SYSTEMIC RISK AND THE MACROECONOMY*

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Abstract

This paper designs a model that delivers joint *forecasts* of indicators of *systemic risk* and *financial system-at-risk* , as well as *stress-tests* of these indicators as impulse responses to structural shocks identified by standard macroeconomic and banking theory. The model is implemented using large sets of quarterly time series of aggregate and sectoral indicators of financial and real activity for the G-7 economies for the 1980Q1-2009Q3 period. We obtain two main results. First, there is evidence of out-of sample forecasting power for tail risk realizations of real activity for several countries, suggesting the usefulness of the model as a risk monitoring tool. Second, in all countries aggregate demand shocks are the main drivers of the real cycle, and bank credit demand shocks are the main drivers of the bank lending cycle. These results challenge the common wisdom that constraints in the supply of credit have been a key driver of the sharp downturn in real activity of the G-7 economies in 2008Q4-2009Q1.

* The views expressed in this paper are those of the authors and do not necessarily represent the views of the International Monetary Fund.

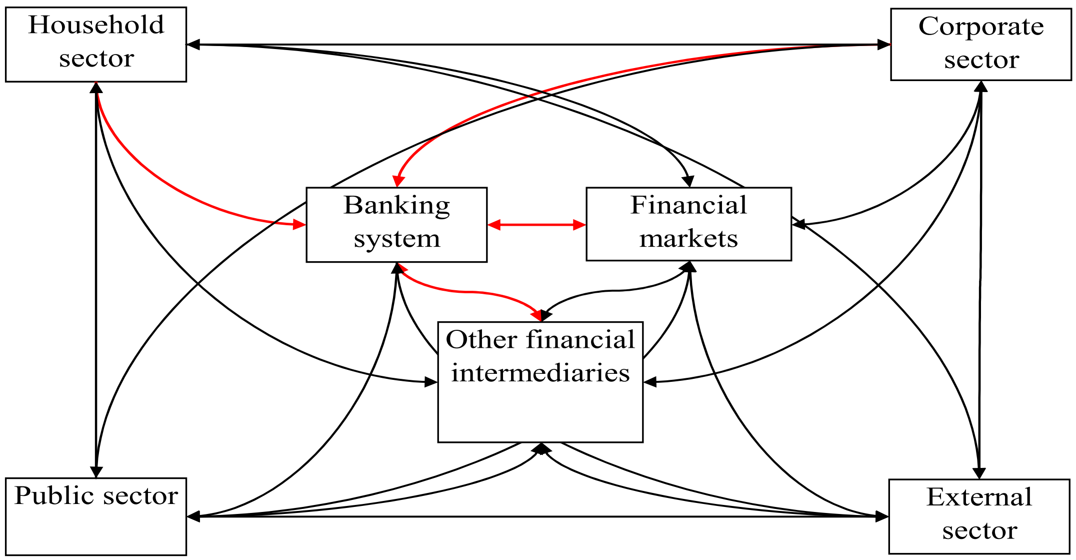
I. INTRODUCTION

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 this goal, 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 this goal is the main objective of this paper.

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 A below, the proposed framework aims at identifying which sectors of the economy are most affected by a shock at impact, to gauge size and persistence of shocks' propagation within and between sectors, and forecast their systemic real and financial outcomes.

Figure A

Financial exposures (stocks and flows) between sectors



Ideally, a computable general equilibrium model specified at a suitable level of dis-aggregation would allow 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, but work in this direction is still in its infancy. Thus far, work-horse 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 has been usually left unmodeled, since the output of these models is used mainly for financial supervisory purposes (see Sorge, 2004 for a review of stress testing, and Huang, Zhou and Zhu, 2009, for a recent contribution).

Our modeling framework delivers joint *forecasts* of indicators of *systemic risk* and *financial system-at-risk* , as well as *stress-tests* of these indicators as impulse responses of structurally identifiable shocks. This framework is novel in two respects. First, it uses a dynamic factor model with structural identification based on theory. This allows to extract information on common sources of shocks contained in a large set of time series and characterize their economic content. Second, it integrates the dynamic factor model with quantile regressions techniques, which provide estimates of tail realizations of systemic risk.

We make a distinction between systemic risk and systemic *financial* risk, based on the notion that *real* effects is what concerns policymakers most, and that real effects are likely to entail welfare consequences. Our systemic risk indicator is GDP-at-Risk (*GDPaR*), defined as the worst predicted realization of quarterly growth in real GDP at 5 percent

[1] However, a rapidly growing literature, briefly reviewed by Walsh (2009), is exploring the implications of specific financial frictions in the context of extensions of the "financial accelerator" model of Bernanke, Gertler and Gilchrist (1999).

probability over a pre-determined forecasting horizon. 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 pre-determined forecasting horizon.

The underlying joint dynamics of GDP growth and the system-wide financial risk indicator is modeled through a factor-augmented VAR (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 a 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 inputting impulse responses to shocks identified in the FAVAR model into the relevant quantile regressions.

We implement this framework using a large set of time series of financial and real activity for the G-7 economies. 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, these results challenge the common wisdom that constraints in the supply of credit have been a key driver of the sharp downturn in real activity experienced by the G-7 economies in 2008Q4-2009Q1

The remainder of the paper is composed of four sections. Section II defines systemic risk and systemic financial risk, and describes indicators consistent with these definitions. Section III outlines the model setup, its estimation and forecasting, and the identification procedure of structural shocks. Section IV describes the implementation of the modeling framework on G-7 country data. Section V concludes.

II. Systemic risk : definitions and measurement

Based on the notions of systemic financial risk introduced in Group of Ten (2001) and De Nicolò and Kwast (2002), we adopt the following definitions:

System-wide financial risk *is the risk that a shock will trigger a loss of economic value or confidence in, and attendant increases in uncertainty about, a substantial portion of the financial system.*

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

These definitions embed a key necessary condition for a system-wide financial shock to induce adverse systemic risk realizations: *system-wide financial shocks must be highly likely to induce significant adverse real effects,* such as substantial reductions in output and employment. Thus, it explicitly requires that the negative externalities of a systemic financial shock that extend to the financial system *also extend* to the real economy. Financial markets turbulence and attendant increases in volatility, and/or failures of financial intermediaries, that are devoid of significant and widespread real effects, are *not* classified as systemic.

We adopt these definitions for two reasons. First, distinguishing systemic *financial* risk from s*ystemic risk as an adverse tail realization in real activity* allows to better assess the extent to which a realization of a system-wide 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 what ultimately concerns policy-makers.

To control risk in financial institutions, risk managers track Value-at-Risk (VaR). VaR measures the worst possible portfolio loss over a given time horizon at a given probability. To control risk in the financial system, policy makers may 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 the easiness with which can be embedded in the model described below. However, other indicators can be adapted to our framework, such as those based on distance-to-default measures as in De Nicolò et al. (2004), or based on CDS spreads, as in Huang, Zhou and Zhu (2009).

To control risk in the economy, policy makers may wish to track measures of worst possible *real macroeconomic* outcomes. One such a measure is GDP-at-Risk ($GDPaR$), defined here as the worst predicted realization of quarterly growth in real GDP at 5 percent probability.

III. The model

A. A Dynamic Factor Model

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:

$$GDPG_t = \lambda^R(L) f_t + \gamma_{11}(L) GDPG_{t-1} + \gamma_{12}(L) FS_{t-1} + u_t^1 \qquad (1)$$

$$FS_t = \lambda^F(L) f_t + \gamma_{21}(L) GDPG_{t-1} + \gamma_{22}(L) FS_{t-1} + u_t^2 \qquad (2)$$

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

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

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. Equation (4) describes the dynamics of these factors through a VAR.

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

$$GDPG_t = \Lambda^{R\prime} F_t + \gamma_{11}(L)GDPG_{t-1} + \gamma_{12}(L)FS_{t-1} + u_t^1 \qquad (5)$$

$$FS_t = \Lambda^{F\prime} F_t + \gamma_{21}(L)GDPG_{t-1} + \gamma_{22}(L)FS_{t-1} + u_t^2 \qquad (6)$$

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

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

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 Factor-Augmented VAR (FAVAR) representation of the DFM, akin to that adopted by Bernanke, Boivin, and Eliasz (2005):

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

$$GDPG_t = \Lambda^{R\prime}\Phi(L)F_{t-1} + \gamma_{11}(L)GDPG_{t-1} + \gamma_{12}(L)FS_{t-1} + u_t^1 \qquad (10)$$

$$FS_t = \Lambda^{F\prime}\Phi(L)F_{t-1} + \gamma_{21}(L)GDPG_{t-1} + \gamma_{22}(L)FS_{t-1} + u_t^2 \qquad (11)$$

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:

$$GDPG_t = \alpha_1^q + \Lambda_q^{R\prime} F_t + \gamma_{11}^q(L) GDPG_{t-1} + \gamma_{12}^q(L) FS_{t-1} + u_t^{1q} \qquad (12)$$

$$FS_t = \alpha_2^q + \Lambda_q^{F\prime} F_t + \gamma_{12}^q(L) GDPG_{t-1} + \gamma_{22}^q(L) FS_{t-1} + u_t^{2q} \qquad (13)$$

Denoting the estimated coefficients of (12) and (13) with a "hat", $GDPaR_t$ and $FSaR_t$ are the fitted values of the quantile regressions (12) and (13) with $q = 0.05$:

$$GDPaR_t = \hat{\alpha}_1^q + \hat{\Lambda}_q^{R\prime} F_t + \hat{\gamma}_{11}^q(L) GDPG_{t-1} + \hat{\gamma}_{12}^q(L) FS_{t-1} \qquad (14)$$

$$FSaR_t = \hat{\alpha}_2^q + \hat{\Lambda}_q^{F\prime} F_t + \hat{\gamma}_{12}^q(L) FS_{t-1} + \hat{\gamma}_{22}^q(L) GDPG_{t-1} \qquad (15)$$

Measures of Systemic Risk Spillovers

It can be informative to compute measures of systemic risk spillovers from real activity to the financial sector (and viceversa) 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 (2009).

Estimates of $Co(GDPaR_t)$ and $Co(FSaR_t)$ are given by:

$$Co(GDPaR_t) = \hat{\alpha}_1^q + \hat{\beta}_1^q F_t + \hat{\gamma}_{11}^q(L) GDPaR_{t-1} + \hat{\gamma}_{12}^q(L) FSaR_{t-1} \qquad (16)$$

$$Co(FSaR_t) = \hat{\alpha}_2^q + \hat{\beta}_2^q F_t + \hat{\gamma}_{12}^q(L) GDPaR_{t-1} + \hat{\gamma}_{22}^q(L) FSaR_{t-1} \qquad (17)$$

The existence of systemic risk spillovers can be gauged comparing $Co(GDPaR)_t$ with $GDPaR_t$, and $Co(FSaR)_t$ with $FSaR_t$. For example, if $Co(GDPaR)_t < GDPaR_t$, 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 can also be found in principle, as 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:

$$Co(GDPaR)_t - GDPaR_t = \hat{\gamma}_{11}^q(L^*)(GDPaR_t - GDPG_t) + \hat{\gamma}_{12}^q(L^*)(FSaR_t - FS_t) \quad (18)$$

$$Co(FSaR)_t - FSaR_t = \hat{\gamma}_{12}^q(L^*)(GDPaR_t - GDPG_t) + \hat{\gamma}_{22}^q(L^*)(FSaR_t - FS_t) \quad (19)$$

B. 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)-(11).

First, we use principal components to extract all factors with eigenvalues greater than 1, in number R. Then, we order factors according to their explanatory power of the variance of the data, and construct $\tilde{F} = \{(F_{r=1}),(F_1,F_{r=2}),....,(F_1,F_2,...,F_{r=R})\}$. 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 below, for our datasets our forecasting criterion yields an optimal number of static factors similar to the number of dynamic factors obtained by applying the statistical criterions based on Bai and Ng (2003).

In the second estimation step, we estimate quantile regressions (12) and (13) applying the optimal number of lags L^* and number of static factors r^* to obtain the systemic risk measures of equations (14)-(17).

Note that quantile regressions (12)-(13) 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 the quantile regressions (12)-(13). In sum, the procedure yield forecasts of $GDPaR$, $FSaR$, $co(GDPaR)$ and $co(FSaR)$ indicators k quarters ahead. [2]

C. 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.

We can obtain impulse responses of shocks to "factors", and translate them into impulse responses of indicators of systemic risk in(14)-(17) 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..

[2] 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 for our datasets is work in progress.

Inverting (9) yields the Moving Average (MA) form of the factor VAR (equation(9)):

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

where $A(L) = (1 - \Phi(L)L)^{-1} G$.

Then,

$$GDPG_t = \Lambda^{R\prime} A(L)\eta_t + \gamma_{11}(L) GDPG_{t-1} + \gamma_{12}(L) FS_{t-1} + u_t^1 \qquad (10a)$$

$$FS_t = \Lambda^{F\prime} A(L)\eta_t + \gamma_{21}(L) GDPG_{t-1} + \gamma_{22}(L) FS_{t-1} + u_t^2 \qquad (11a)$$

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, i.e. $\gamma_{12}(L) = \gamma_{21}(L) = 0$. This converts our forecasting model into the standard Factor VAR detailed in Stock and Watson (2005). Under such an assumption, inverting (10a) and (11a) yields the MA form of the FAVAR:

$$GDPG_t = B^R(L)\eta_t + w_t^1 \qquad (10b),$$

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

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 :

$$GDPaR_t = B_q^R(L)\eta_t + v_1^{1q} \qquad (14a),$$

$$FSaR_t = B_q^R(L)\eta_t + v_t^{2q} \qquad (15a),$$

where $B_q^R(L) = (1-\gamma_{11}^q(L)L)^{-1}\Lambda_q^{R\prime}A(L)$, $B_q^F(L) = (1-\gamma_{22}^q(L)L)^{-1}\Lambda_q^{F\prime}A(L)$,

$v_t^{q1} = (1-\gamma_{11}^q(L)L)^{-1}u_t^{1q}$ and $v_t^{q2} = (1-\gamma_{22}^q(L)L)^{-1}u_t^{2q}$.

Following a version of the identification procedure described in Canova and De Nicolò (2002), we identify a chosen set of orthogonal innovations as *structural* shocks if they satisfy certain sign restriction 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. As shown in Canova and De Nicolò (2002), these sign restrictions can be derived from a wide class of general equilibrium monetary macroeconomic models with different microfoundations.

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 (2007) , 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 the 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 household 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 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 A below 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:

Table A. 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

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.

IV. Implementation

Our modeling procedure is implemented using quarterly macroeconomic and financial series for the G-7 economies for the period 1980:Q1-2009: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.* In addition to real GDP growth, 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 sequel, 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.

