Volume Title: Quantifying Systemic Risk

Volume Author/Editor: Joseph G. Haubrich and Andrew W. Lo, editors

Volume Publisher: University of Chicago Press

Volume ISBN: 0-226-31928-8; ISBN-13: 978-0-226-31928-5

Volume URL: http://www.nber.org/books/haub10-1

Conference Date: November 6, 2009

Publication Date: January 2013

Chapter Title: Systemic Risks and the Macroeconomy

Chapter Author(s):  Gianni De Nicolò, Marcella Lucchetta

Chapter URL: http://www.nber.org/chapters/c12051

Chapter pages in book: (p. 113 - 148)

# 3

# 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

Gianni De Nicolò is a senior economist in the Research Department of the International Monetary Fund. Marcella Lucchetta is assistant professor of economics at the University of Venice Ca' Foscari.

We thank without implications Fabio Canova, David Romer, Ken West, Hao Zhou, Harry Mamaysky, and seminar participants at the IMF and at the November 2009 NBER-Federal Reserve Bank of Cleveland Research Conference on Quantifying Systemic Risk for comments and suggestions. The views expressed in this chapter are those of the authors and do not necessarily represent the views of the International Monetary Fund. For acknowledgments, sources of research support, and disclosure of the authors' material financial relationships, if any, please see http://www.nber.org/chapters/c12051.ack.

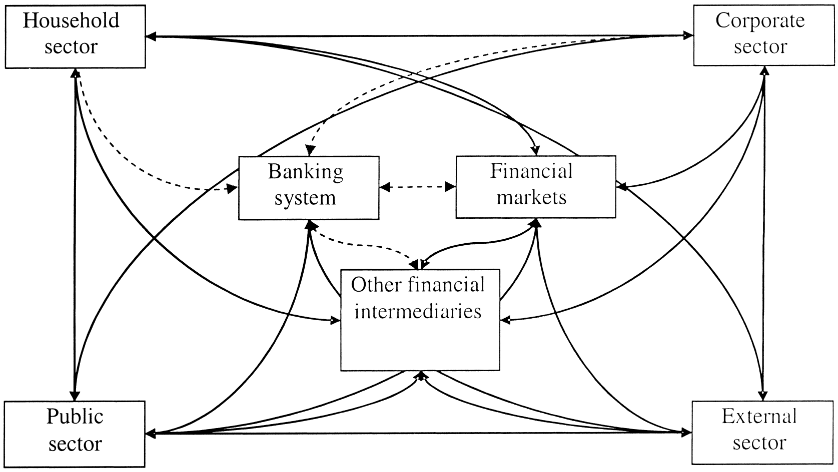



**Fig. 3.1 Financial exposures (stocks and flows) between sectors**

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.[1]

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.[2]

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 co yntext 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.[3] 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 $\text{GDPG}_t$, and the indicator of system-wide financial risk with $\text{FS}_t$. The joint dynamics of $\text{GDPG}_t$ and $\text{FS}_t$ 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:

$$\text{GDPG}_t = \lambda^R(L)f_t + \gamma_{11}(L)\text{GDPG}_{t-1} + \gamma_{12}(L)\text{FS}_{t-1} + u_t^1 \tag{1}$$

$$\text{FS}_t = \lambda^F(L)f_t + \gamma_{21}(L)\text{GDPG}_{t-1} + \gamma_{22}(L)\text{FS}_{t-1} + u_t^2 \tag{2}$$

$$X_{it} = \lambda_i(L)f_t + \delta_i X_{it-1} + v_{it} \tag{3}$$

$$f_t = \Gamma(L)f_{t-1} + \eta_t. \tag{4}$$

Equations (1) and (2) describe a VAR in $\text{GDPG}_t$ and $\text{FS}_t$ 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.[4] 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 $F_t \equiv [f_t', f_{t-1}', \ldots, f_{t-p-1}']$, one obtains the *static form* representation of the DFM:

$$\text{GDPG}_t = \Lambda^{R\prime}F_t + \gamma_{11}(L)\text{GDPG}_{t-1} + \gamma_{12}(L)\text{FS}_{t-1} + u_t^1 \tag{5}$$

$$\text{FS}_t = \Lambda^{F\prime}F_t + \gamma_{21}(L)\text{GDPG}_{t-1} + \gamma_{22}(L)\text{FS}_{t-1} + u_t^2 \tag{6}$$

$$X_{it} = \Lambda_i'F_t + \delta_i X_{it-1} + v_{it} \tag{7}$$

$$F_t = \Phi(L)F_{t-1} + G\eta_t. \tag{8}$$

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 $rxq$, 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 Eliasz (2005):

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

$$\text{GDPG}_t = \Lambda^{R\prime}\Phi(L)F_{t-1} + \gamma_{11}(L)\text{GDPG}_{t-1} + \gamma_{12}(L)\text{FS}_{t-1} + u_t^1 \tag{10}$$

$$\text{FS}_t = \Lambda^{F\prime}\Phi(L)F_{t-1} + \gamma_{21}(L)\text{GDPG}_{t-1} + \gamma_{22}(L)\text{FS}_{t-1} + u_t^2. \tag{11}$$

#### 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:

$$\text{GDPG}_t = \alpha_1^q + \Lambda_q^{R\prime}F_t + \gamma_{11}^q(L)\text{GDPG}_{t-1} + \gamma_{12}^q(L)\text{FS}_{t-1} + u_t^{1q} \tag{12}$$

$$\text{FS}_t = \alpha_2^q + \Lambda_q^{F\prime}F_t + \gamma_{12}^q(L)\text{GDPG}_{t-1} + \gamma_{22}^q(L)\text{FS}_{t-1} + u_t^{2q}. \tag{13}$$

Denoting the estimated coefficients of (12) and (13) with a "hat," $\text{GDPaR}_t$ and $\text{FSaR}_t$ are the fitted values of the quantile regressions (12) and (13) with $q = 0.05$:

$$\text{GDPaR}_t = \hat{\alpha}_1^q + \hat{\Lambda}_q^{R\prime}F_t + \hat{\gamma}_{11}^q(L)\text{GDPG}_{t-1} + \hat{\gamma}_{12}^q(L)\text{FS}_{t-1} \tag{14}$$

$$\text{FSaR}_t = \hat{\alpha}_2^q + \hat{\Lambda}_q^{F\prime}F_t + \hat{\gamma}_{12}^q(L)\text{FS}_{t-1} + \hat{\gamma}_{22}^q(L)\text{GDPG}_{t-1}. \tag{15}$$

#### 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 $\text{Co}(\text{GDPaR}_t)$ and $\text{Co}(\text{FSaR}_t)$ are given by:

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

$$\text{Co}(\text{FSaR}_t) = \hat{\alpha}_2^q + \hat{\beta}_2^q F_t + \hat{\gamma}_{12}^q(L)\text{GDPaR}_{t-1} + \hat{\gamma}_{22}^q(L)\text{FSaR}_{t-1}. \tag{17}$$

The existence of systemic risk spillovers can be gauged comparing $\text{Co}(\text{GDPaR})_t$ with $\text{GDPaR}_t$, and $\text{Co}(\text{FSaR})_t$ with $\text{FSaR}_t$. For example, if $\text{Co}(\text{GDPaR})_t < \text{GDPaR}_t$, 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:

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

$$(19)\quad \text{Co(FSaR)}_t - \text{FSaR}_t = \hat{\gamma}^q_{12}(L)(\text{GDPaR}_{t-1} - \text{GDPG}_{t-1}) + \hat{\gamma}^q_{22}(L)(\text{FSaR}_{t-1} - \text{FS}_{t-1}).$$

### 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 $\tilde{F} = \{(F_{r=1}), (F_1, F_{r=2}), \ldots, (F_1, F_2, \ldots, F_{r=R})\}$. Lastly, we choose the number of lags $L$ and the number of static factors $r \in \tilde{F}$ that maximize FPE$(L, r)$ + 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 criterions 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.[5]

### 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:

$$F_t = A(L)\eta_t, \tag{9a}$$

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

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

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

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:

$$GDPG_t = B^R(L)\eta_t + w_t^1 \tag{10b}$$

$$FS_t = B^F(L)\eta_t + w_t^2, \tag{11b}$$

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

$$\text{GDPaR}_t = B_q^R(L)\eta_t + v_1^{1q} \tag{14a}$$

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

where $B_q^R(L) = (1 - \gamma_{11}^q(L)L)^{-1}\Lambda_q^{R\prime} A(L)$, $B_q^F(L) = (1 - \gamma_{22}^q(L)L)^{-1}\Lambda_q^{F\prime} A(L), = (1 - \gamma_{11}^q(L)L)^{-1}u_t^{1q}$, and $v_t^{q2} = (1 - \gamma_{22}^q(L)L)^{-1}u_t^{2q}$.

