48	0.52

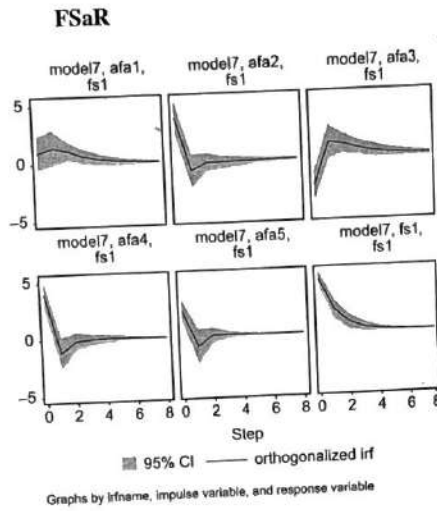
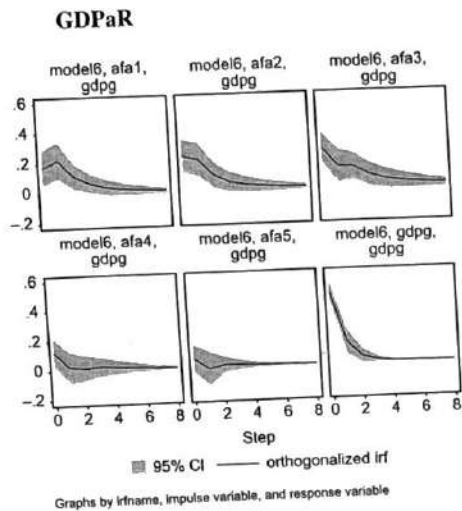
Note: Boldfaced values denote estimates significantly different from zero at 5 percent confidence levels.

these structural shocks originate? To which other sectors are they transmitted? In terms of figure 3.1 of the introduction, answering these questions amounts to identifying in which box shocks originate, and disentangles the linkages between the originating box and other boxes in the picture; that is, the web of linkages implied by the transmission mechanism of these shocks.

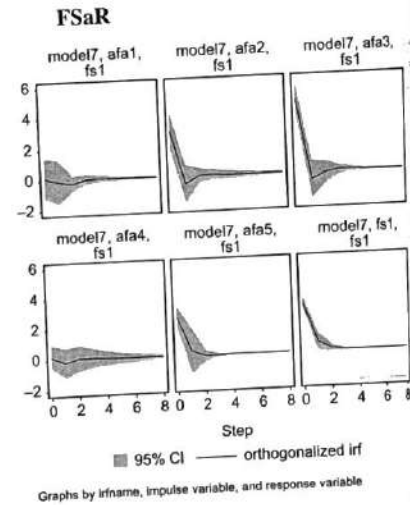
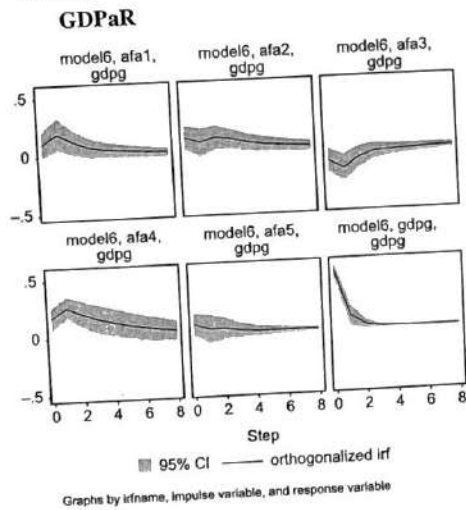
Answering these questions amounts to exploit further the rich information structure provided by the factor model. We believe that such an explora-