A. Descriptive statistics

Table 1 reports basic statistics for GDP growth ($GDPG$) and our system-wide indicator of financial risk FS. Three facts are worth noticing. First, 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. Second, volatilities as well as the ranges of $GDPG$ and FS appear to differ markedly across countries, suggesting differential sensitivities of these indicators to underlying shocks. Lastly, the contemporaneous correlation between *GDPG* and *FS* appears relatively small, with no significant correlation for the U.S., Canada,, Japan and Italy, and a positive and significant—albeit small—correlation for the U.K., France and Germany.

As clearly shown in Figure Set 1, however, the comovement between GDPG and FS appears to be the most pronounced during the latest "crisis" period for most 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.

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. In fact, whether the recent crisis has been one in which the sharp contraction in real activity registered at end-2008 and beginning 2009 has been *caused* by sharp declines in the supply of credit, or alternatively, sharp declines in real activity are the main drivers of the reduction in the *demand* for 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 U.S. 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 likely reflects the sharp decline in the demand for credit resulting from the severe contraction in consumption growth and investment.[3]

Some statistics across countries can provide some glimpse on this issue. In Table 2 we report bivariate Granger-causality tests between GDPG and FS, as well as between GDPG and bank lending growth (BLG) for the seven countries considered. These tests seem to indicate that the role of real activity in affecting financial risk appears prominent, although there is some evidence that bank lending growth predicts movements in real activity in some country. Specifically, in no country our indicator of financial risk seems to anticipate movements in real activity (column (2)), while the reverse is true in the U.S., the U.K., and Italy (column (1)). By contrast, real activity seems to anticipate changes in bank lending growth in the U.S. , Canada, Japan and the U.K (column (3)), with the reverse appearing to be the case in Canada, France and Italy (column (4)). Overall, these statistics suggests the existence of complex interactions and differences across countries in the transmission mechanism of shocks within and between real and financial sectors. As shown below, the identification of structural shocks may throw light on this issue.

[3] For the U.S., 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. The issue is still open, as for example witnessed by the IMF *GFSR* (2009) report, which states that "This *GFSR* contends that the credit disruption has been an exogenous and significant factor in the global recession that began in 2008. However, it could be argued that the slowdown in credit is a symptom rather than a cause of the economic slowdown and merely reflects the lower demand of credit – by households and corporates – rather than a supply disruption.".

B. Estimation and Forecasting

We estimated static factors by principal components and autoregressive coefficients of each variable 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 seven country datasets the forecasting criterion identified the same number of static factors and lags, 5 factors and 1 lag.

For comparison, we also estimated the number of static factors chosen according to the Bai and Ng's IC_{p1} and IC_{p2} criterions, obtaining 11 static factors for the U.S.—consistent with Stock and Watson (2005) results—and between 9 and 12 static factors for the other countries. We also estimated the number of dynamic factors as principal components of the residuals of each variable in equation (10) and (11), obtaining 6 dynamic factors for the U.S., and between 4 and 6 dynamic factors for the other countries.

In light of these results, and because our focus is on forecasting and on interpreting factors 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 1 lag. The resulting *GDPaR* and *FSaR* estimates were used to compute Covar measures (16) and (17).

As detailed in the previous section, forecasts of *GDPaR* and *FSaR* 8 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-2009Q3. Note, however, that at that time actual GDP was available only up to 2009Q2, so that the first effective forecast date for GDPaR is 2009Q3.

Figure Set 2 reports estimated *GDPaR* and *FSaR* series, together with their forecasts 8 quarters ahead of 2009Q3. Table 3 reports basic descriptive statistics of the systemic risk indicators, as well as the difference between Covar and at-risk measures, the latter being useful to gauge risk spillovers in excess of those implied by the dependence of both measures on common factors.

We point out three main results. First, the overall impact of factors on *GDPaR* and *FSaR* results in these measures being highly contemporaneously correlated. Second, 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 appear to vary markedly. Third, risk spillovers are present for *GDPaR* measures, as Table 3 exhibits negative values for all countries, while spillovers for *FSaR* measures are on average small and not significantly different from 0. Overall, common factors appear to be the dominant drivers of systemic risk indicators, whereas risk spillovers seem relatively small in all countries.

Turning to *GDPaR* and *FSaR* forecasts, Figure Set 2 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 probability of tail realization of systemic risk and systemic financial risk events.

One informal but intuitive 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 evaluation of forecasting performance of the model is work in progress. However, here we report perhaps the most demanding assessment of the model's forecasting ability. Namely, we assess if the model signals a deterioration in *GDPaR* prior to one of the largest historical decline is real activity, that experienced in 2008Q4-2009Q1 in all G-7 countries.

Figure Set 3 reports the results of this comparison: the blue line is the out-of-sample *GDPaR* forecasts made in 2008Q3, the yellow line actual GDP growth, and the red line the forecast made in 2009Q3. Predicted changes in *GDPaR* and actual GDP growth go in the same direction for the U.S. (1 quarter ahead), Canada (4 quarters ahead), the U.K. (3 quarters ahead), and Italy (5 quarters ahead). However, such positive comovements are absent for the other countries.

Although preliminary, we view this evidence as notable. The out-of sample consistency of *GDPaR* forecasts with the future evolution of actual GDP growth for four countries out of seven, tested for the most unpredictable event in decades, suggests the potential usefulness of our model as a real-time risk monitoring tool.

C. Identification of Structural Shocks

We implemented the identification procedure outlined previously as follows. First, we selected an orthogonal decomposition of the MA representation (9a), then we computed impulse responses of FAVARs for GDP Growth, Inflation, Bank Lending Growth and first differences in Loan Rates for each country, and lastly checked whether the joint signs of the responses of these variables conform to the signs predicted for different shocks by the basic macro and banking models summarized in Table A.

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. However, we examined alternative decompositions with inverted ordering of the variables and obtained 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 each VAR, and such matrix 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.[4]

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[4] In work in progress, we examine the sign responses under alternative orthogonal decompositions— not necessarily recursive—applying the systematic statistical search implemented by Canova and De Nicolò (2002) .

Figure Set 3 reports impulse responses of GDP growth, Inflation, Bank Lending Growth and changes in Lending Rates for the U.S.. It is apparent that the response of all variables to all shocks at impact or for at least up to 2 quarters after impact is either strictly positive (in most cases) or non negative (in few cases). Hence, according to Table A, all orthogonal shocks can be classified as structural aggregate demand shocks associated with bank credit demand shocks. Strikingly, when we look at impulse responses of the remaining six countries, we find responses of each variable exactly of the same sign of those found for the U.S. (figures not reported). In sum, *under the assumed benchmark orthogonalization, all structural shocks in these economies are 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 exactly the findings by Canova and De Nicolò (2003), who used only a small dimension VAR for the G-7 countries, but a full search for shocks interpretable according to aggregate macroeconomic theory in the entire space of non-recursive orthogonalizations of the VAR of each country.

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

Furthermore, 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 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.

Similar results are obtained when we look at the impulse responses and variance decompositions of *GDPaR* and *FSaR* measures. As shown in Figure Set 5 , with very few (interesting) exceptions, the sign of the impact of each shock on systemic risk indicators is essentially the same in each country, although magnitude and persistence of these shocks widely differ. As shown in Table 5, variance decompositions indicate the importance of most shocks for the systemic risk indicators in each country.

There remain deeper questions that need yet to be answered: where do these shocks originate? And, to which other sectors are they transmitted? In terms of Figure A of the introduction, answering these questions amounts to identify in which "box" shocks originate, and which are the linkages between the originating box and other boxes in the picture, that is, the web of linkages produced by the transmission mechanism of these shocks. Answering these questions amounts to further exploiting the rich information structure provided by the factor model, which we are currently undertaking.

V. Conclusion

This paper has developed a modeling framework that can be used as a risk monitoring tool as it delivers forecasts of indicators of systemic risk and financial system-at-risk that can be updated in real time. In addition, the proposed identification procedure allows to gauge the sensitivity of these indicators to structural shocks identified by theory, giving economic contents to stress tests.

We view this framework as a first building block for an analysis of the determinants of systemic risk. As it can be inferred from our discussion, refinements and extensions of our framework are aplenty. We have exploited the rich information provided by the factor model only in a limited way. We intend to explore it more fully, and believe such an exploration is likely to yield increasing returns. It can guide a more effective integration of financial frictions into current macroeconomic modeling, and encourage the development of more disaggregated versions of such macroeconomic modeling, by incorporating the insights of partial equilibrium models in which financial intermediation is essential.

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TABLES

TABLE 1. DESCRIPTIVE STATISTICS

GDPG is real GDP growth, FS is the system-wide financial risk indicator. Bold values of correlation indicate a value significantly different from 0 at 5 percent confidence level.

		Mean	Std. Dev	Min	Max	correlation
United States	GDPG	1.41	0.84	-1.38	4.57	0.08
	FS	-0.19	8.58	-33.50	38.34	
Canada	GDPG	0.63	0.78	-1.52	2.47	-0.04
	FS	0.47	6.97	-17.56	25.06	
Japan	GDPG	0.53	1.07	-3.43	3.09	0.15
	FS	-0.17	10.19	-29.09	56.07	
U.K.	GDPG	0.54	0.71	-2.43	2.17	**0.23**
	FS	-0.17	8.57	-38.68	19.52	
France	GDPG	0.46	0.50	-1.46	1.48	**0.12**
	FS	-0.27	10.45	-41.30	29.16	
Germany	GDPG	0.34	0.79	-3.87	1.75	**0.37**
	FS	-0.80	6.79	-34.26	19.66	
Italy	GDPG	0.36	0.67	-2.67	2.19	0.03
	FS	-0.27	7.70	-17.69	29.26	

Table 2. Granger-Causality Tests

The tests are conducted estimating two bi-variate VAR(4), the first with GDPG and FS, the second with GDPG and bank lending growth, denoted by BLG. The table reports p-values, where boldfaced p-values are those less than or equal to 0.05. A p-value<=0.05 indicates that the null hypothesis in each column is ***rejected at 5 percent confidence level***.

	GDPG does **NOT** Granger-cause **FS** (1)	**FS** Does **NOT** Granger-cause **GDPG** (2)	**GDPG** does **NOT** Granger-cause **BLG** (3)	**BLG** does **NOT** Granger-cause **GDPG** (4)
United States	**0.03**	0.43	**0.02**	0.37
Canada	0.90	0.15	**0.00**	**0.00**
Japan	0.75	0.39	**0.01**	0.39
U.K.	**0.01**	0.18	**0.01**	0.73
France	0.43	0.56	0.62	**0.00**
Germany	0.30	0.22	0.56	0.98
Italy	**0.02**	0.90	0.61	**0.01**

Table 3. Descriptive Statistics of Systemic Risk Indicators

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 risk indicator; dcoFSaR = co(FSaR)-FSaR, where co(FSaR) is the Covar version if the systemic *financial* risk indicator.

		Mean	Std. Dev.	Min	Max
United States	GDPaR	0.24	0.81	-4.51	1.46
	FsaR	-13.60	5.95	-33.50	2.32
	dcoGDPaR	-0.73	0.56	-3.43	0.60
	dcoFSaR	-2.97	2.78	-13.98	3.63
Canada	GDPaR	-0.43	0.82	-3.63	1.16
	FsaR	-9.74	2.51	-17.86	2.75
	dcoGDPaR	-0.40	0.25	-1.28	0.09
	dcoFSaR	0.19	0.51	-1.67	1.62
Japan	GDPaR	-0.98	0.81	-3.70	1.66
	FsaR	-13.84	5.54	-31.03	1.22
	dcoGDPaR	-0.21	0.24	0.84	0.24
	dcoFSaR	0.48	4.18	-12.16	16.35
U.K	GDPaR	-0.27	0.62	-2.67	1.13
	FsaR	-12.82	5.66	-38.68	3.90
	dcoGDPaR	-0.62	0.35	-1.51	0.36
	dcoFSaR	3.09	4.97	-8.14	16.91
France	GDPaR	-0.32	0.40	-1.53	0.64
	FsaR	-13.78	6.59	-41.30	5.24
	dcoGDPaR	-0.50	0.30	-1.19	0.07
	dcoFSaR	4.39	6.08	-17.39	18.97
Italy	GDPaR	-0.46	0.61	-2.67	0.88
	FsaR	-13.06	3.29	-26.93	-2.53
	dcoGDPaR	-0.15	0.37	-1.26	0.70
	dcoFSaR	1.41	1.09	-0.51	4.28

Table 4. Variance Decomposition of GDP Growth, Inflation, Bank Lending Growth and Changes in Loan Rates to Identified Aggregate Demand and Bank Credit Demand Shocks

Boldfaced values are variance decompositions significantly different from 0 at 5 percent confidence levels.