### 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**

| | | |
|---|---|---|
| *Macroeconomic model* | *Aggregate supply* | *Aggregate demand* |
| GDP growth | Positive | Positive |
| Inflation | Negative | Positive |
| *Banking model* | *Bank credit demand* | *Bank credit supply* |
| 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 $X_t$ 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 interbank 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 reminder 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 | **0.20** |
| | FS | –0.06 | 8.61 | –38.68 | 19.52 | |
| France | GDPG | 0.46 | 0.51 | –1.52 | 1.48 | **0.15** |
| | FS | 0.46 | 9.81 | –41.3 | 29.16 | |
| Germany | GDPG | 0.32 | 0.75 | –3.6 | 1.8 | **0.38** |
| | 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.

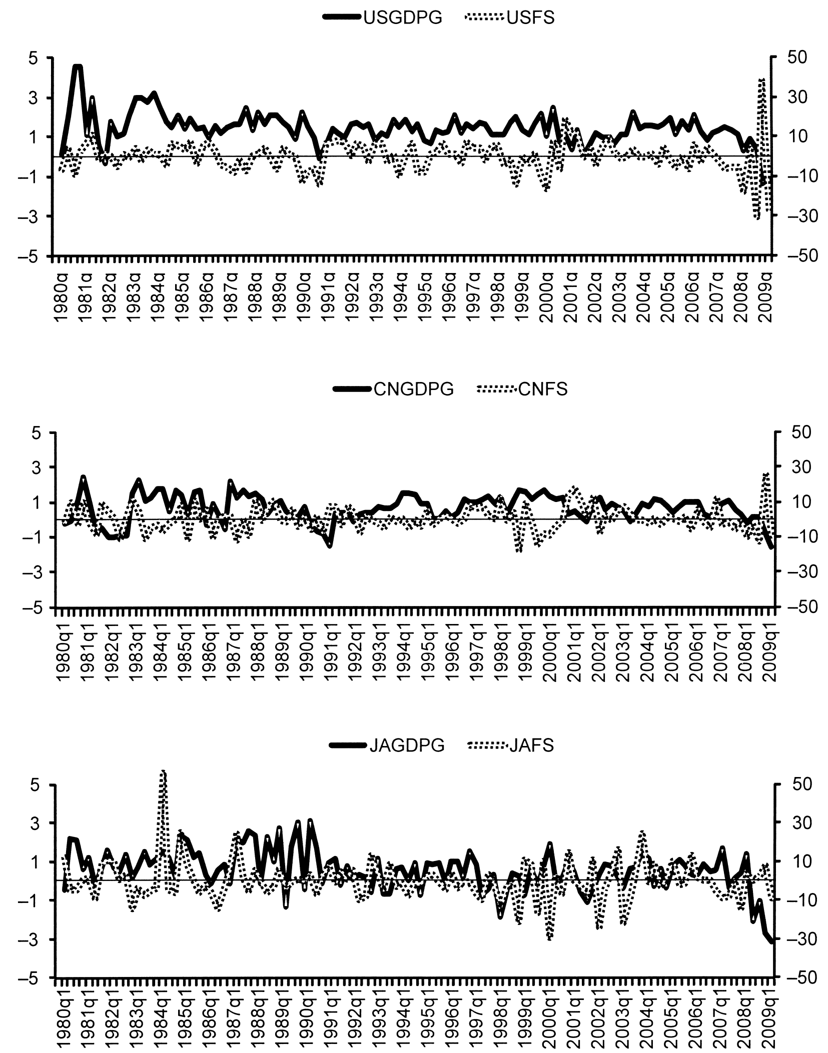



**Fig. 3.2 GDP growth and FS indicators**

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

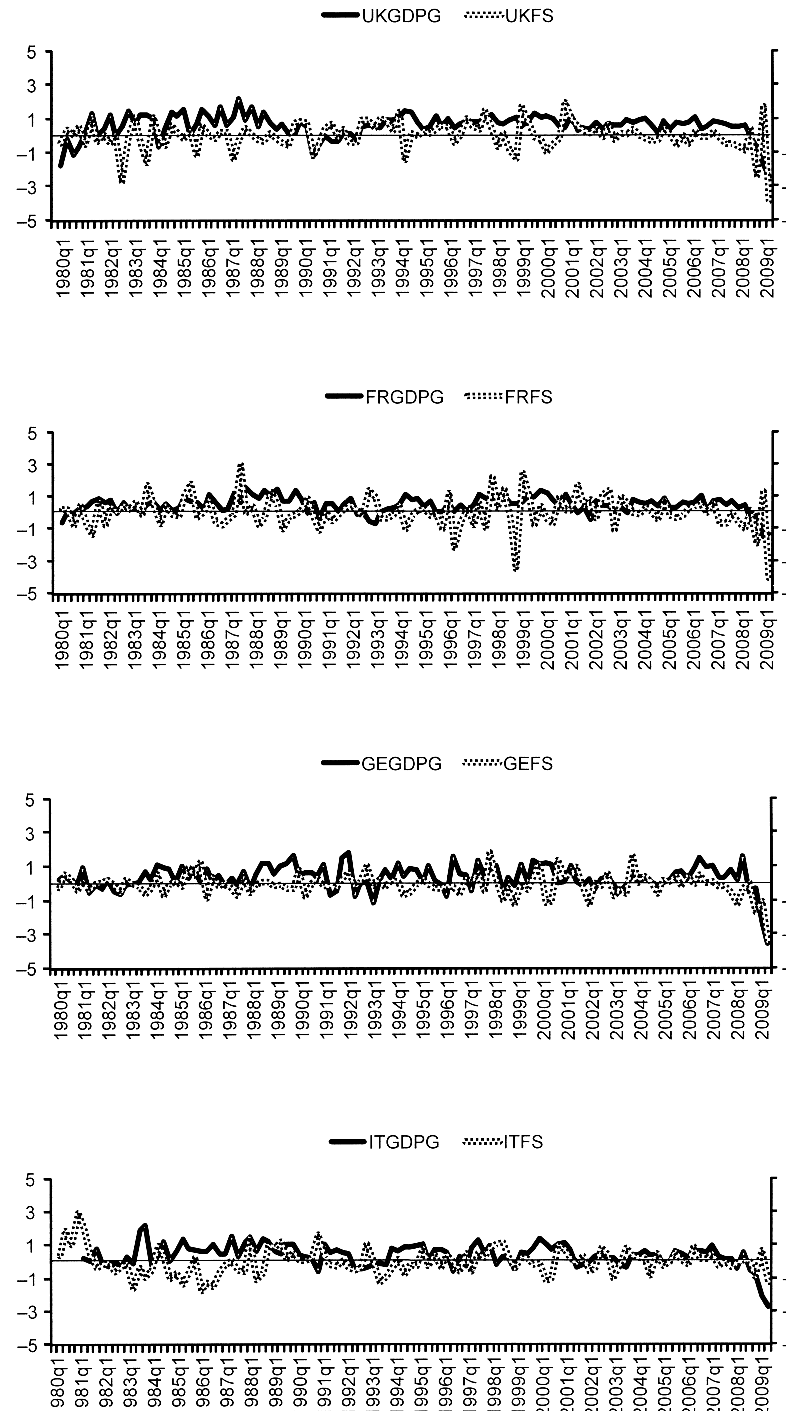

UKGDPG
UKFS
FRGDPG
FRFS
GEGDPG
GEFS
ITGDPG
ITFS
5
3
1
−1
−3
−5
50
30
10
−10
−30
−50
1980q1
1981q1
1982q1
1983q1
1984q1
1985q1
1986q1
1987q1
1988q1
1989q1
1990q1
1991q1
1992q1
1993q1
1994q1
1995q1
1996q1
1997q1
1998q1
1999q1
2000q1
2001q1
2002q1
2003q1
2004q1
2005q1
2006q1
2007q1
2008q1
2009q1

**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.[6]

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 $IC_{p2}$ criterions, 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