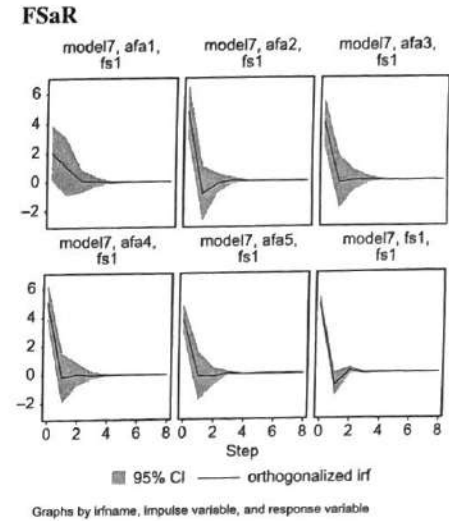
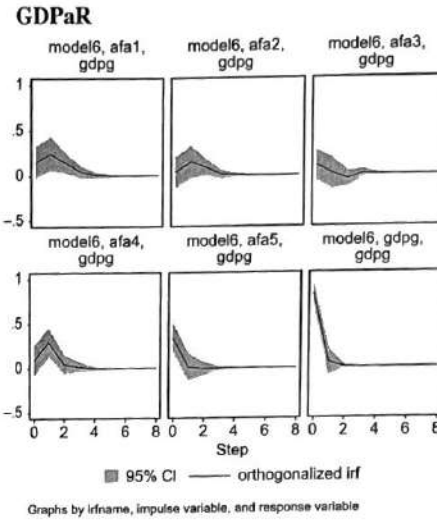
**United States**



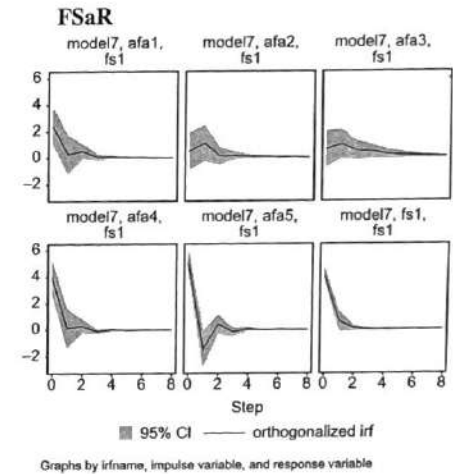
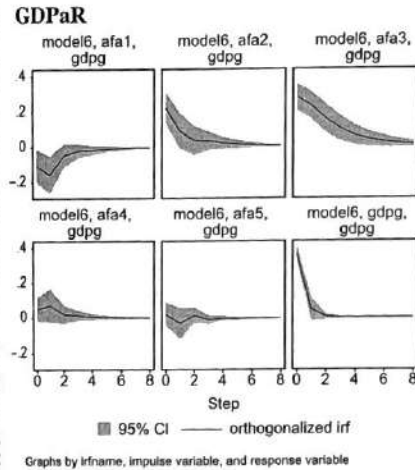
**Canada**



**Japan**



**United Kingdom**

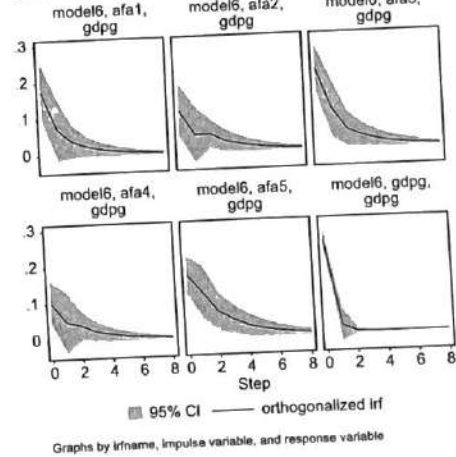


**Fig. 3.6** Impulse responses of GDPaR and FSaR to identified aggregate demand and bank credit demand shocks and own shock

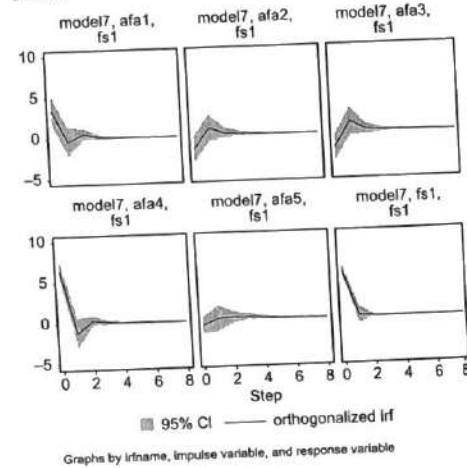
**Fig. 3.6** (cont.)

