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Systemic Real and Financial Risks: Measurement, Forecasting, and Stress Testing

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Systemic Real and Financial Risks: Measurement, Forecasting, and Stress Testing*

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Abstract

Building on De Nicolò and Lucchetta (2010), this paper presents a novel modeling framework that delivers: (a) *density forecasts* of indicators of real activity and financial health, and implied indicators of *systemic real risk* and *systemic financial risk;* (b) *reduced-form stress tests* as historical simulations, and *structural stress-tests* as impulse responses of systemic risk indicators to structural shocks identified by standard macroeconomic and banking theory. This framework is implemented using large sets of quarterly time series of indicators of financial and real activity for the G-7 economies in 1980Q1-2010Q2. We show that the model exhibits significant out-of sample forecasting power for tail real and financial risk realizations in each country and stress tests provide important early warnings on the build-up of real and financial vulnerabilities. Furthermore, we find that 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 suggest that sharp declines in real activity may have been the key drivers of the observed decline of bank credit in the G-7 economies in the aftermath of Lehman's collapse in 2008Q3.

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Systemic Risks, Dynamic Factor Model, Quantile Auto-regressions, Density Forecasts

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"Pangloss enseignait la métaphysico-théologo-cosmolonigologie. Il prouvait admirablement qu'il n'y a point d'effet sans cause, et que, dans ce meilleur des mondes possibles, le château de monseigneur le baron était le plus beau des châteaux et madame la meilleure des baronnes possibles.[1]

Voltaire, "Candide, ou l'Optimisme", 1759

I. Introduction

Systemic *financial* risk is not new to researchers and policy-makers. About ten years ago, Group of Ten (2001) concluded that "... [Risk] interdependencies between large and complex banking organizations have increased over the last decade in the United States and Japan, and are beginning to do so in Europe. ....*Areas of increased interdependency include interbank loans, market activities such as OTC derivatives, and payment and settlement systems (our italics)*" (p.4). In the early 2000s several other studies documented the increased potential for systemic financial risk realizations in several advanced economies, consistent with the conclusion of the Group of Ten study.[2]

However, buoyant growth and record profits in the financial industries of advanced economies until the early 2007 lead many to lean toward a Panglossian view of the world. More significantly, the monitoring technologies tracking systemic financial risk available to central banks and international organizations failed to provide strong early warnings on the eruption of the crisis in 2007-2008. Since then, a number of contributions have proposed new ways of measuring and tracking systemic financial risk. Nevertheless, what are the best technologies to accomplish these tasks is still an open issue.

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[1] "*Master Pangloss taught the metaphysico-theologo-cosmolonigology. He could prove to admiration that there is no effect without a cause; and, that in this best of all possible worlds the Baron's castle was the most magnificent of all castles, and My Lady the best of all possible baronesses."*

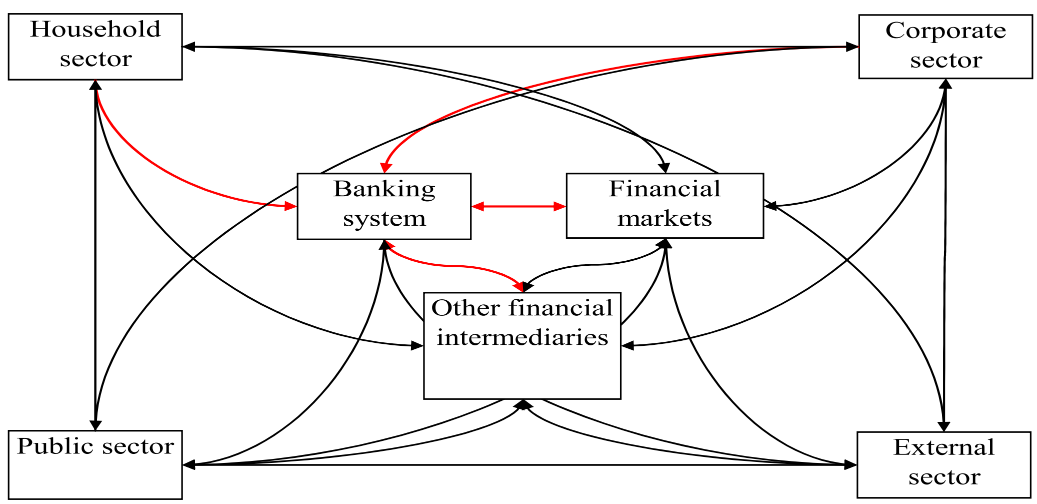
[2] See De Bandt and Hartmann (2000) and for a review of the literature of the 1990s, and Summer (2002) for an early discussion of regulatory implications. De Nicolò (2000) documented increased risk-taking at large banking organizations in the U.S., Europe and Japan since the late 1980s. De Nicolò and Kwast (2002) found increased risk interdependencies among U.S. large and complex banking organizations since the mid-1990s.. Under a variety of measures, systemic risk profiles of large and complex financial institutions were found to continue to increase during the early 2000s in the U.S. and in Europe (De Nicolò, Hayward, and Vir Bhatia, 2004, Stiroh, 2004, Hartmann, Straetmans, and de Vries, 2005, De Nicolò et al., 2005, Stiroh and Rumble, 2006, and Houston and Stiroh, 2006), as well as globally (De Nicolò et al, 2004).