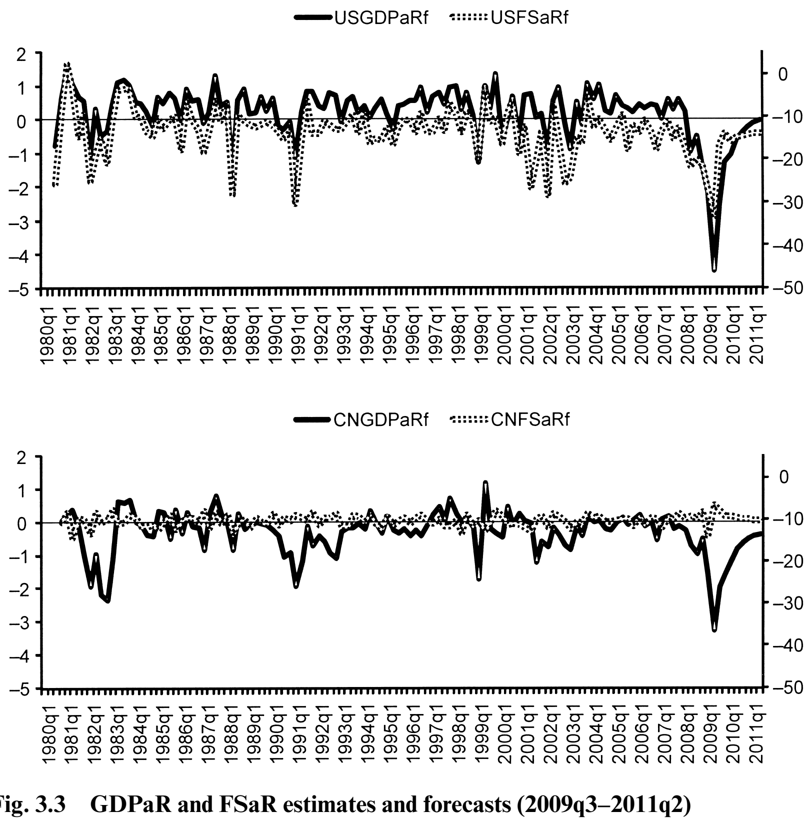



**Fig. 3.3 GDPaR and FSaR estimates and forecasts (2009q3–2011q2)**

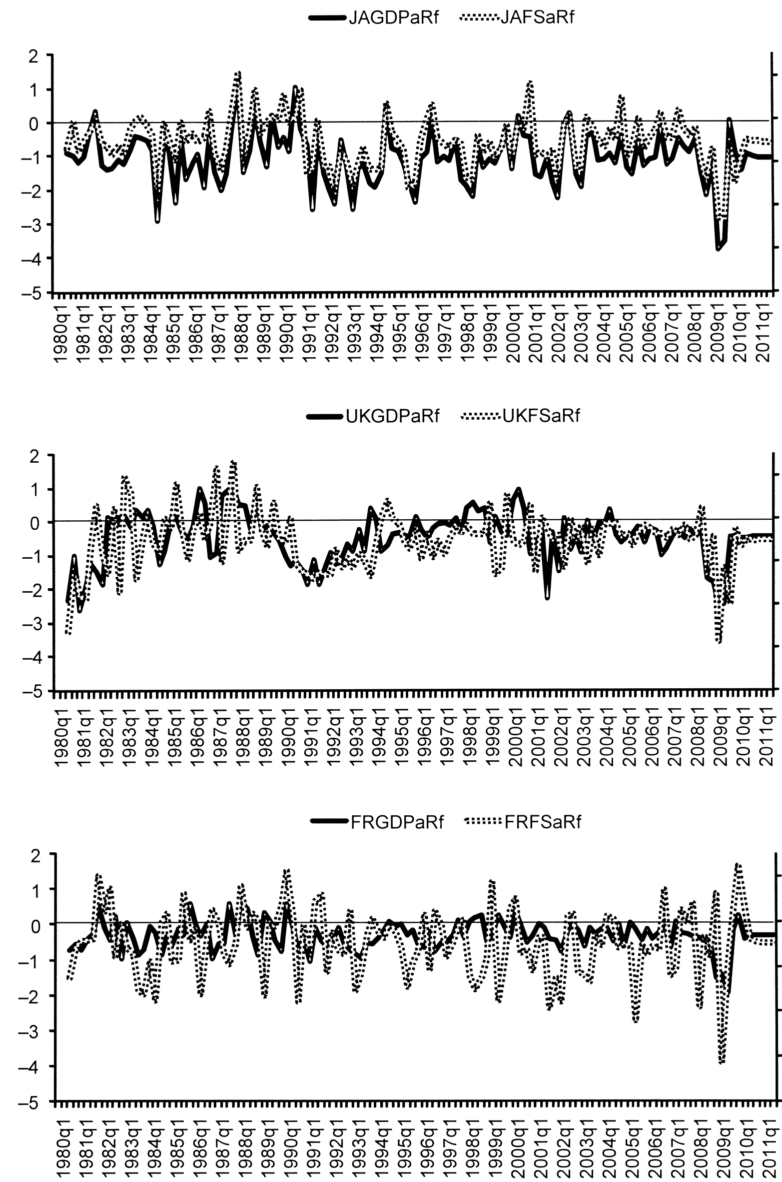
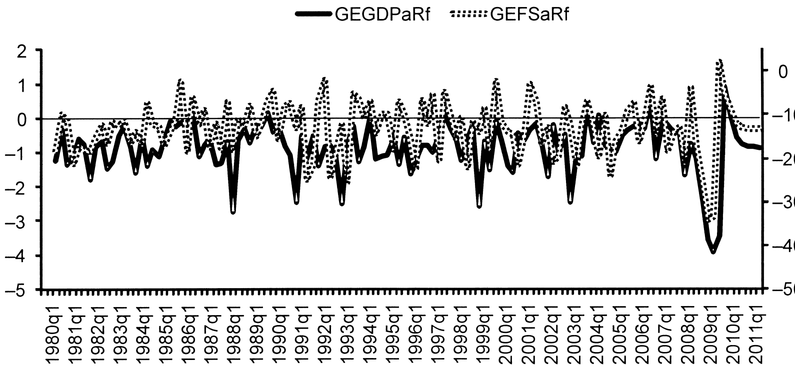



**Fig. 3.3 (cont.)**



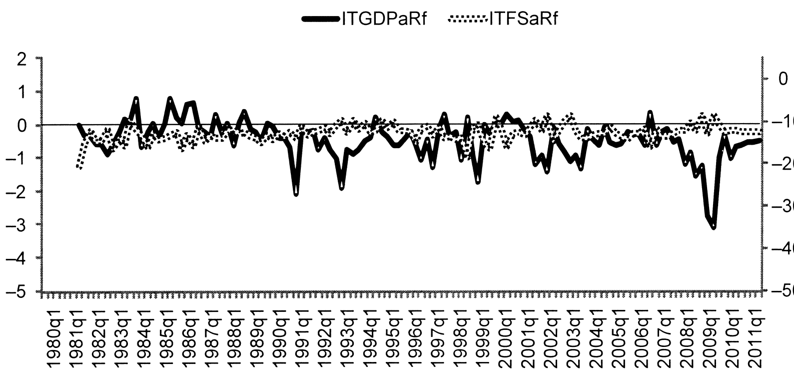




**Fig. 3.3 (cont.)**

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 = co(GdPaR) – GDPaR, where co(GDPaR) is the CoVaR version of the systemic real risk indicator; dcoFSaR = co(FSaR) – FSaR, where co(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

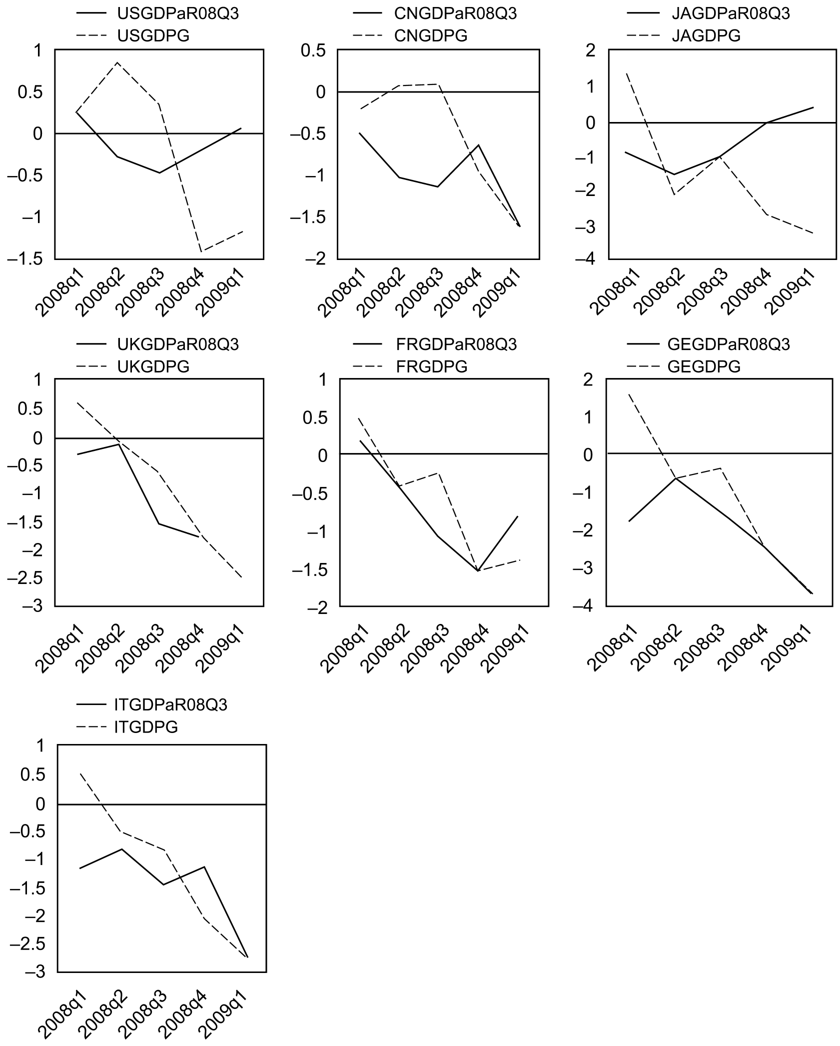



**Fig. 3.4 GDPaR out-of-sample forecasts and actual GDP growth (2008q3–2009q1)**

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 differences 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).[7] 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

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.