France

GDPaR

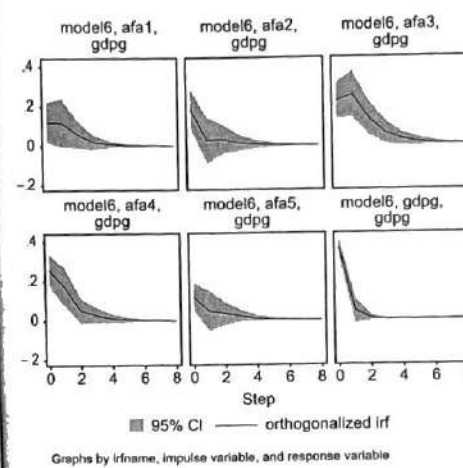


FSaR

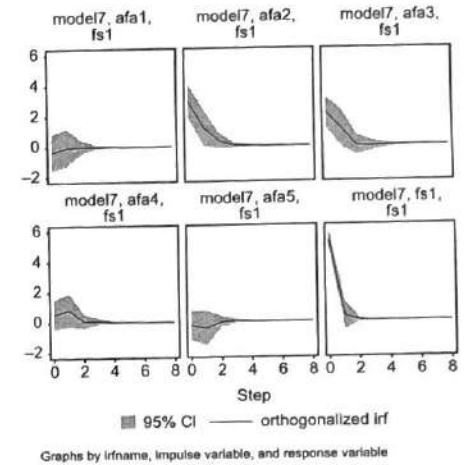


Italy

GDPaR

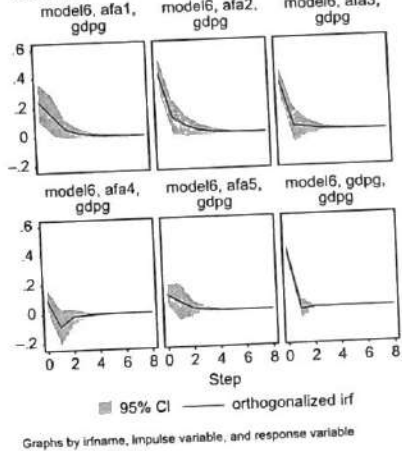


FSaR



Germany

GDPaR



FSaR

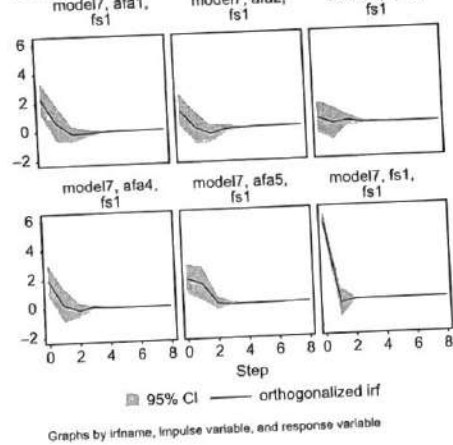


Fig. 3.6 (cont.)

Table 3.5

Variance decomposition of GDPaR and FSaR to identified aggregate demand and bank credit demand shocks