		Shock 1	Shock2	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
	Δ Loan Rate	0.02	**0.58**	0.01	**0.14**	0.00	0.75	0.25
Canada	GDP Growth	**0.15**	0.02	0.08	**0.17**	0.06	0.48	0.52
	Inflation	0.01	0.08	0.01	0.01	**0.27**	0.38	0.62
	Bank Credit Growth	0.02	**0.23**	0.09	0.07	0.06	0.47	0.53
	Δ Loan Rate	0.09	0.03	0.03	**0.17**	0.01	0.33	0.67
Japan	GDP Growth	**0.11**	0.03	0.08	0.06	0.08	0.36	0.64
	Inflation	0.03	0.02	0.10	0.09	**0.21**	0.45	0.55
	Bank Credit Growth	0.01	0.03	0.09	**0.12**	**0.33**	0.58	0.41
	Δ Loan Rate	0.02	**0.15**	**0.20**	**0.11**	0.07	0.55	0.64
U.K	GDP Growth	0.07	**0.26**	**0.26**	**0.14**	0.04	0.77	0.23
	Inflation	0.01	0.04	**0.17**	0.04	0.06	0.32	0.67
	Bank Credit Growth	**0.02**	**0.22**	**0.21**	0.10	**0.13**	0.68	0.33
	Δ Loan Rate	0.02	**0.57**	0.04	0.02	0.05	0.70	0.30
France	GDP Growth	**0.18**	0.11	0.15	0.00	0.08	0.52	0.47
	Inflation	0.02	**0.41**	0.04	**0.16**	0.03	0.66	0.34
	Bank Credit Growth	0.06	**0.15**	0.05	0.01	0.02	0.29	0.70
	Δ Loan Rate	0.00	**0.41**	0.05	**0.02**	**0.14**	0.62	0.39
Germany	GDP Growth	**0.14**	**0.32**	**0.22**	0.08	0.05	0.81	0.18
	Inflation	0.03	0.05	**0.22**	0.02	0.01	0.33	0.68
	Bank Credit Growth	0.01	0.02	0.02	0.05	**0.16**	0.26	0.73
	Δ Loan Rate	**0.11**	**0.18**	0.04	0.01	**0.12**	0.46	0.54
Italy	GDP Growth	0.09	0.07	**0.12**	**0.29**	0.02	0.59	0.40
	Inflation	0.03	0.03	**0.48**	0.01	0.01	0.56	0.45
	Bank Credit Growth	0.07	**0.26**	**0.24**	**0.10**	0.03	0.70	0.29
	Δ Loan Rate	**0.12**	**0.28**	0.01	0.02	0.01	0.44	0.55

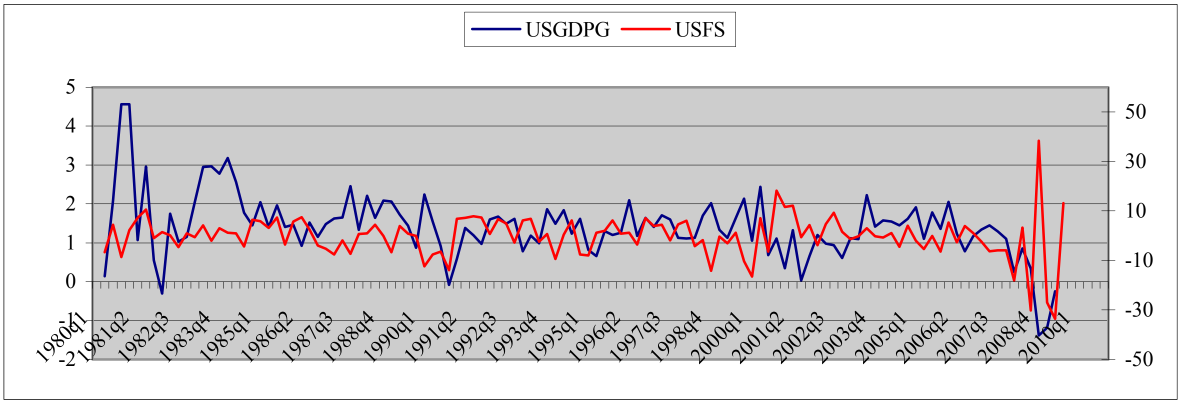
Table 5. Variance Decomposition of GDPaR and FSaR to Identified Aggregate Demand and Bank Credit Demand Shocks

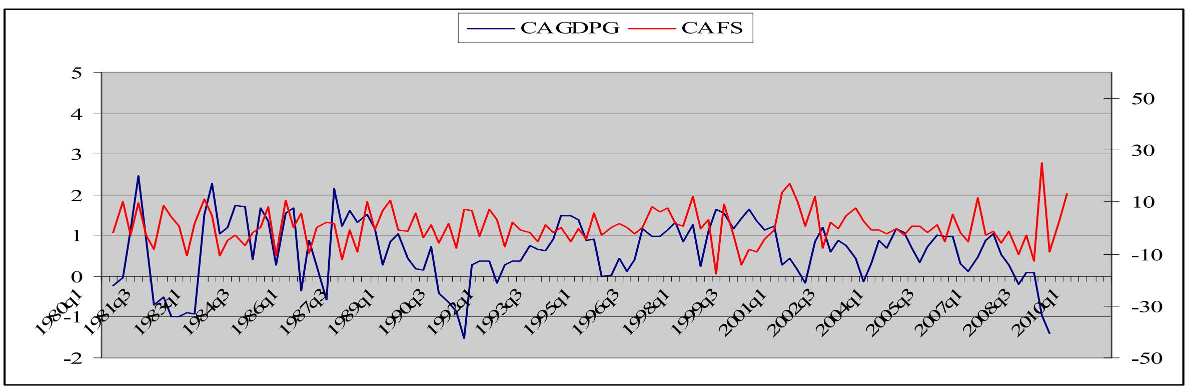
Boldfaced values are variance decompositions significantly different from 0 at 5 percent confidence levels.

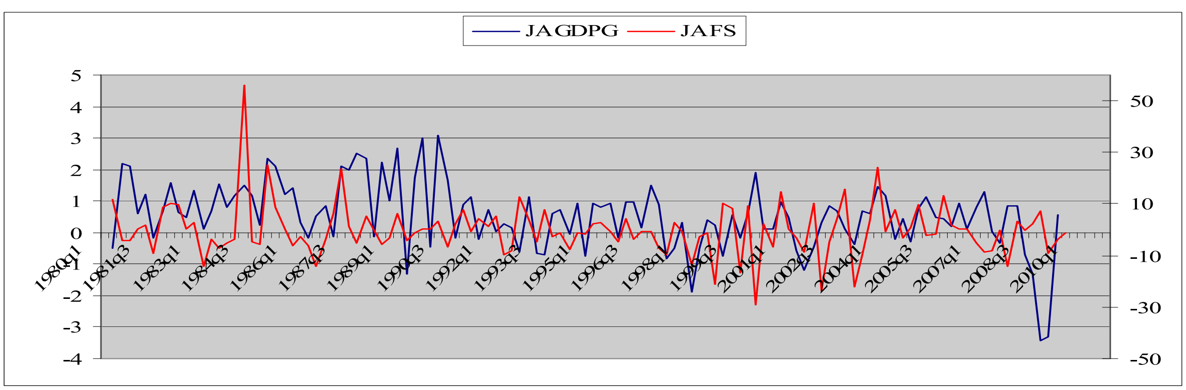
		Shock 1	Shock2	Shock 3	Shock 4	Shock 5	Shock Sum	Idiosyncratic
United States	GDPaR	**0.17**	**0.18**	**0.19**	0.03	0.01	0.58	0.42
	FSaR	0.06	**0.19**	**0.12**	**0.22**	0.07	0.67	0.33
Canada	GDPaR	**0.15**	0.02	0.08	**0.17**	0.06	0.48	0.52
	FSaR	0.002	**0.23**	**0.44**	0.05	0.02	0.74	0.26
Japan	GDPaR	**0.11**	0.03	0.08	0.06	0.08	0.36	0.64
	FSaR	0.05	**0.24**	**0.37**	0.02	0.08	0.76	0.24
U.K	GDPaR	0.07	**0.26**	**0.26**	**0.14**	0.04	0.77	0.23
	FSaR	0.07	0.01	0.2	0.3	**0.14**	0.72	0.28
France	GDPaR	**0.18**	**0.11**	**0.15**	0.003	0.08	0.52	0.48
	FSaR	**0.14**	0.06	**0.19**	**0.1**	**0.13**	0.62	0.38
Germany	GDPaR	**0.15**	**0.32**	**0.22**	0.08	0.05	0.82	0.18
	FSaR	0.08	0.1	0.03	**0.12**	0.02	0.35	0.65
Italy	GDPaR	0.09	0.07	**0.12**	0.3	0.02	0.60	0.4
	FSaR	0.01	**0.24**	0.07	0.04	0.04	0.40	0.60

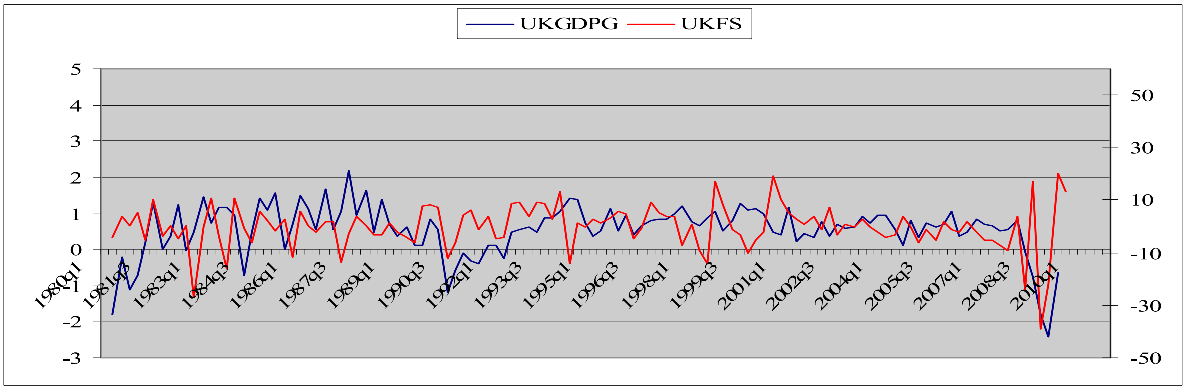
FIGURES

Figure Set 1: GDP Growth and FS Indicators





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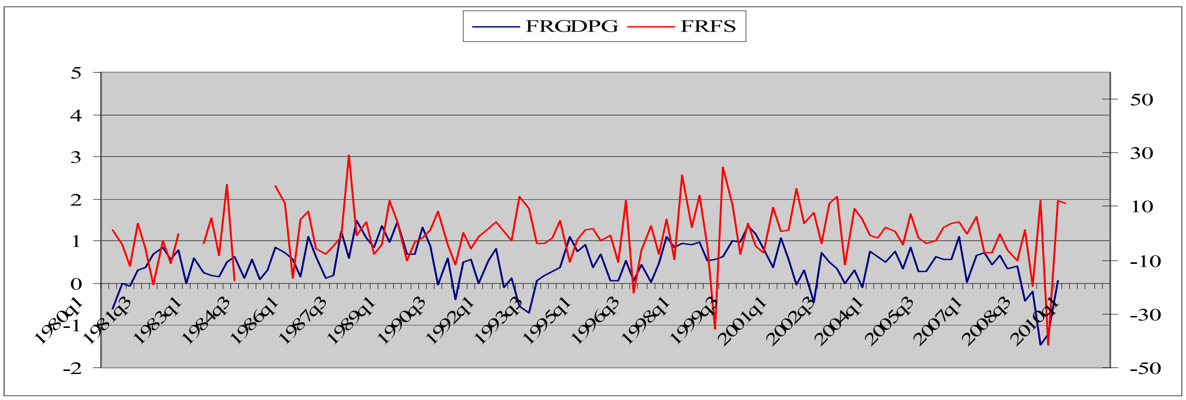
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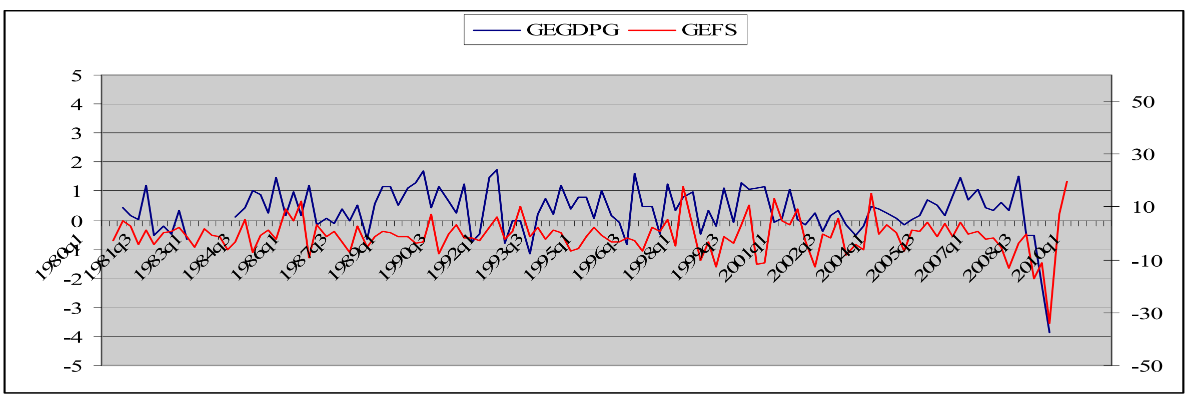
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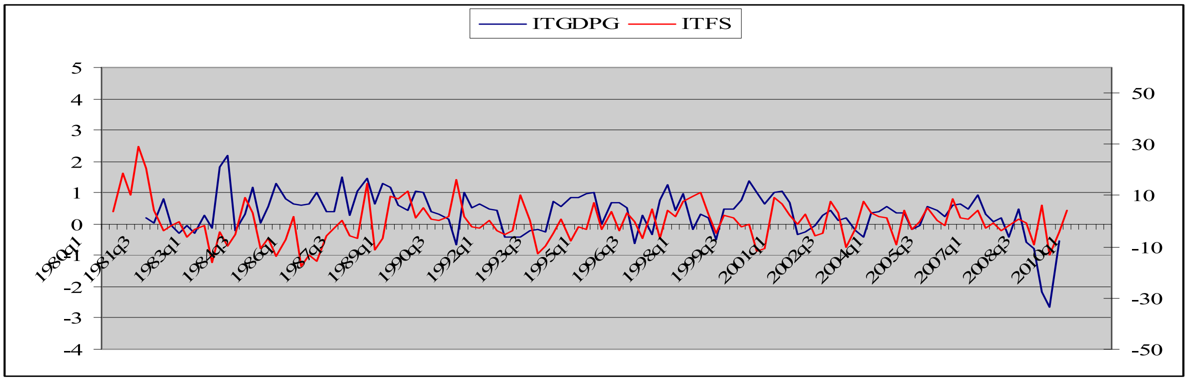

Figure Set 2: GDPaR and FSaR Estimates and Forecasts

United States

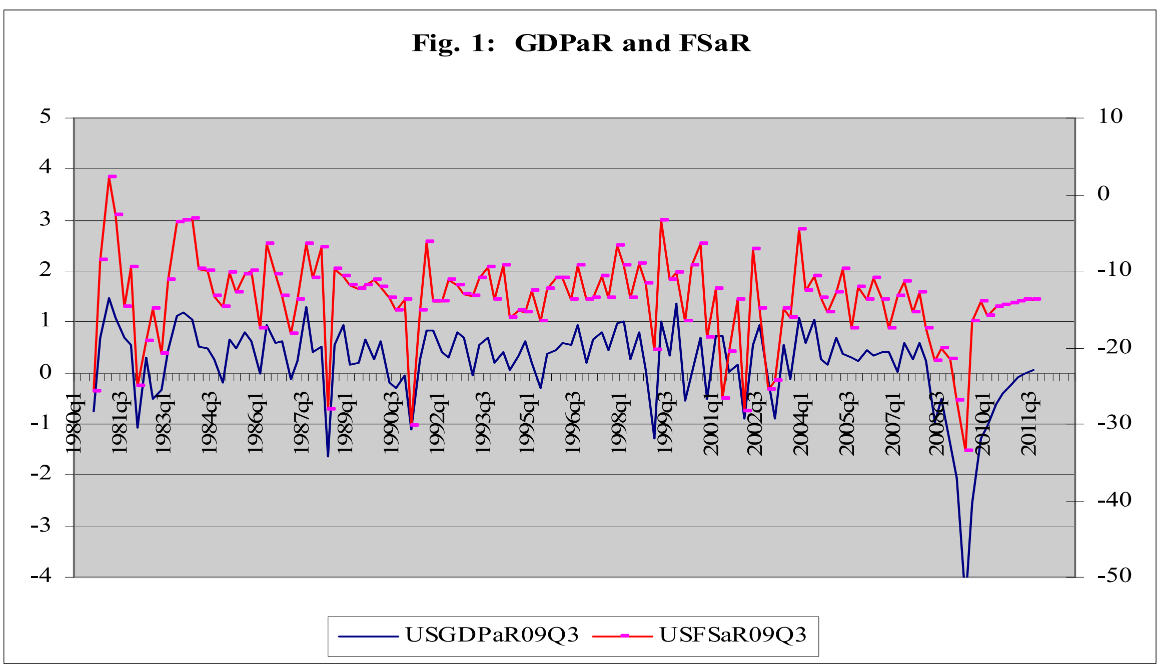

Figure Set 2: GDPaR and FSaR Estimates and Forecasts (cont.)