**United States**

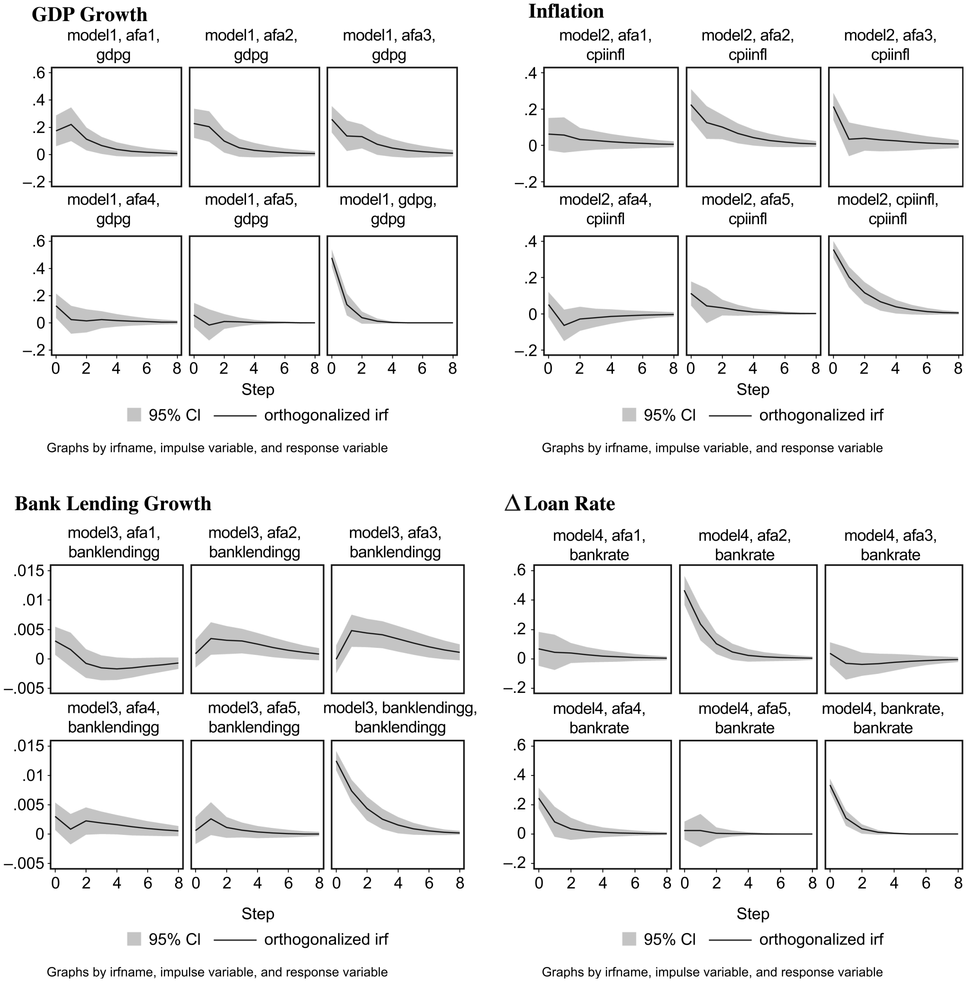



**Fig. 3.5 Impulse responses of GDP growth, inflation, bank lending growth, and change in lending rate to shocks to factors and own shock**