	Shock 1	Shock 2	Shock 3	Shock 4	Shock 5	Shock sum	Idiosyncratic
United States							
GDPaR	<b>0.12</b>	0.09	0.09	<b>0.30</b>	0.01	0.61	0.39
FSaR	0.06	<b>0.19</b>	<b>0.12</b>	<b>0.22</b>	0.07	0.67	0.33
Canada							
GDPaR	<b>0.15</b>	0.02	0.08	<b>0.17</b>	0.06	0.48	0.52
FSaR	0.00	<b>0.18</b>	<b>0.47</b>	0.00	<b>0.13</b>	0.79	0.21
Japan							
GDPaR	<b>0.10</b>	0.03	0.01	0.09	<b>0.11</b>	0.34	0.66
FSaR	0.05	<b>0.22</b>	<b>0.14</b>	<b>0.24</b>	<b>0.13</b>	0.78	0.22
United Kingdom							
GDPaR	0.09	<b>0.14</b>	<b>0.42</b>	0.02	0.00	0.67	0.33
FSaR	0.09	0.02	0.03	<b>0.22</b>	<b>0.40</b>	0.76	0.24
France							
GDPaR	<b>0.15</b>	0.07	<b>0.25</b>	0.06	<b>0.21</b>	0.74	0.26
FSaR	<b>0.13</b>	0.04	<b>0.05</b>	<b>0.45</b>	0.01	0.68	0.32
Germany							
GDPaR	<b>0.15</b>	<b>0.33</b>	<b>0.20</b>	0.03	0.03	0.74	0.26
FSaR	<b>0.12</b>	0.04	0.01	0.08	<b>0.11</b>	0.36	0.64
Italy							
GDPaR	0.07	0.08	<b>0.30</b>	<b>0.22</b>	0.04	0.71	0.29
FSaR	0.00	0.22	<b>0.13</b>	0.02	0.01	0.38	0.62

Note: Boldfaced values denote estimates significantly different from zero at 5 percent conf.

tion is likely to yield increasing returns. It can guide a more effective integration of financial frictions into current macroeconomic modeling, encourage the development of more disaggregated versions of such macroeconomic modeling by incorporating the insights of models of financial intermediation, and can be a powerful monitoring tool available to policymakers. Carrying out some of these extensions is already part of our research agenda.

## Appendix

Table A3.1 List of variables

Equity markets	Transformations
Equity indices, price earnings ratios, and dividend yields total and by sector	
Market	$\Delta \ln$
Oil and gas	$\Delta \ln$
Chemicals	$\Delta \ln$
Basic resources	$\Delta \ln$
Construction and materials	$\Delta \ln$
Industrial goods and services	$\Delta \ln$
Auto and parts	$\Delta \ln$
Food and beverages	$\Delta \ln$
Personal and household goods	$\Delta \ln$
Health care	$\Delta \ln$
Retail	$\Delta \ln$
Media	$\Delta \ln$
Travel and leisure	$\Delta \ln$
Telecom	$\Delta \ln$
Utilities	$\Delta \ln$
Banks	$\Delta \ln$
Insurance	$\Delta \ln$
Financial services	$\Delta \ln$
Technology	$\Delta \ln$
Credit conditions	
3-month money rate	$\Delta \text{levels}$
Treasury bonds	
2 YR	$\Delta \text{levels}$
3 YR	$\Delta \text{levels}$
5 YR	$\Delta \text{levels}$
7 YR	$\Delta \text{levels}$
10 YR	$\Delta \text{levels}$
30 YR	$\Delta \text{levels}$
Financial variables	
Money base	$\Delta \ln$
Money supply M1	$\Delta \ln$
Interbank rate	$\Delta \text{levels}$
Prime rate charged by banks (month AVG)	$\Delta \text{levels}$
Bank lending	$\Delta \ln$
Real sector variables	
GDP	$\Delta \ln$
Personal consumption expenditure	$\Delta \ln$
Government consumption and investment	$\Delta \ln$
Private domestic fixed investment	$\Delta \ln$
Export of goods on balance of payments basis	$\Delta \ln$
Import of goods on balance of payments basis	$\Delta \ln$
Net export or capital and financial account balance	$\Delta \ln$
Consumer confidence index	$\Delta \text{levels}$
Personal income	$\Delta \ln$

Table A3.1 (continued)

Equity markets	Transformations
Personal savings as percent of disposal income	$\Delta \text{levels}$
Unemployment rate	$\Delta \text{levels}$
Output per hour of all persons	$\Delta \ln$
Industrial production-total index	$\Delta \ln$
CPI all items	$\Delta \ln$
New orders manufacturing	$\Delta \ln$
Capacity utilization	$\Delta \text{levels}$
Housing market index	$\Delta \text{levels}$

Notes: All variables are extracted for each country in the G-7 group during the 1980Q1–2009Q3 period. The frequency of all series is quarterly. Data transformations are implemented to make all series stationary.  $\Delta \ln$  = log level difference;  $\Delta \text{levels}$  = level difference. CPI = consumer price index.