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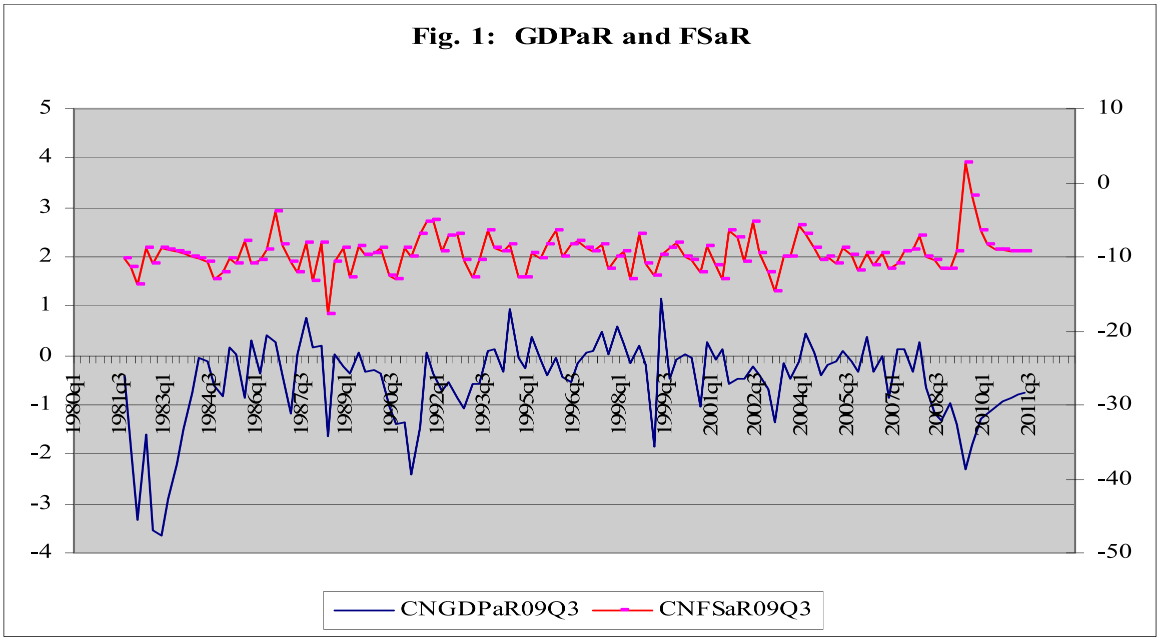


Japan

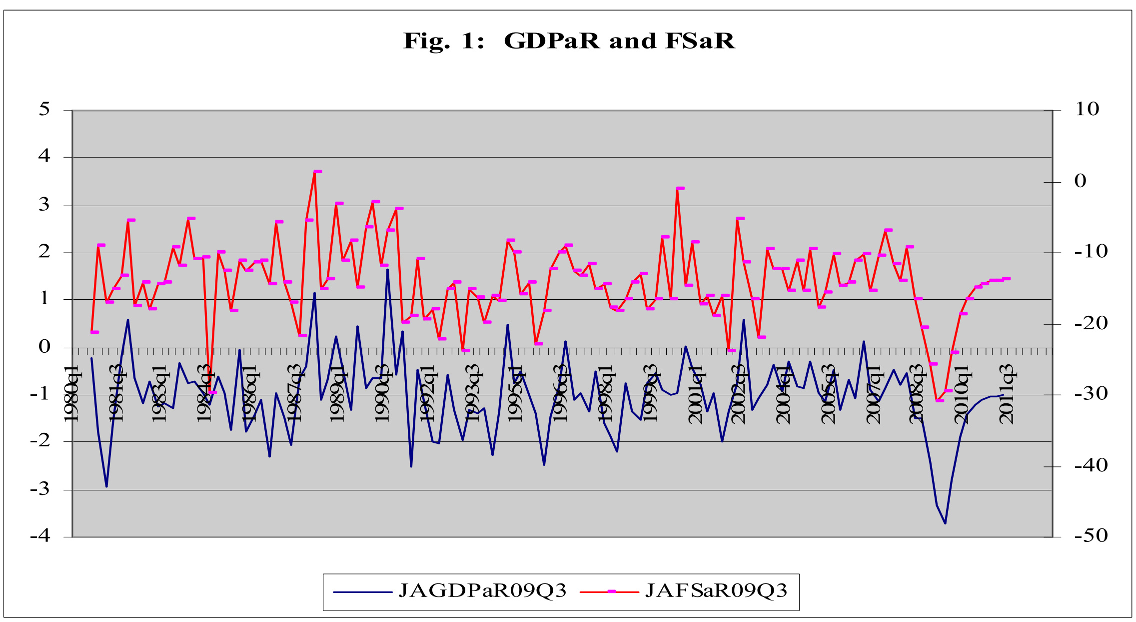
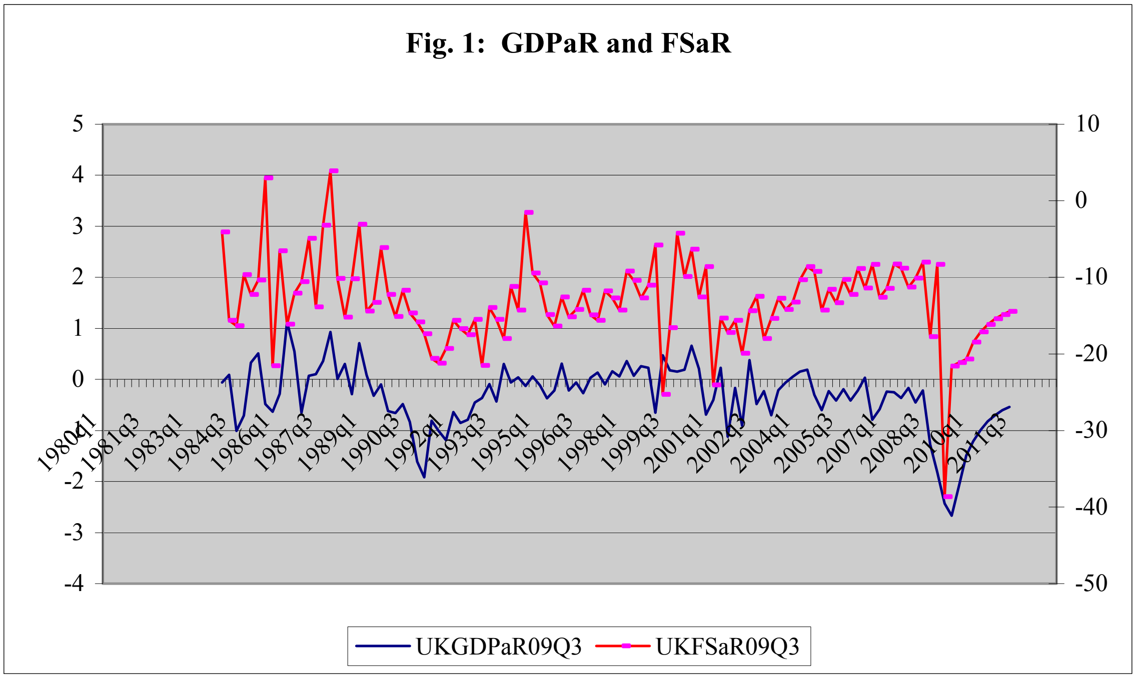


Figure Set 2: GDPaR and FSaR Estimates and Forecasts (cont.)

U.K.



France

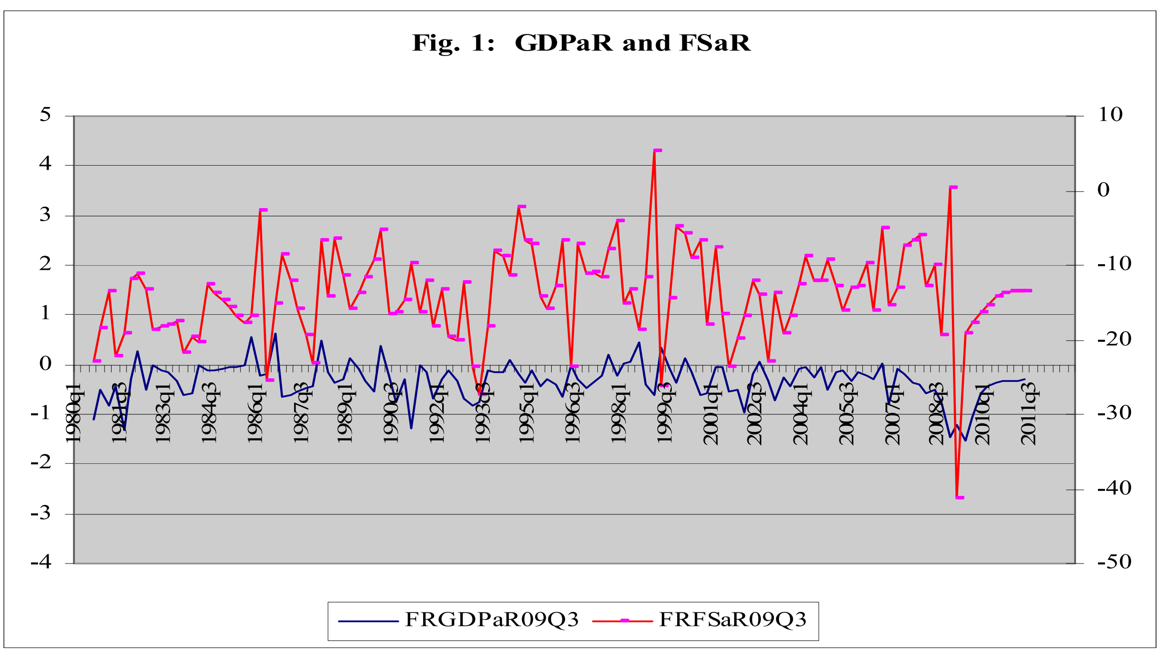
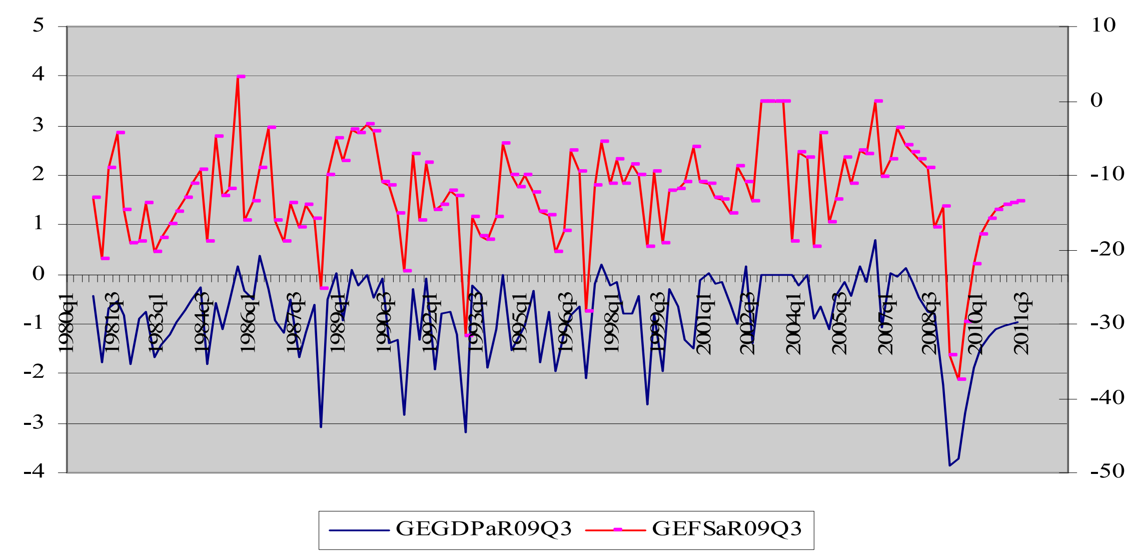


Figure Set 2: GDPaR and FSaR Estimates and Forecasts (cont.)