## Canada

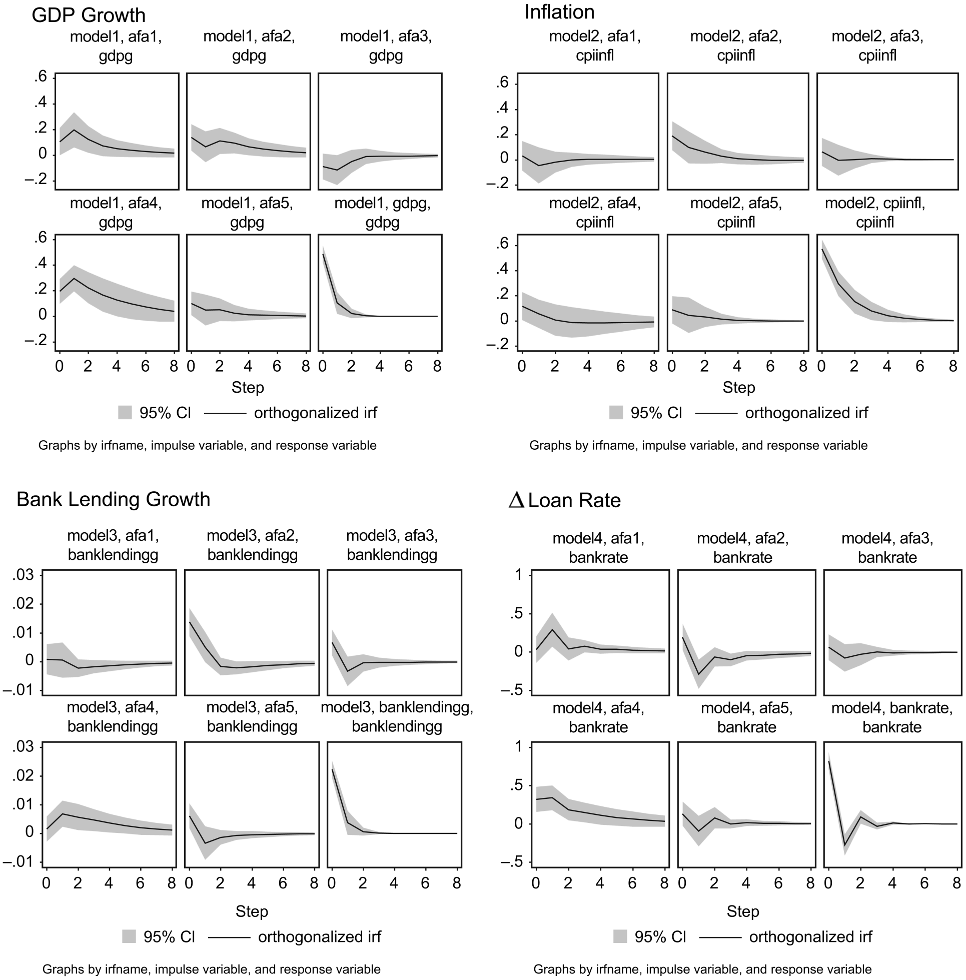



**Fig. 3.5 (cont.)**

**Japan**

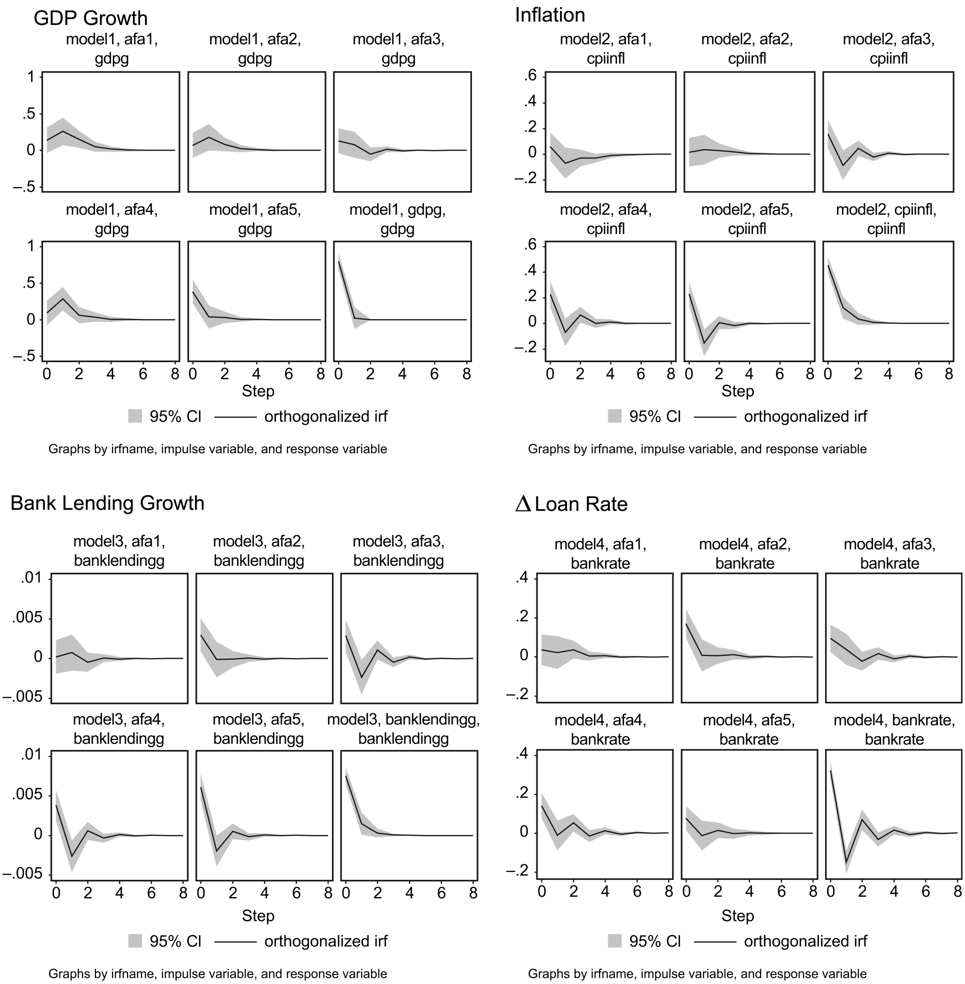



**Fig. 3.5 (cont.)**

## United Kingdom

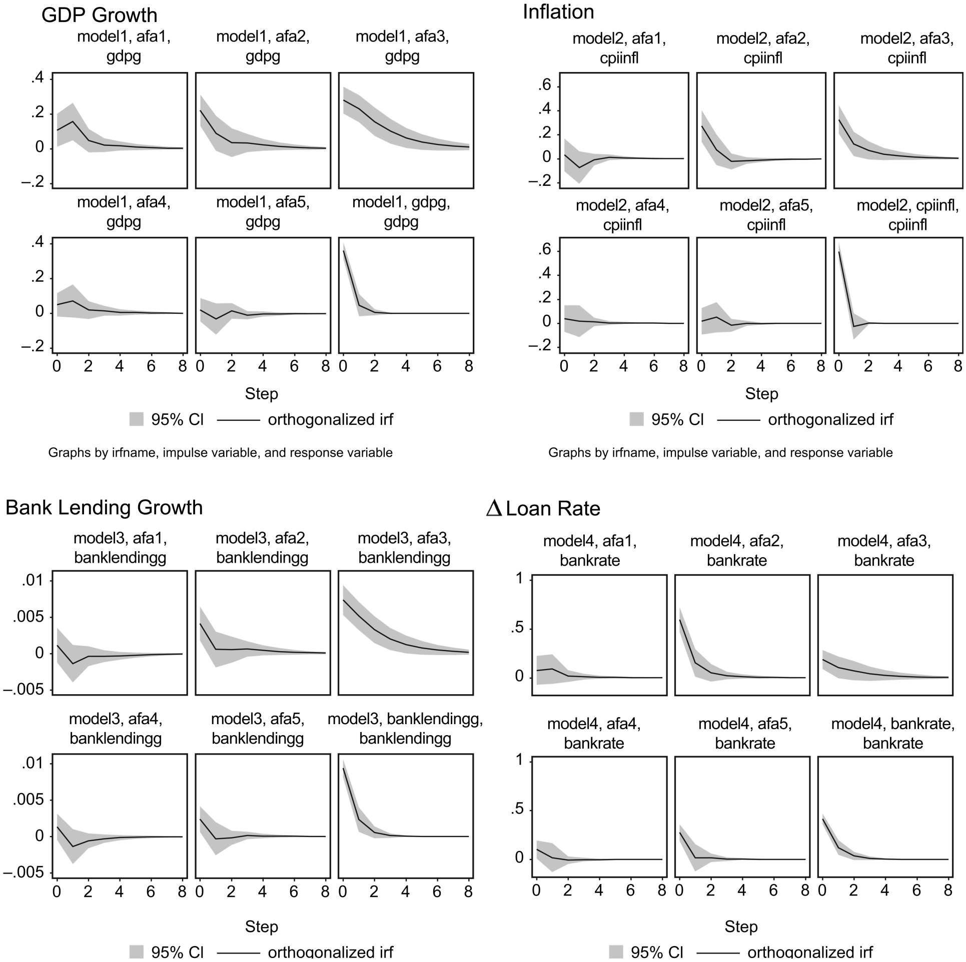
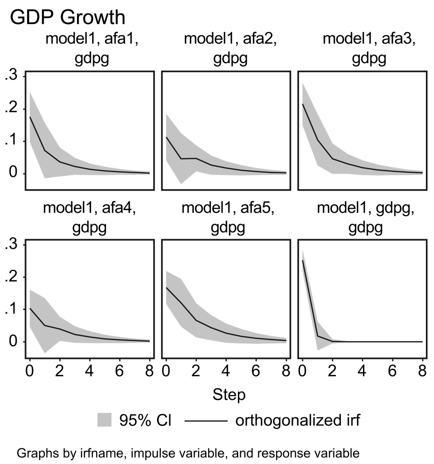
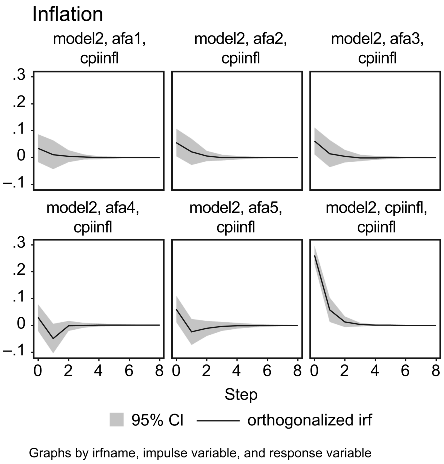
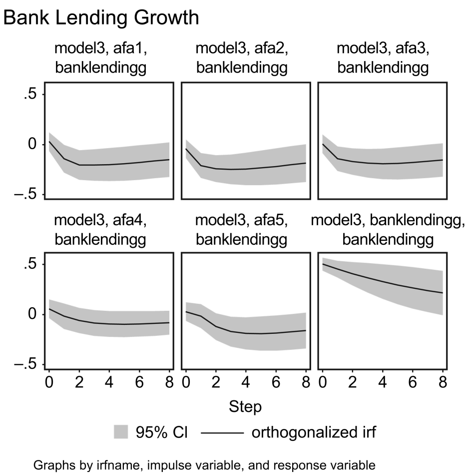