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## Comment Hao Zhou

There are two approaches to understanding the issue of systemic risk and macroprudential regulation—one is empirical macroeconomics based, and the other is financial market based. These two approaches have different methodologies, emphases, and purposes. De Nicolò and Lucchetta's chapter belongs to the macro-centric approach. It helps us to better understand the fundamental linkage between the real economy and the financial sector, especially in the long run. However, unlike a financial-centric approach, the chapter is silent on the interaction among large banks, the nonlinear feedback effect, and the identification of individual institutions that are systemically important.

### Two Approaches to Systemic Risk

There is a long tradition in the empirical macroeconomics literature (see, e.g., Bernanke, Gertler, and Gilchrist 1998) that introduces the financial sector as a market imperfection into a real business cycle framework. Such an add-on approach typically labels the financial sector as an accelerator, multiplier, or amplifier, in that shocks into the economy come from the real side and are magnified by the financial sector. The recent financial crisis and deep recession have also prompted more research along this direction.<sup>1</sup>

This chapter follows De Nicolò and Kwast (2002) in defining systemic risk as the risk that either a real or a financial shock will trigger a significant decline in real activity. The systemic financial risk is measured as the value at risk (VaR) for the market-adjusted return of a large portfolio of financial firms at the 5 percent level, and the systemic real risk is measured by the similar GDP 5 percentile. The empirical implementation builds on the dynamic factor model of Stock and Watson (2005) with quarterly data. For estimating systemic risks, GDP and financial VaRs are estimated via quantile regressions, and can be explicitly related to the conditional VaR (CoVaR) framework advocated by Adrian and Brunnermeier (2009). Empirical estimation consists of two steps: first, a standard dynamic factor approach is adopted to estimate the VaR parameters and to filter out the latent factors; then, the standard quantile regression is applied to the GDP and financial and impulse-response or stress testing is conducted.

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1. One example is the Federal Reserve and JMCB (*Journal of Money, Credit, and Banking*) Conference on Financial Market and Monetary Policy held in June 2009, which emphasizes the linkage between financial market and macroeconomy and the implications for monetary policy.



An alternative approach is to focus on the microeconomic structure of the financial industry, while treating macroeconomy only as a background. The CoVaR measure (Adrian and Brunnermeier 2009) looks at the VaR of one portfolio conditional on the VaR of another portfolio, which focuses on the spillover effect from one bank's failure to the safety of another bank or the whole banking system. The "Shapley Value" decomposition approach (Tarashev, Borio, and Tsatsaronis 2009) constructed in the game theory used by Tarashev, Borio, and Tsatsaronis (2009) allocates the systemic risk to individual banks by defining the contribution of each bank as a weighted average of its add-on effect to each subsystem of that bank. Huang, Zhou, and Zhu (2010) consider bank's systemic importance as its marginal contribution to a hypothetical insurance premium of distress loss that a banking system may suffer. Such an intuitive method has advantages of being both subadditive, as opposed to the CoVaR measure, and simple to implement, as opposed to the Shapley value approach.

#### Advantages and Disadvantages

For the impulse-response analysis in empirical macroeconomics, typically the shocks to factors are extracted through orthogonalization but without meaningful economic interpretations. This chapter uses economic theory implied sign restrictions to help identify whether the real or financial shocks are coming from supply side or demand side. A large class of general equilibrium monetary macroeconomic models can identify aggregate demand shock if both GDP and inflation responses are positive and identify aggregate supply shock if GDP response is positive, while inflation response is negative (Canova and De Nicolò, 2002). On the other hand, partial equilibrium banking models (see, e.g., Boyd, De Nicolò, and Loukoianova 2009) can identify credit demand shock from positive responses in both bank credit growth and lending rate change and identify credit supply shock from positive response of bank credit growth and negative response of lending rate change.