Germany

Fig. 1: GDPaR and FSaR



Italy

Fig. 1: GDPaR and FSaR

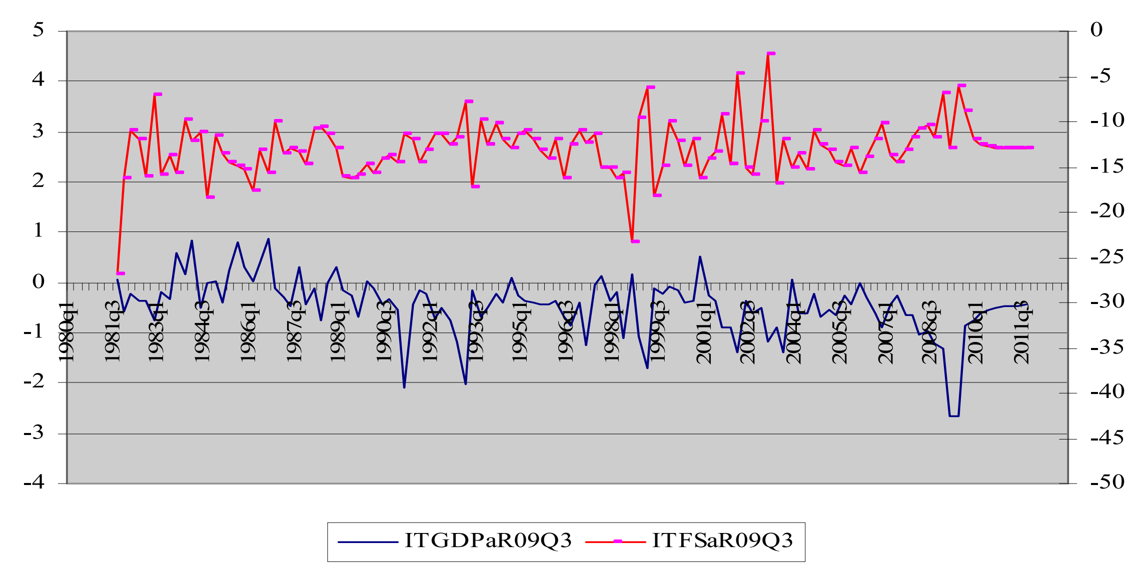
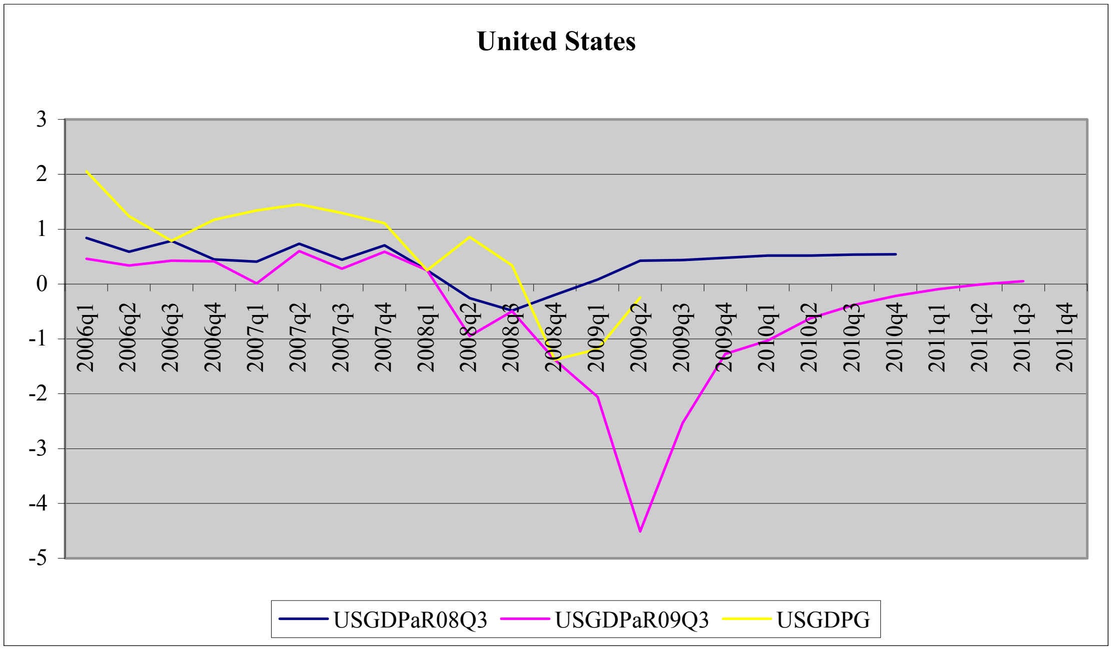


Figure Set 3: GDPaR Out-of-Sample Forecasts and Actual GDP growth



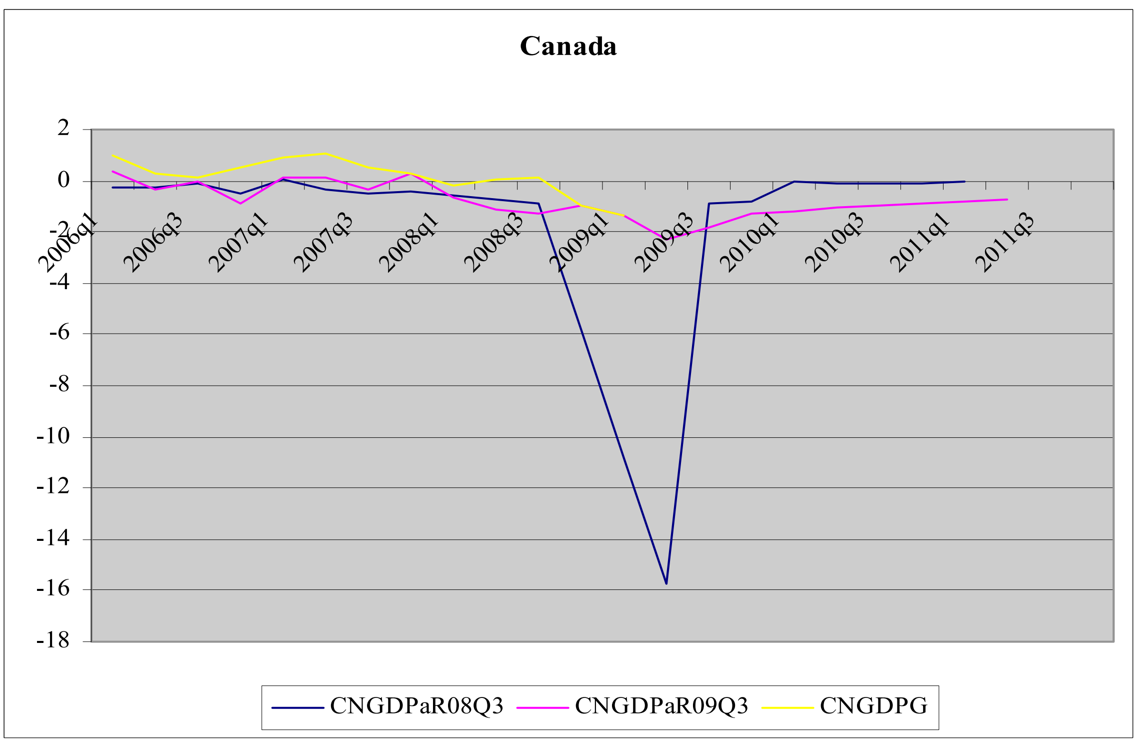
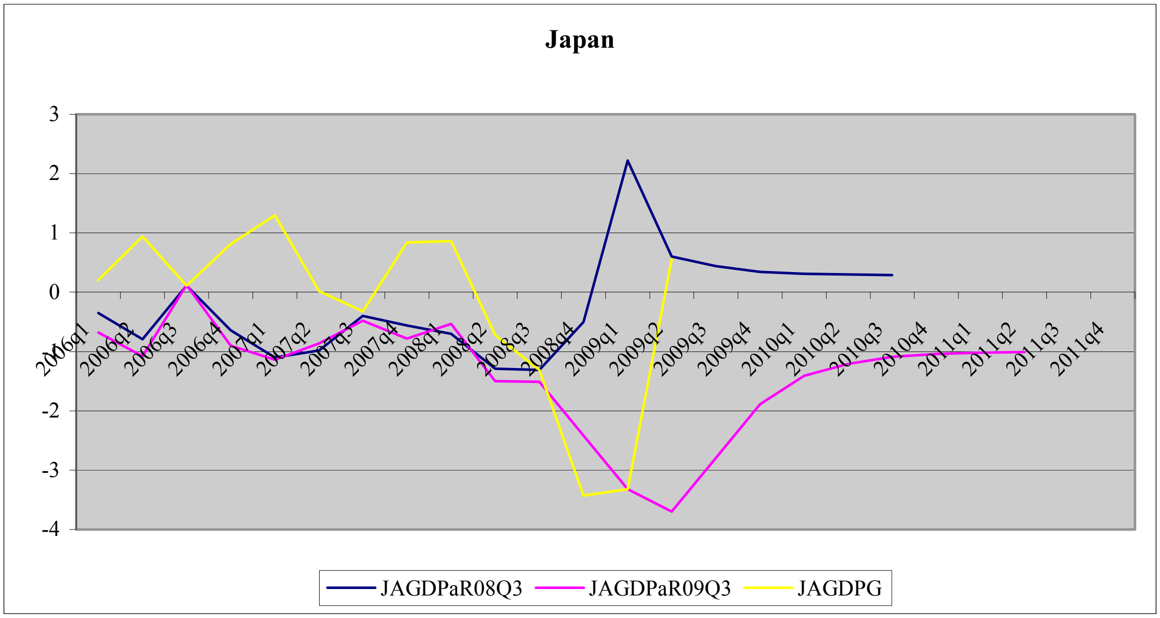


Figure Set 3: GDPaR Out-of-Sample Forecasts and Actual GDP growth (cont.)



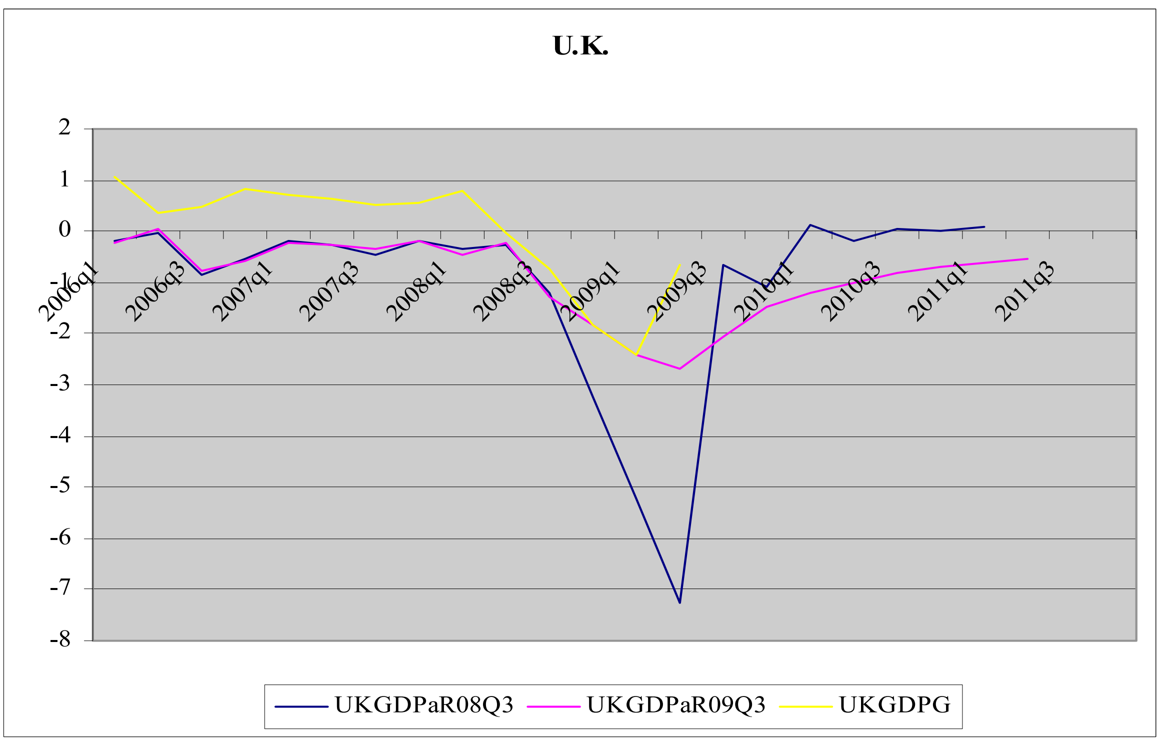
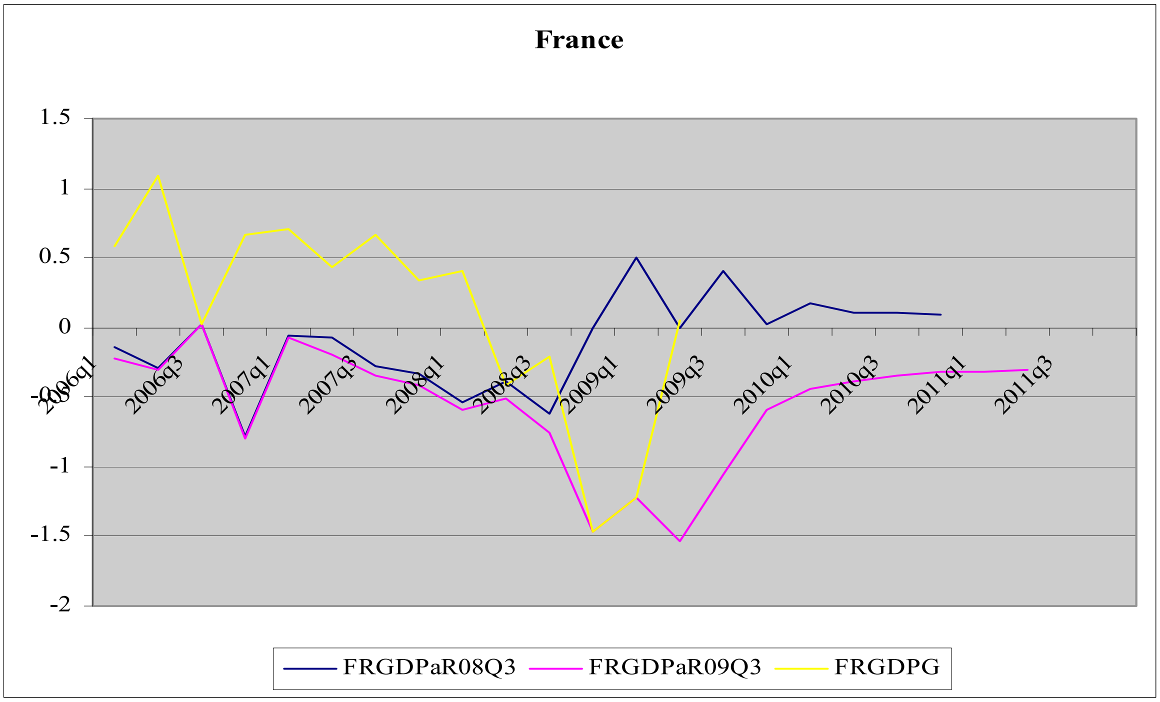


Figure Set 3: GDPaR Out-of-Sample Forecasts and Actual GDP growth (cont.)