**Fig. 3.5 (cont.)**

## France



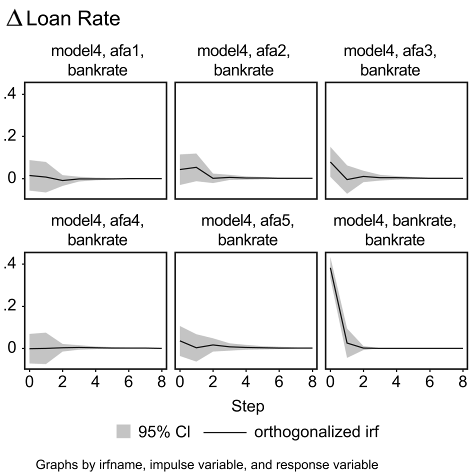




**Fig. 3.5 (cont.)**

**Germany**

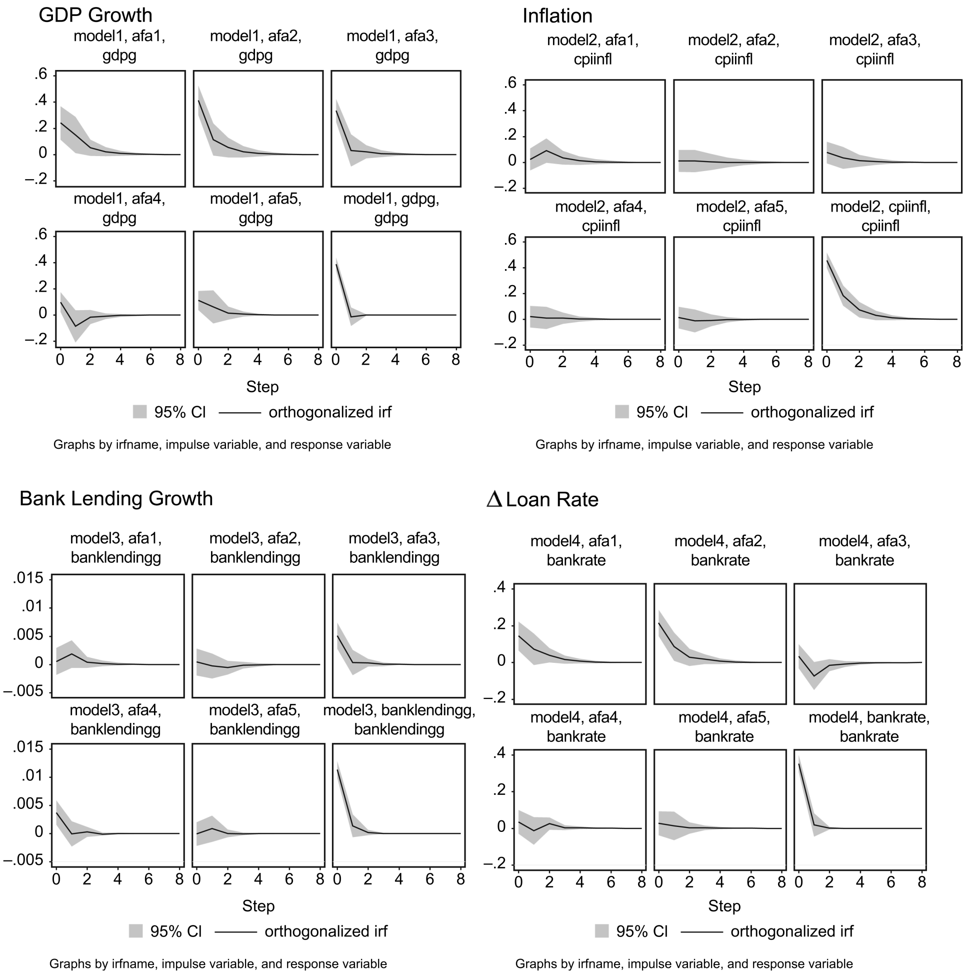



**Fig. 3.5 (cont.)**

**Italy**

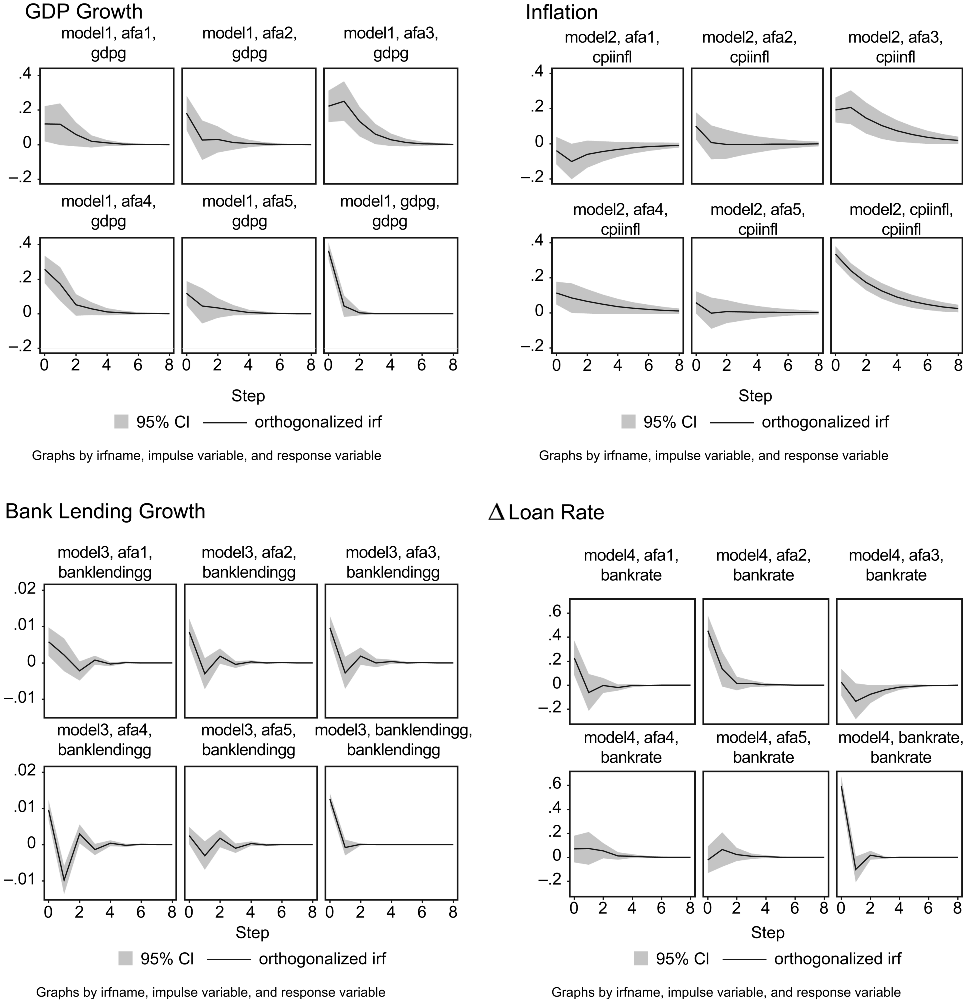



**Fig. 3.5 (cont.)**

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.[8]

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 aplenty, 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 | **0.17** | **0.18** | **0.19** | 0.03 | 0.01 | 0.58 | 0.42 |
| Inflation | 0.03 | **0.24** | **0.14** | 0.02 | 0.05 | 0.48 | 0.52 |
| Bank credit growth | 0.05 | **0.11** | **0.20** | 0.06 | 0.02 | 0.44 | 0.56 |
| Loan rate | 0.02 | **0.58** | 0.01 | **0.14** | 0.00 | 0.75 | 0.25 |
| Canada | | | | | | | |
| GDP growth | **0.12** | 0.09 | 0.09 | **0.30** | 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 | **0.21** | 0.06 | **0.13** | 0.05 | 0.46 | 0.54 |
| Loan rate | 0.07 | 0.10 | 0.02 | **0.22** | 0.03 | 0.44 | 0.56 |
| Japan | | | | | | | |
| GDP growth | **0.10** | 0.03 | 0.01 | 0.09 | **0.11** | 0.34 | 0.66 |
| Inflation | 0.03 | 0.02 | 0.04 | **0.15** | **0.23** | 0.47 | 0.53 |
| Bank credit growth | 0.02 | 0.01 | 0.05 | **0.17** | **0.29** | 0.54 | 0.46 |
| Loan rate | 0.02 | **0.14** | **0.08** | **0.10** | 0.01 | 0.35 | 0.65 |
| United Kingdom | | | | | | | |
| GDP growth | 0.09 | **0.14** | **0.42** | 0.02 | 0.00 | 0.67 | 0.33 |
| Inflation | 0.01 | **0.14** | **0.22** | 0.00 | 0.01 | 0.38 | 0.62 |
| Bank credit growth | 0.02 | 0.08 | **0.44** | 0.02 | 0.03 | 0.59 | 0.41 |
| Loan rate | 0.02 | **0.53** | 0.08 | 0.01 | 0.10 | 0.74 | 0.26 |
| France | | | | | | | |
| GDP growth | 0.15 | 0.07 | **0.25** | 0.06 | **0.20** | 0.73 | 0.27 |
| Inflation | 0.01 | 0.04 | 0.05 | 0.04 | 0.05 | 0.19 | 0.81 |
| Bank credit growth | **0.11** | **0.17** | **0.10** | 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 | **0.15** | **0.33** | **0.20** | 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 | **0.15** | 0.08 | 0.00 | 0.25 | 0.75 |
| Loan rate | **0.13** | **0.25** | 0.03 | 0.01 | 0.00 | 0.42 | 0.58 |
| Italy | | | | | | | |
| GDP growth | 0.07 | 0.08 | **0.30** | **0.22** | 0.04 | 0.71 | 0.29 |
| Inflation | 0.05 | 0.02 | **0.29** | 0.07 | 0.01 | 0.44 | 0.56 |
| Bank credit growth | 0.07 | **0.14** | **0.17** | **0.33** | 0.03 | 0.74 | 0.26 |
| Loan rate | 0.08 | **0.33** | 0.04 | 0.02 | 0.01 | 0.48 | 0.52 |

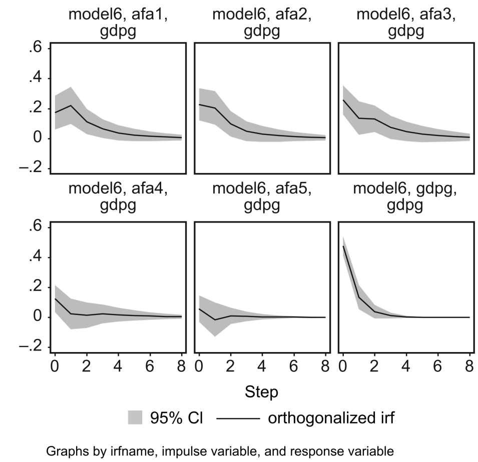
*Note:* Boldfaced values denote estimates significantly different from zero at 5 percent confidence levels.

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.