Such an identification scheme for shocks to the system generates meaningful empirical findings about systemic risk and stress testing. For example, a common misunderstanding of the 2007 to 2009 economic crisis is that it was caused by the credit crunch and de-leveraging, rather than the sharp declines in real activity since December 2007. With a rigorous identification scheme, this chapter finds that in the long run it is (always) the real shocks in final demand that ultimately determine the investment fluctuations, in association with the indirect credit demand channel. And bank credit growth slowdowns are primarily the results of the declines in aggregate real demand, not the other way around. It is the most important finding in the chapter, which also has implications for the financial-centric approach in systemic risk. For a

financial crisis to have enduring effect on the business cycle, the crisis must be originated from the real economy.

What is missing in such a macro-centric approach for systemic risk monitoring? One obvious problem is that by treating all the financial firms in one sector, the approach overlooks the interaction among large institutions, which is a main cause for this and previous financial crises. Also, by adopting the empirical macroeconomic VaR, the chapter cannot address the nonlinear feedback effect that is instrumental in spreading fear during the recent financial turmoil. Last, but not least, the macro-centric method cannot identify individual institutions that are deemed too-big-to-fail or systemically important.

#### Alternative Financial-Centric Approach

An alternative approach to systemic risk is a micro-based financial-centric one, with attention to individual firms' asset correlations, leverage ratios, and liability sizes (Huang, Zhou, and Zhu 2009). Such a systemic risk indicator, a hypothetical insurance premium against catastrophic losses in a banking system, is constructed from real-time financial market data using the portfolio credit risk technique. The two key default risk factors, the probability of default (PD) of individual banks and the asset return correlations among banks, are estimated from credit default swap (CDS) spreads and equity price comovements, respectively. Together with the banks' liability sizes, these inputs effectively capture the three main ingredients missed by the macro-centric approach—interconnectedness, leverage, and too-big-to-fail—for large complex financial institutions.

For the purpose of macroprudential regulation, it is important not only to monitor the level of systemic risk, but also to understand the sources of risks in a financial system. One perspective is to decompose the credit risk of the portfolio into the risk contributions associated with individual sub-portfolios (either a bank or a group of banks). As demonstrated by Huang, Zhou, and Zhu (2010), the total risk can be usefully decomposed into a sum of marginal risk contributions. Each marginal risk contribution is the conditional expected loss from that subportfolio or a bank, conditional on a large loss for the full portfolio. It is important that the marginal contribution of each subgroup or bank adds up to the aggregate systemic risk. This additivity property is desirable from an operational perspective, because it allows the macroprudential regulation to be implemented at individual bank level.

Huang, Zhou, and Zhu (2010, figure 3) shows that such a systemic risk indicator for twenty-two Asia-Pacific banks was very low at the beginning of the global crisis. The indicator then moved up significantly, reaching the first peak when Bear Stearns was acquired by JP Morgan on March 16, 2008. Things changed dramatically in September 2008 with the failure of Lehman

Brothers. The distress insurance premium hiked up and hovered in the range of 150 and 200 basis points (or 50 to 70 billion USD). The situation did not improve until late March 2009. Since the G20 Summit in early April 2009, the distress insurance premium has come down quickly and returned to pre-Lehman levels in May 2009.

Huang, Zhou, and Zhu (2010, figure 8) further divide banks into six groups: Australian banks, Hong Kong banks, Indian banks, Korean banks, Singapore banks, and banks from Indonesia, Malaysia, and Thailand. In relative terms, the marginal contribution of each group of banks was quite stable before mid-2008. Australian banks were obviously the most important ones and contributed the most to the systemic vulnerability. However, since September 2008, the relative contribution of Australian banks decreased substantially, whereas banks from Hong Kong and Singapore became more important from a systemic perspective.

### Summary

To conclude, the macro-centric approach to financial systemic risk, as in De Nicolò and Lucchetta's chapter, among others, can help us better understand why the business cycle is ultimately driven by the shocks from the real side of the economy, especially in the long run. However, such an approach lacks attention to details—asset correlation, leverage ratio, and too-big-to-fail—for identifying individual institutions that are systemically important. A micro-centric approach, as in Huang, Zhou, and Zhu (2009, 2010), among others, captures these missing ingredients critical in systemic risk regulation and is potentially more operational in practice than a macro-centric approach.

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