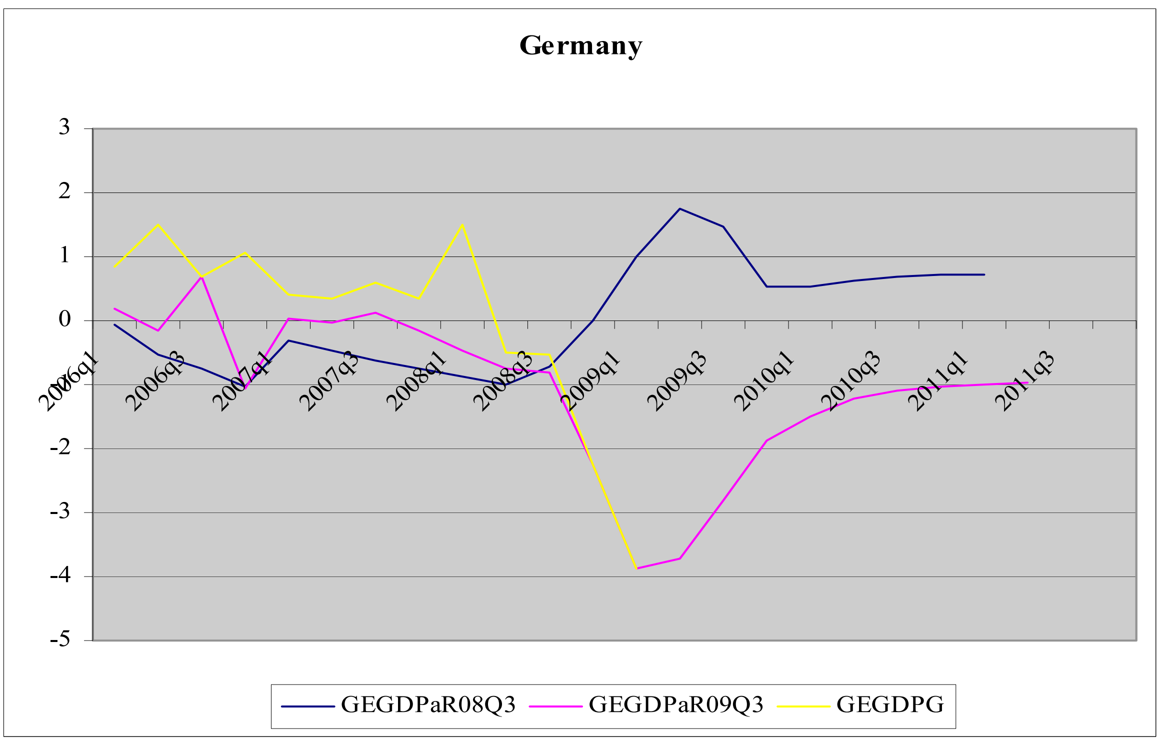


Figure Set 3: GDPaR Out-of-Sample Forecasts and Actual GDP growth (cont.)

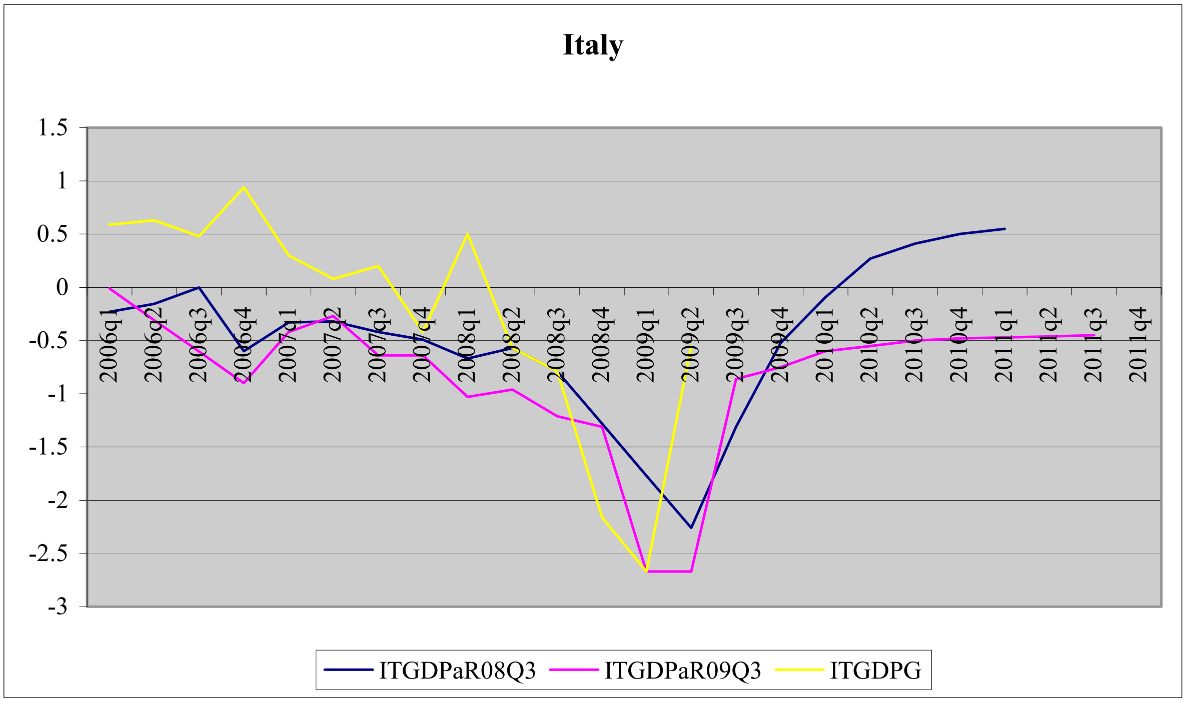
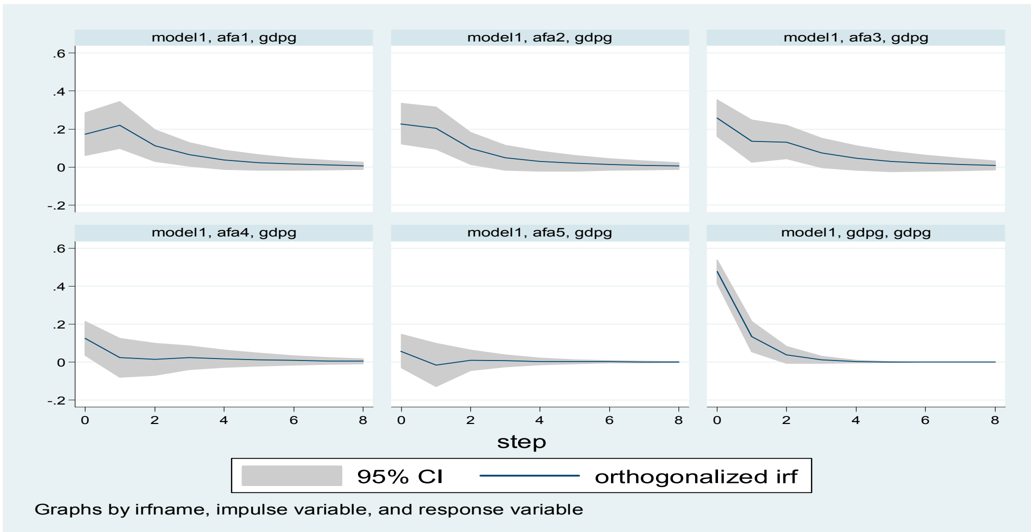


Figure Set 4: U.S. Impulse Responses of GDP Growth, Inflation, Bank Lending Growth and Change in Lending Rate to Shocks to Factors

GDP Growth



Inflation

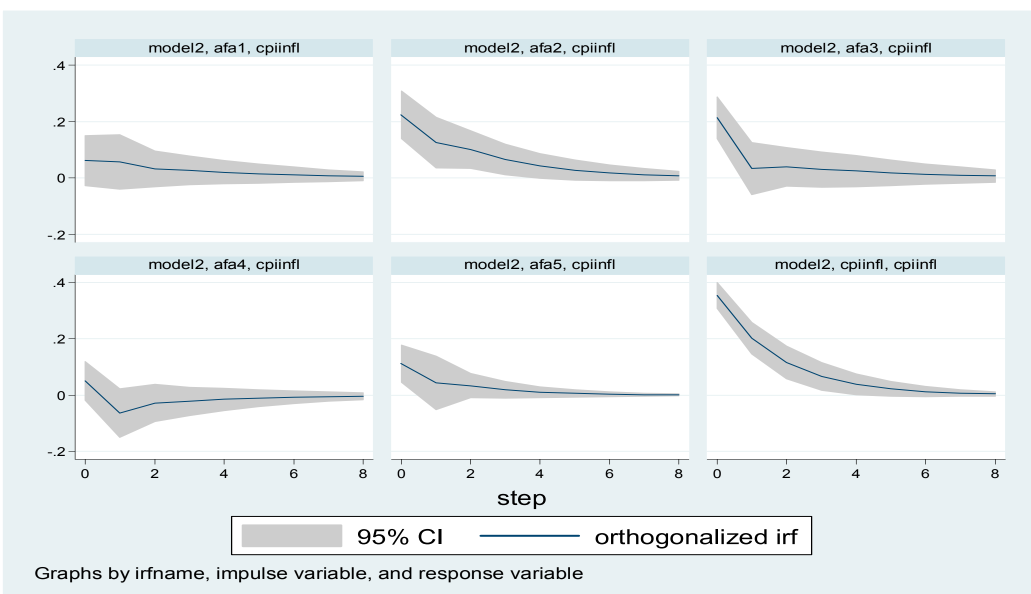
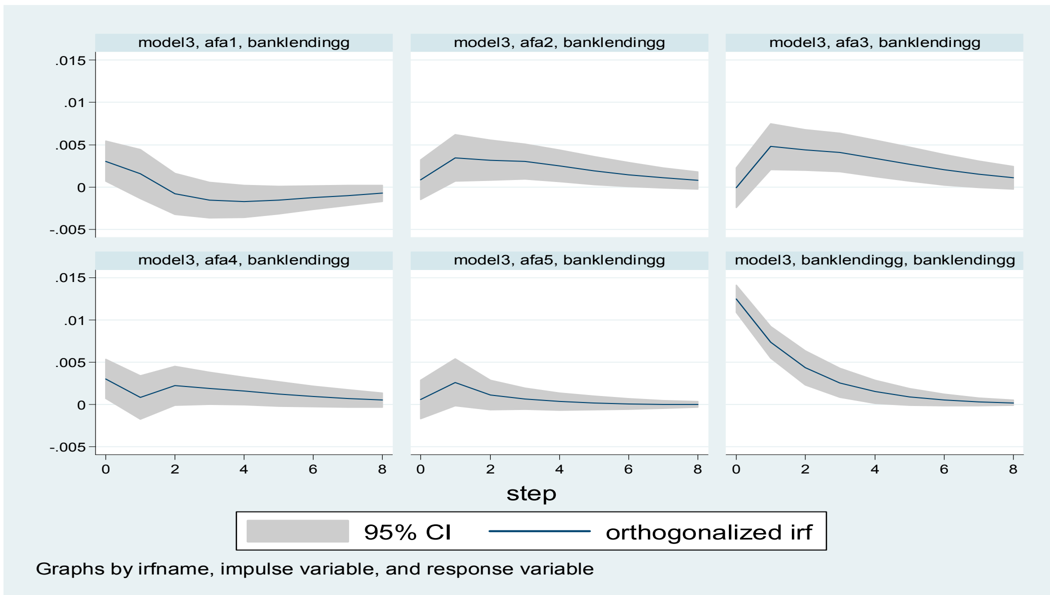


Figure Set 4: U.S. Impulse Responses of GDP Growth, Inflation, Bank Lending Growth and Change in Lending Rate to Shocks to Factors (cont.)

Bank Lending Growth



Δ Loan Rate

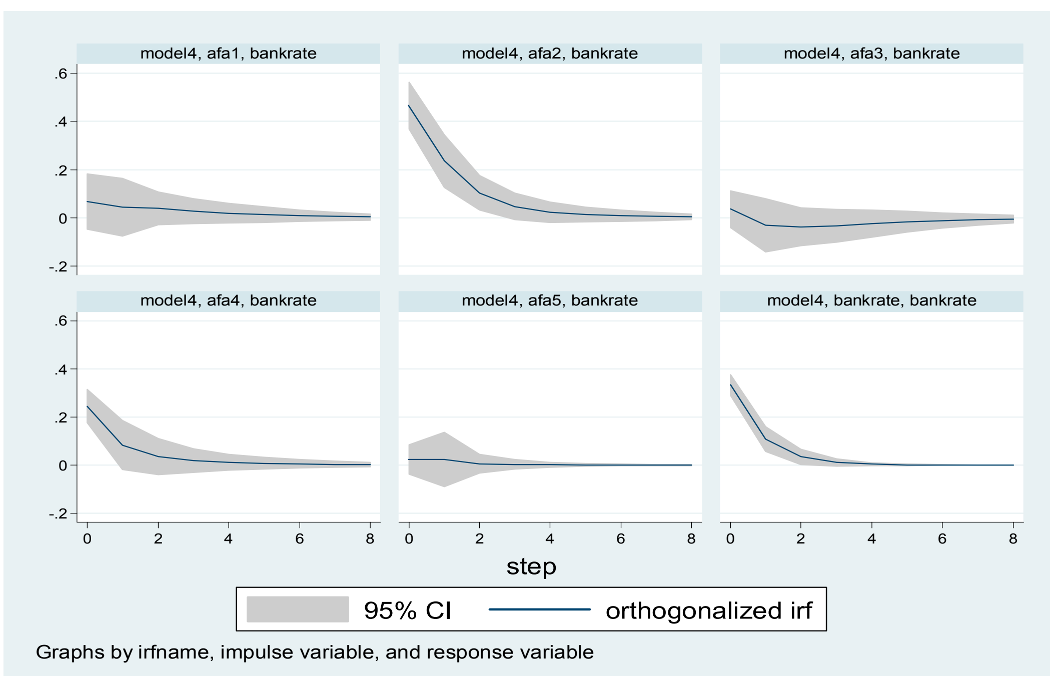
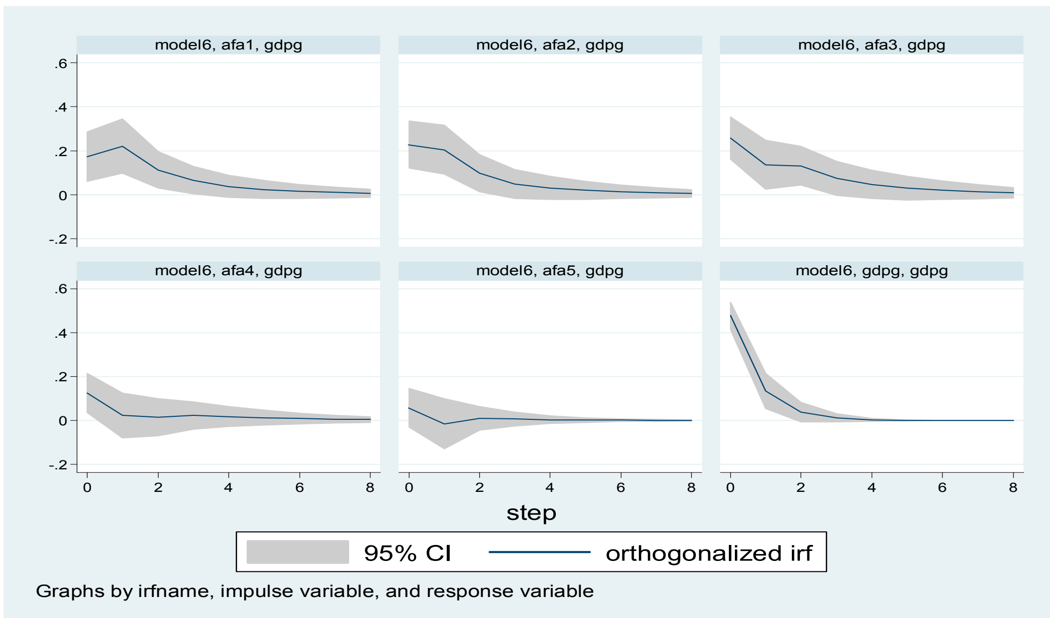