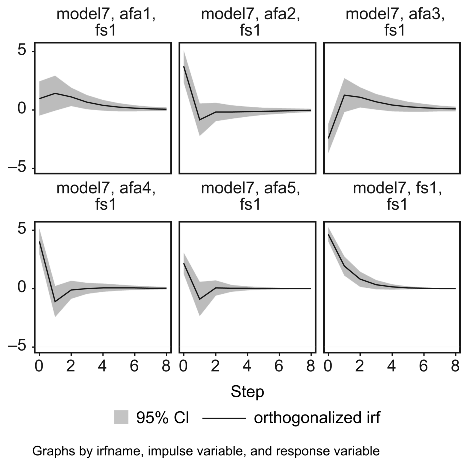
Answering these questions amounts to exploit further the rich information structure provided by the factor model. We believe that such an explora-

***United States***

**GDPaR**

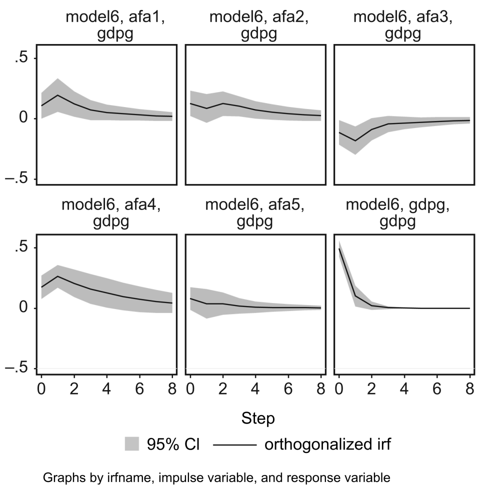



**FSaR**




***Canada***

**GDPaR**




**FSaR**

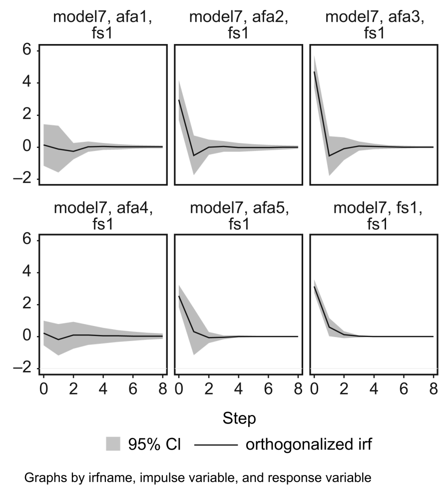
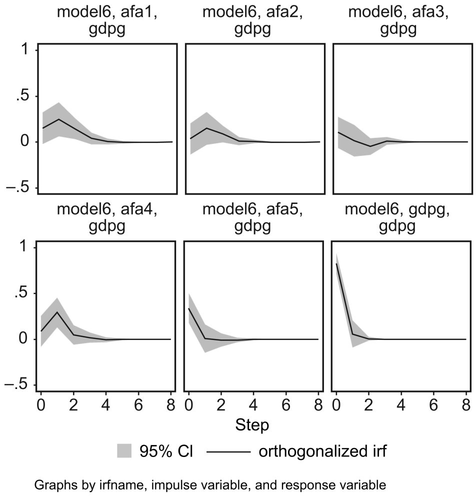


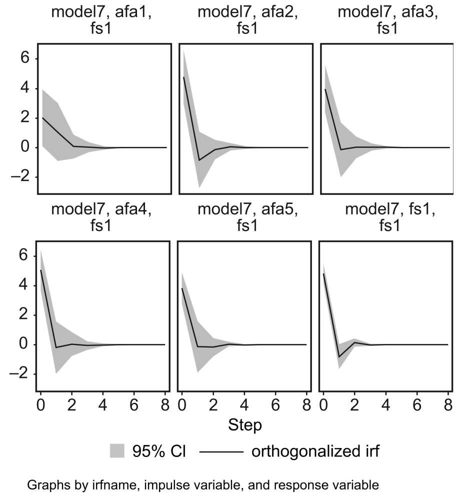

**Fig. 3.6 Impulse responses of GDPaR and FSaR to identified aggregate demand and bank credit demand shocks and own shock**

***Japan***

**GDPaR**

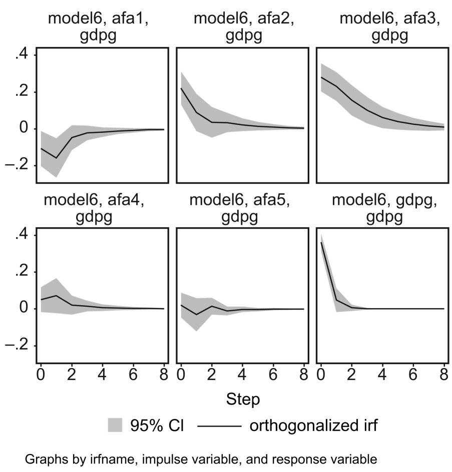



**FSaR**




***United Kingdom***

**GDPaR**




**FSaR**

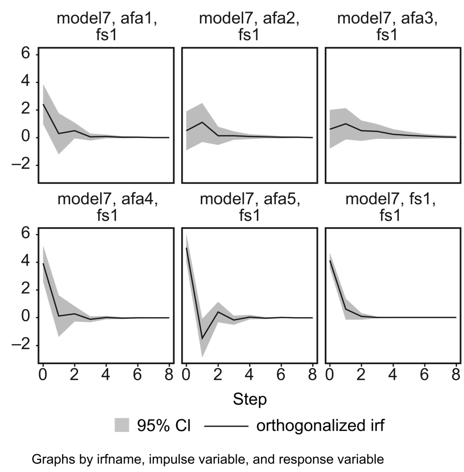
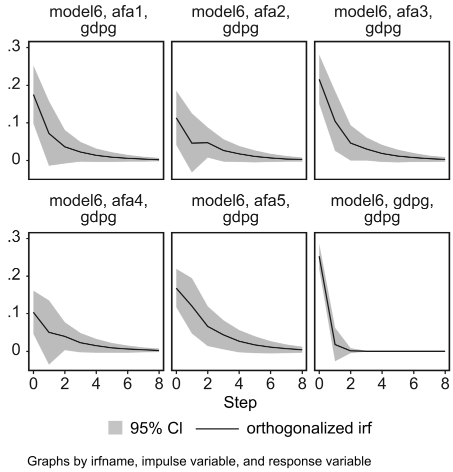


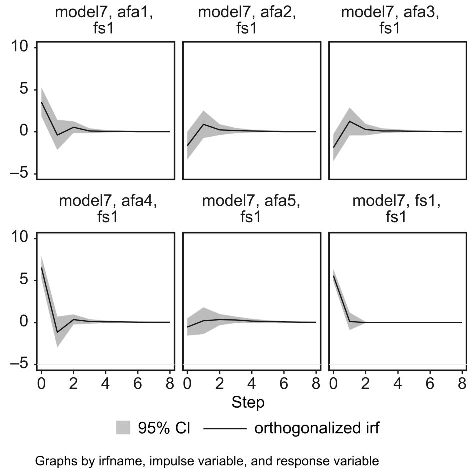

**Fig. 3.6 (cont.)**

***France***

**GDPaR**

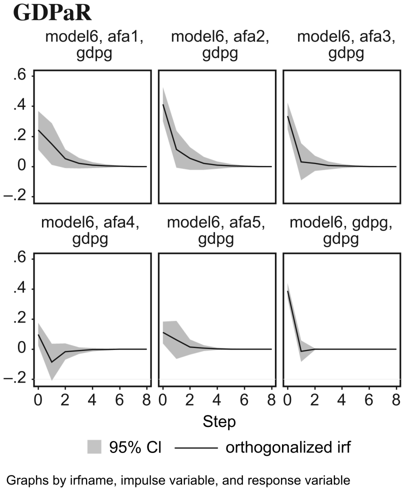



**FSaR**




***Germany***

**GDPaR**




**FSaR**

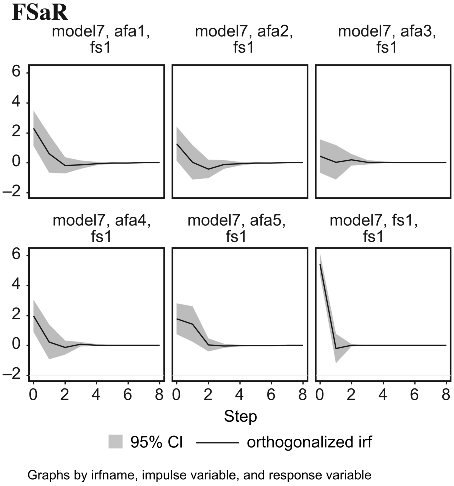
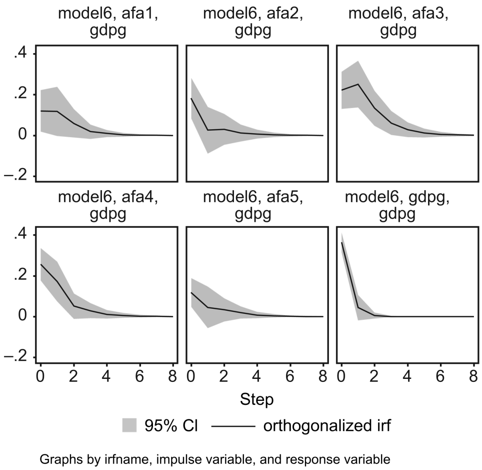



**Fig. 3.6 (cont.)**

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.