Building on our previous effort (De Nicolò and Lucchetta, 2010), this paper develops a tractable model that can be used for positive analysis as well as a real-time *systemic risk monitoring system*. The model combines dynamic factor VARs and quantile regressions techniques to deliver density forecasts of systemic risk indicators, and employs theory-based structural identification to detect the sources of shocks and their propagation mechanisms.

Our model is rooted in the architecture underpinning standard Dynamic Stochastic General Equilibrium (DSGE) modeling. Its objectives are to track and quantify the impact and transmission of structural shocks within/between real sectors, financial markets and intermediaries, as well as their "tail" realizations. In terms of Figure A below, we aim at identifying which sectors of the economy are most affected by a shock at impact as well as size and persistence of shocks' propagation within and between sectors. In addition, we require our model to have a satisfactory *forecasting performance:* such performance is a necessary condition for a model to qualify as a useful risk monitoring tool.

Figure A

Financial exposures (stocks and flows) between sectors



Ideally, a computable general equilibrium model with satisfactory forecasting properties and specified at a suitable level of dis-aggregation, would allow us to identify the sources of shocks, the linkages through which they are propagated, and to conduct informative policy experiments and stress tests. In practice, formulating and implementing such a model is a formidable theoretical and computational task.

Work on DSGE modeling is advancing significantly (see e.g. Shorfheide, 2010), but progress is still in its infancy in at least two dimensions: the incorporation of meaningful interactions between financial and real sectors, for which no consensus paradigm is yet available, and forecasting. The forecasting ability of current DSGE models is still a relatively under-researched area to-date, and in particular, the superiority of the forecasting performance of DSGE models relative to other data-driven models is not yet established.[3] As a result, available modeling technologies providing systemic risk monitoring tools based on explicit linkages between financial and real sectors are still underdeveloped. Contributing to fill in this void is a key objective of this paper.

Three features characterize our model. First, we make a distinction between systemic *real* risk and systemic *financial* risk, and show it is operationally relevant. This distinction is based on the notion that *real* effects with potential adverse welfare consequences are what ultimately concerns policymakers. Second, the model produces real-time density forecasts of indicators of real activity and financial health, and uses them to construct measures of systemic real and financial risks. To obtain these forecasts, we use a dynamic factor model (DFM) with many predictors combined with quantile regression techniques. The choice of the DFM with many predictors is motivated by its superior forecasting performance over both univariate time series specifications and standard VAR-type models (see Watson, 2006). Third, our design of stress tests can be flexibly linked to selected implications of DSGE models and other theoretical constructs. Structural identification provides economic content of these tests, and imposes discipline in designing stress test scenarios.[4] In essence, our model is designed to exploit and make operational the forecasting power of DFM models and structural identification based on explicit theoretical constructs, such as DSGE models.

Our framework can be designed to deliver *density forecasts* of any set of variables that a researcher wishes to predict. However, in this paper we focus on two key indicators: one of real activity, and one of financial health. Real activity is measured by GDP growth. Financial health

[3] For a recent review of the literature on forecasting with DSGE models see Christoffel, Coenen and Warne (2010).

[4] For a discussion of the problems in designing consistent stress test scenarios, see Drehmann (2008). For guidelines of best practice on stress testing for individual financial institutions, see Basel Committee on Banking Supervision (2009).

is measured by an indicator based on equity market valuation, called FS. The joint dynamics of GDP growth and the FS indicator is modeled through a factor-augmented VAR (FAVAR) model, following the methodology detailed in Stock and Watson (2002, 2005).