Figure Set 5: Impulse Responses of GDPaR and FSaR to Identified Aggregate Demand and Bank Credit Demand Shocks

United States

GDPaR



FSaR

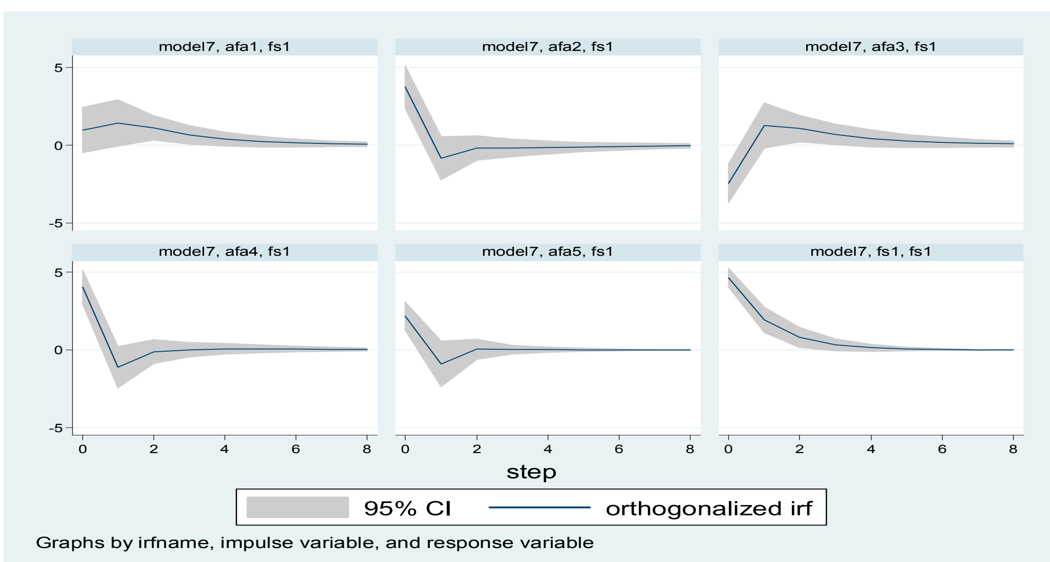
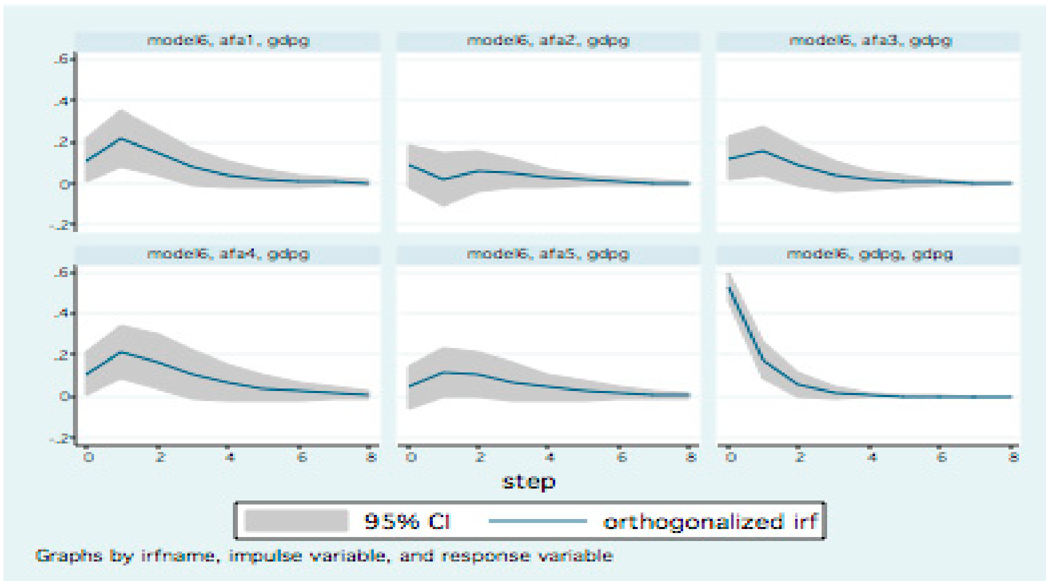


Figure Set 5: Impulse Responses of GDPaR and FSaR to Identified Aggregate Demand and Bank Credit Demand Shocks (cont.)

Canada

GDPaR



FSaR

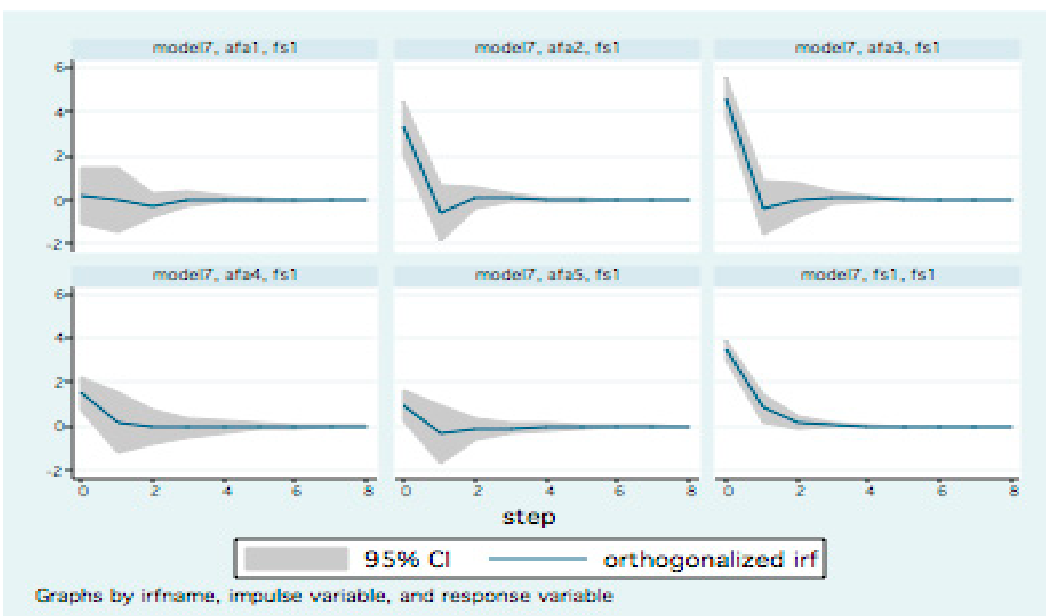
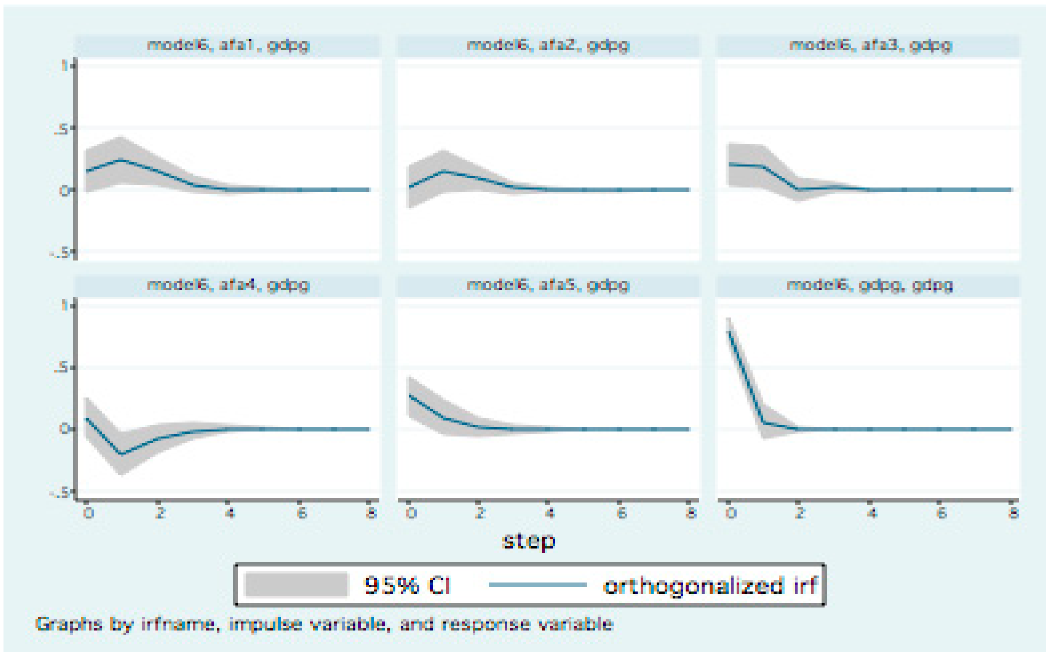


Figure Set 5: Impulse Responses of GDPaR and FSaR to Identified Aggregate Demand and Bank Credit Demand Shocks (cont.)

Japan

GDPaR



FSaR

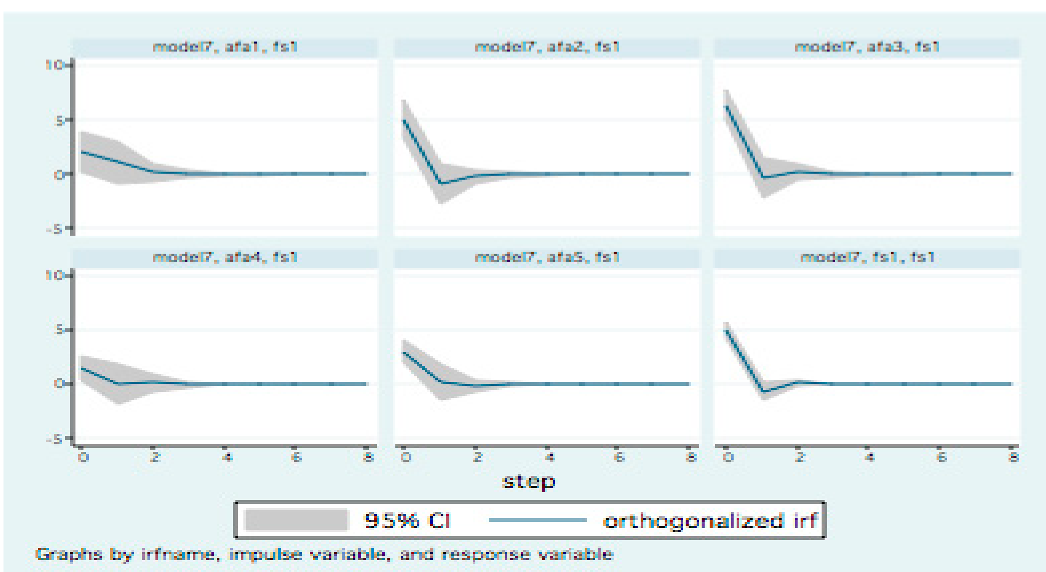
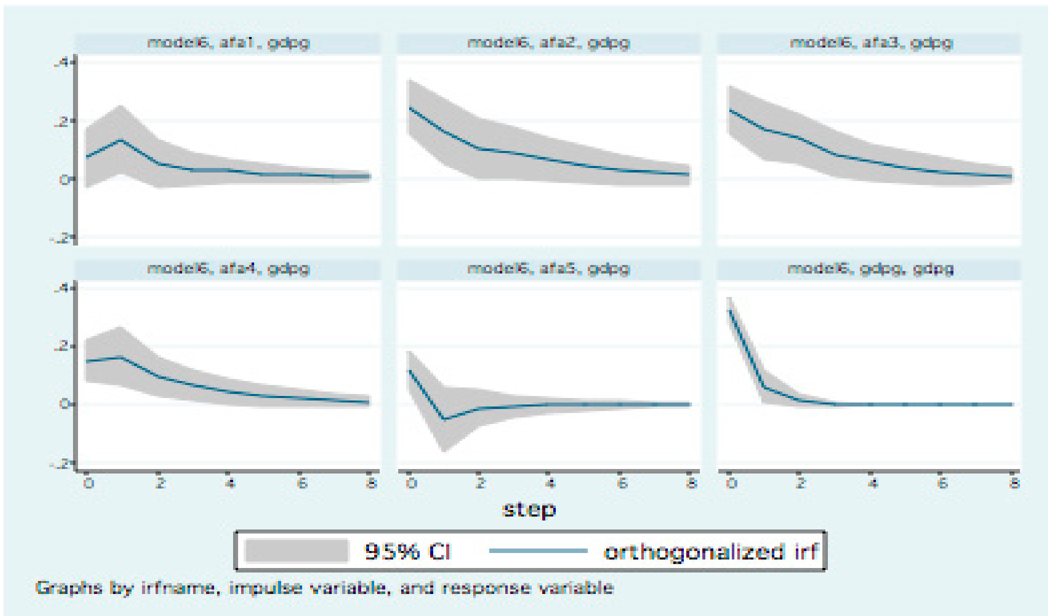


Figure Set 5: Impulse Responses of GDPaR and FSaR to Identified Aggregate Demand and Bank Credit Demand Shocks (cont.)