*Italy*

**GDPaR**




**FSaR**

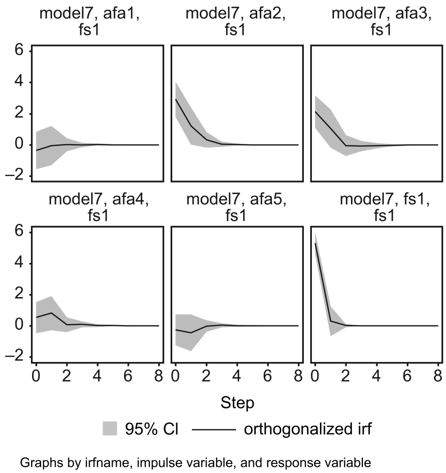



**Fig. 3.6 (cont.)**

**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 | **0.12** | 0.09 | 0.09 | **0.30** | 0.01 | 0.61 | 0.39 |
| FSaR | 0.06 | **0.19** | **0.12** | **0.22** | 0.07 | 0.67 | 0.33 |
| Canada | | | | | | | |
| GDPaR | **0.15** | 0.02 | 0.08 | **0.17** | 0.06 | 0.48 | 0.52 |
| FSaR | 0.00 | **0.18** | **0.47** | 0.00 | **0.13** | 0.79 | 0.21 |
| Japan | | | | | | | |
| GDPaR | **0.10** | 0.03 | 0.01 | 0.09 | **0.11** | 0.34 | 0.66 |
| FSaR | 0.05 | **0.22** | **0.14** | **0.24** | **0.13** | 0.78 | 0.22 |
| United Kingdom | | | | | | | |
| GDPaR | 0.09 | **0.14** | **0.42** | 0.02 | 0.00 | 0.67 | 0.33 |
| FSaR | 0.09 | 0.02 | 0.03 | **0.22** | **0.40** | 0.76 | 0.24 |
| France | | | | | | | |
| GDPaR | **0.15** | 0.07 | **0.25** | 0.06 | **0.21** | 0.74 | 0.26 |
| FSaR | **0.13** | 0.04 | **0.05** | **0.45** | 0.01 | 0.68 | 0.32 |
| Germany | | | | | | | |
| GDPaR | **0.15** | **0.33** | **0.20** | 0.03 | 0.03 | 0.74 | 0.26 |
| FSaR | **0.12** | 0.04 | 0.01 | 0.08 | **0.11** | 0.36 | 0.64 |
| Italy | | | | | | | |
| GDPaR | 0.07 | 0.08 | **0.30** | **0.22** | 0.04 | 0.71 | 0.29 |
| FSaR | 0.00 | 0.22 | **0.13** | 0.02 | 0.01 | 0.38 | 0.62 |

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

# Appendix

**Table A3.1 List of variables**

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

**Table A3.1** (continued)

| Equity markets | Transformations |
|---|---|
| Personal savings as percent of disposal income | Δlevels |
| Unemployment rate | Δlevels |
| Output per hour of all persons | Δln |
| Industrial production-total index | Δln |
| CPI all items | Δln |
| New orders manufacturing | Δln |
| Capacity utilization | Δlevels |
| Housing market index | Δlevels |

*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. Δln = log level difference; Δlevels = level difference. CPI = consumer price index.

## References

Acharya, Viral, Lasse Pedersen, Thomas Philippon, and Matthew Richardson. 2010. "Measuring Systemic Risk." Unpublished Manuscript. New York University Stern School of Business, May.

Adrian, Tobias, and Markus K. Brunnermeier. 2008. "CoVar." Federal Reserve Bank of New York Staff Report no. 348. September.

Aruoba, S. Boragan, and Francis X. Diebold. 2010. "Real-Time Macroeconomic Monitoring: Real Activity, Inflation, and Interactions." *American Economic Review* 100:20–24.

Bai, Jushan, and Serena Ng. 2002. "Determining the Number of Factors in Approximate Factor Models." *Econometrica* 70 (1): 191–221.

Bernanke, Ben, Jean Boivin, and Piotr Eliasz. 2005. "Measuring the Effects of Monetary Policy: A Factor-Augmented Vector Autoregressive (FAVAR) Approach." *Quarterly Journal of Economics* 120:387–422.

Bernanke, Ben, Mark Gertler, and Simon Gilchrist. 1999. "The Financial Accelerator in a Quantitative Business Cycle Framework." In *Handbook of Macroeconomics,* edited by John Taylor and Michael Woodford, 1341–393. Amsterdam: North Holland.

Berrospide, Jose, and Rochelle Edge. 2010. "The Effects of Bank Capital on Lending: What Do We Know? What Does it Mean?" *International Journal of Central Banking* December:5–54.

Boyd, John, Gianni De Nicolò, and Elena Loukoianova. 2009. "Banking Crises and Crisis Dating: Theory and Evidence." IMF Working Paper no. 09/141. Washington, DC: International Monetary Fund.

Campbell, John Y., Andrew W. Lo, and A. Craig MacKinley. 1997. *The Econometrics of Financial Markets.* Princeton, NJ: Princeton University Press.

Canova, Fabio, and Gianni De Nicolò. 2002. "Monetary Disturbances Matter for Business Cycle Fluctuations in the G-7." *Journal of Monetary Economics* 49 (6): 1121–159.

———. 2003. "On the Sources of Business Cycles in the G-7." *Journal of International Economics* 59 (1): 77–100.

Chari, V. V., Lawrence Christiano, and Patrick J. Kehoe. 2008. "Facts and Myths About the Financial Crisis of 2008." Federal Reserve Bank of Minneapolis Working Paper 666, October.
Christiano, Lawrence, Roberto Motto, and Massimo Rostagno. 2010. "Financial Factors in Economic Fluctuations." ECB Working Paper no. 1192. Frankfurt: European Central Bank.
Cohen-Cole, Ethan, Burcu Duygan-Bump, José Fillat, and Judit Montoriol-Garriga. 2008. "Looking Behind the Aggregates: A Reply to Facts and Myths about the Financial Crisis of 2008." Federal Reserve Bank of Boston, Working Paper no. QAU08-5.
De Nicolò, Gianni, Peter Hayward, and Ashok Bathia. 2004. "US Large Complex Banking Groups: Business Strategies, Risks and Surveillance Issues." Special Issue Paper, IMF Country Report no. 04/228, July. Washington, DC: International Monetary Fund.
De Nicolò, Gianni, and Myron Kwast. 2002. "Systemic Risk and Financial Consolidation: Are They Related?" *Journal of Banking and Finance* 26 (5): 861–80.
De Nicolò, Gianni, and Marcella Lucchetta. 2012. "Systemic Real and Financial Risks: Measurement, Forecasting and Stress Testing." IMF Working Paper no. 12/58, February. Washington, DC: International Monetary Fund.
Foerster, Andrew T., Pierre-Daniel G. Sarte, and Mark W. Watson. 2008. "Sectoral vs. Aggregate Shocks: A Structural Factor Analysis of Industrial Production." NBER Working Paper no. 14389. Cambridge, MA: National Bureau of Economic Research, October.
Freixas, Xavier, and Jean-Charles Rochet. 2008. *Microeconomics of Banking,* 2nd ed. Cambridge, MA: MIT Press.
Group of Ten. 2001. *Report on Consolidation in the Financial Sector.* Basel: Bank for International Settlements. http://www.bis.org/publ/gten05.pdf.
Huang, Xin, Hao Zhou, and Hai Zhu. 2009a. "A Framework for Assessing the Systemic Risk of Financial Institutions." BIS Working Paper no. 281, April. Basel: Bank for International Settlements.
———. 2009b. "Assessing the Systemic Risk of a Heterogeneous Portfolio of Banks during the Recent Financial Crisis." FEDS Working Paper 2009-44. Washington, DC: Board of Governors of the Federal Reserve System.
Ivashina, Victoria, and David Scharfstein. 2008. "Bank Lending during the Financial Crisis of 2008." Working Paper. Harvard Business School.
Kahle, Kathreen, and Rene Stulz. 2010. "Financial Policies and the Financial Crisis: Impaired Credit Channel or Diminished Demand for Capital?" Unpublished Manuscript, October.
Stock, James, and Mark Watson. 2002. "Macroeconomic Forecasting Using Diffusion Indexes." *Journal of Business Economics and Statistics* April:147–62.
———. 2005. "Implications of Dynamic Factor Models for VAR Analysis." NBER Working Paper no. 11467. Cambridge, MA: National Bureau of Economic Research, July.
———. 2006. "Forecasting with Many Predictors." In *Handbook of Economic Forecasting,* edited by Graham Elliott, Clive W. J. Granger, and Allan Timmermann, 516–54. Amsterdam: North Holland.
Sorge, Marco. 2004. "Stress Testing Financial Systems: An Overview of Current Methodologies." BIS Working Paper no. 165. Basel: Bank for International Settlements.
Walsh, Carl. 2009. "Using Monetary Policy to Stabilize Real Activity." Unpublished Manuscript, September.