UK

GDPaR



FSaR

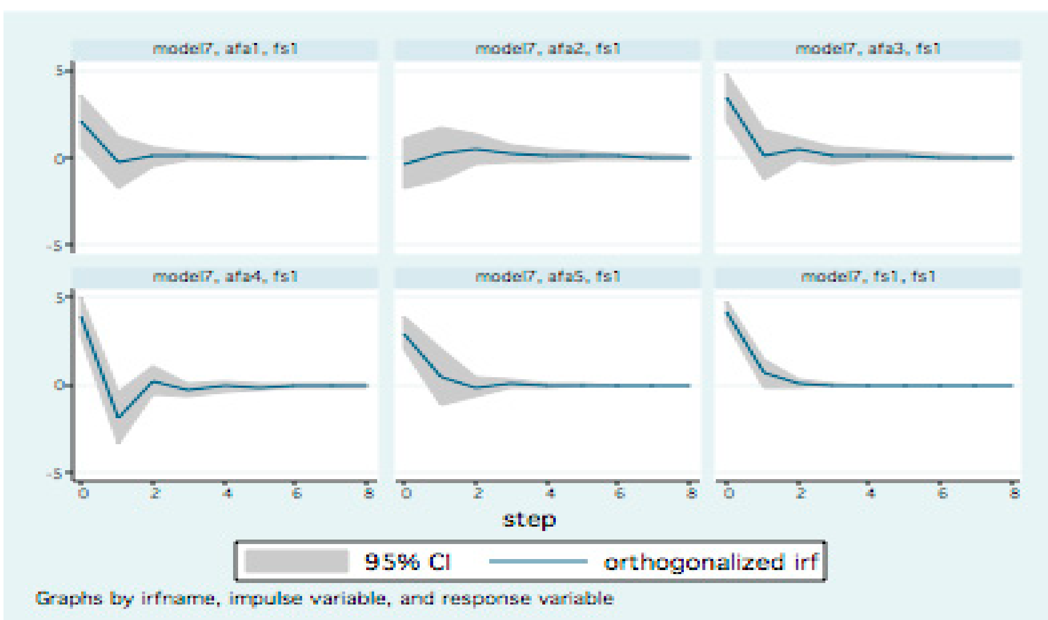
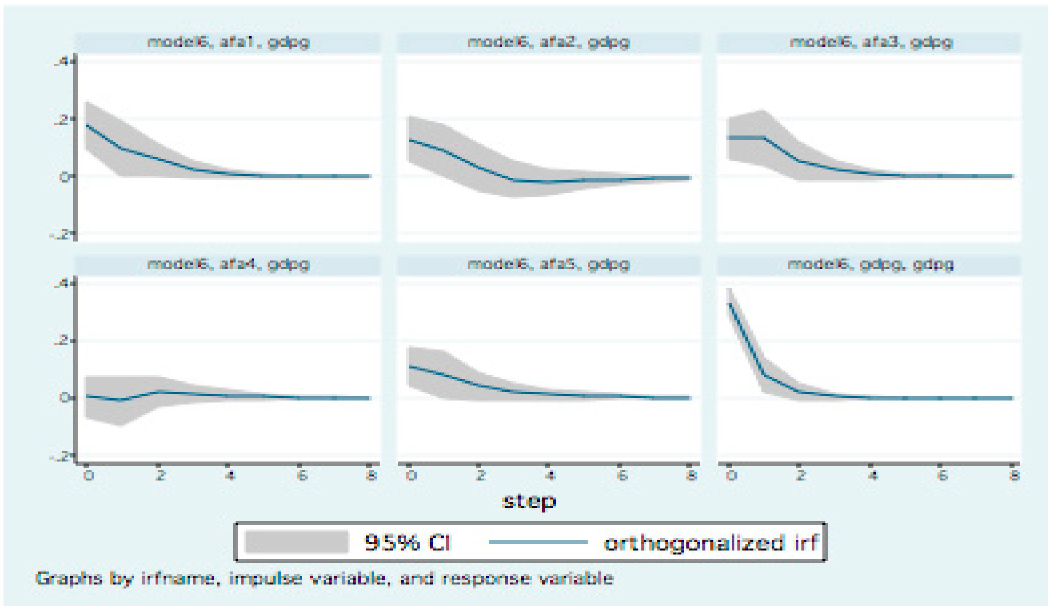


Figure Set 5: Impulse Responses of GDPaR and FSaR to Identified Aggregate Demand and Bank Credit Demand Shocks (cont.)

France

GDPaR



FSaR

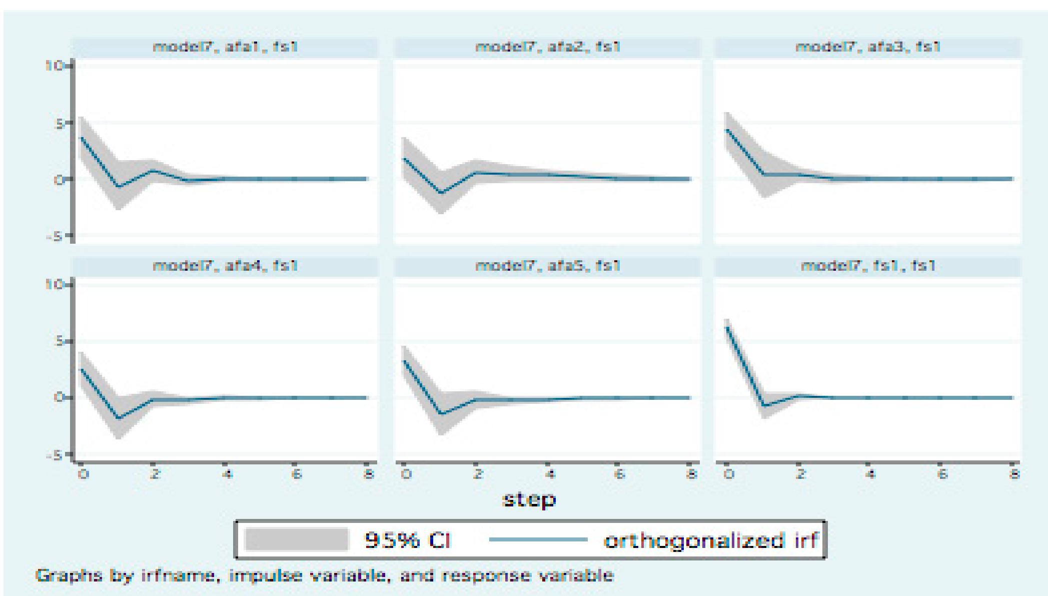
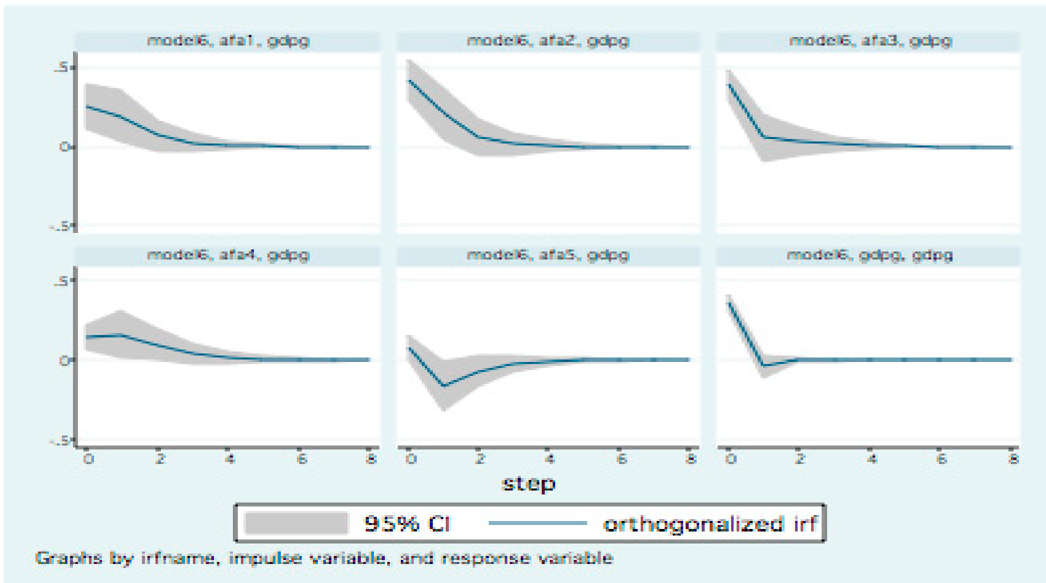


Figure Set 5: Impulse Responses of GDPaR and FSaR
to Identified Aggregate Demand and Bank Credit Demand Shocks (cont.)

Germany

GDPaR



FSaR

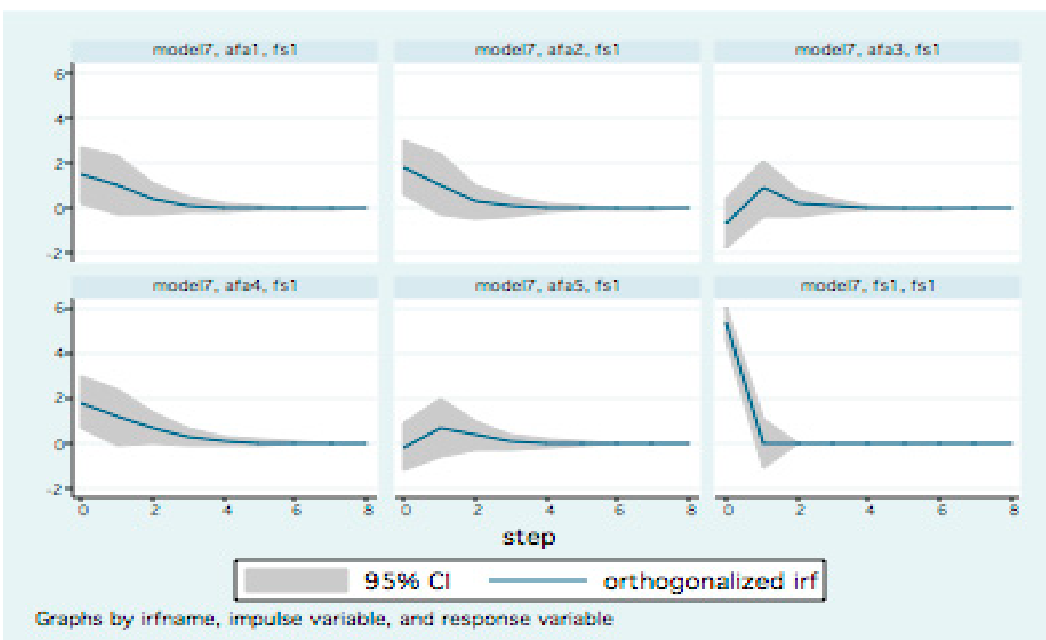
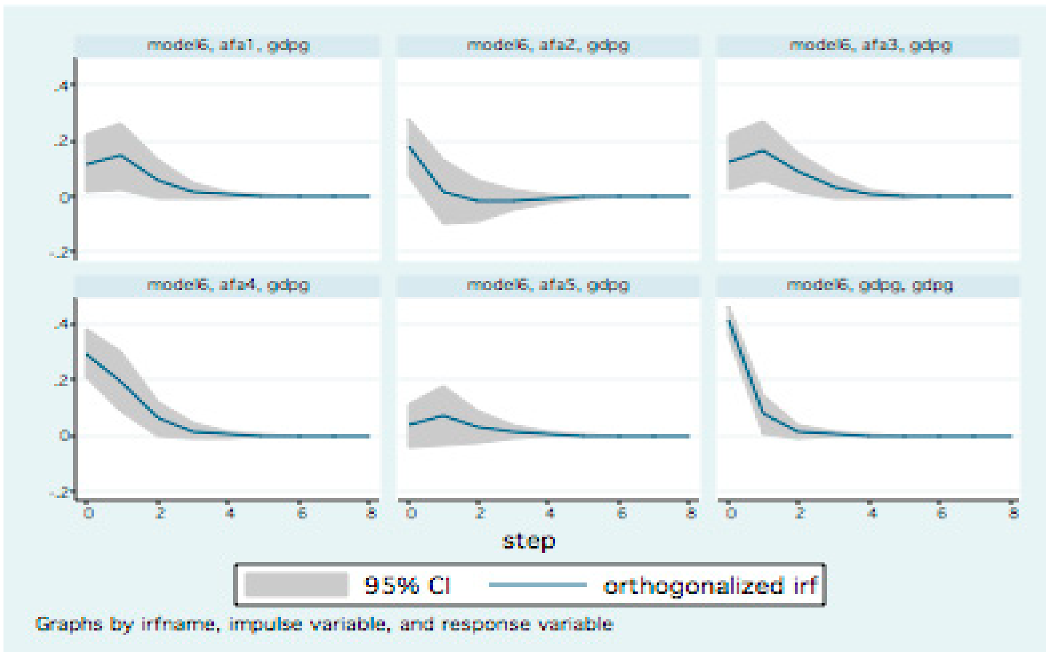


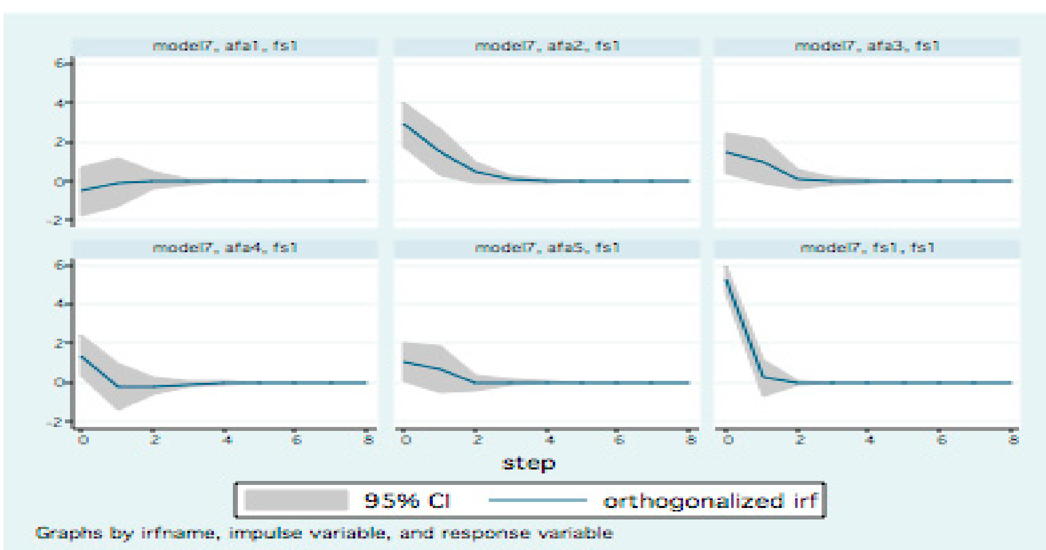
Figure Set 5: Impulse Responses of GDPaR and FSaR to Identified Aggregate Demand and Bank Credit Demand Shocks (cont.)

Italy

GDPaR



FSaR



APPENDIX : LIST OF VARIABLES

All variables below are extracted for each country in the G-7 group during the 1980.Q1-2009.Q3 period. The frequency of all series is quarterly. Data transformations are implemented to make all series stationary. Δln = log level difference; Δlevels = level difference.

Equity Markets	**Transformations**
Equity indices, Price Earnings ratios and Dividend yields total and by sector:	
Market	Δln
Oil & gas	Δln
Chemicals	Δln
Basic resources	Δln
Construction & 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
Personal savings as % 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