Density forecasts of GDP growth and the FS indicator are obtained by estimating sets of quantile auto-regressions, using forecasts of factors derived from the companion factor VAR as predictors. The blending of a dynamic factor model with quantile auto-regressions is a novel feature of our model. The use of quantile auto-regressions is advantageous, since it allows us to avoid making specific assumptions about the shape of the underlying distribution of GDP growth and the FS indicator.

Systemic risk indicators and their forecasts are constructed on the basis of density estimates of GDP growth and the FS indicator. The systemic *real* risk indicator is *GDP-Expected Shortfall* (*GDPES*), defined as the expected decline of GDP growth conditional on such growth being lower than a certain tail level. The systemic *financial* risk indicator is FS-Expected Shortfall (*FSES*), defined analogously.

S*tress-tests* of systemic risk indicators are implemented by either historical simulation (*reduced-form* stress tests), or by gauging their impulse responses to structural shocks (*structural* stress tests). The identification of structural shocks is accomplished with a version of the sign restriction methodology introduced by Canova and De Nicolò (2002), where aggregate shocks are extracted based on standard macroeconomic *and* banking theory.

We wish to emphasize that our approach to stress testing differs markedly from many—although not all—implementations of stress testing currently used in central banks and international organizations. In these implementations, shock scenarios are imposed on sets of observable variables, and their effects are traced through "behavioral" equations of certain variables of interest. Yet, the "shocked" observable variables are typically *endogenous:* thus, it is unclear whether we are shocking the symptoms and not the causes. As a result, it is difficult to assess the quantitative implications of the stress test results. This is, essentially, the problem of "endogeneity of risk" pointed out by Drehmann (2008). Under the assumption that the deep parameters underlying our estimates are policy-invariant—as commonly assumed in simulations based on DSGE models—our stress testing procedures are immune to this problem.

We implement our model using a large set of quarterly time series of financial and real activity for the G-7 economies during the 1980Q1-2010Q1 period. We obtain two main results.

First, we find significant evidence of out-of sample forecasting power for tail real and financial risk realizations for all countries. Moreover, stress tests based on historical simulations and structural identification provide early warnings of vulnerabilities in the real and financial sectors. 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 suggest that sharp declines in real activity may have been the key drivers of the observed decline of bank credit in the G-7 economies in the aftermath of Lehman's collapse in 2008Q3.

The remainder of the paper is composed of six sections. Section II defines systemic risks and describes indicators consistent with these definitions. Section III outlines the model setup, estimation and forecasting. Section IV details the stress testing procedures. Section V describes the implementation of the modeling framework on data for the G-7 countries and the relevant forecasting results. Section VI illustrates implementations of stress testing. Section VII concludes.

II. SYSTEMIC RISKS: DEFINITIONS AND MEASUREMENT

We adopt the following definitions:

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

As in Group of Ten (2001) and in De Nicolò and Kwast (2002), these definitions embed a key necessary condition for a financial shock to induce adverse systemic real risk realizations: *financial shocks must be highly likely to induce significant adverse real effects,* such as substantial reductions in output and employment. In other words, the negative externalities of a financial shock that extend to the financial system are required to *extend also* to the real economy. Financial markets turbulence, attendant increases in volatility and/or failures of financial intermediaries that are devoid of significant real effects are *not* classified as systemic. Importantly, distinguishing systemic *financial* risk from systemic *real* risk allows us to 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.

Guided by these definitions, our measurement follows a risk management approach.[5]

To control risk in financial institutions, risk managers may track a portfolio's Expected Shortfall (ES), given by the expected loss of its value conditional on a given level of Value-at-Risk (VaR). VaR is defined as the worst possible portfolio loss over a given time horizon at a given (low) probability. To control risk in the economy, policy makers may wish to track measures of worst possible *real aggregate* outcomes. A measure of systemic *real* risk is *GDP-Expected Shortfall* ($GDPES$), given by the expected loss in GDP growth conditional on a given level of GDP-at-Risk (*GDPaR*). *GDPaR* is defined here as the worst predicted realization of quarterly growth in real GDP at a given (low) probability.

To control risk in the financial system, policy-makers may also wish to track measures of worst possible *system-wide financial* outcomes. Following Campbell, Lo and MacKinlay (1997), our measure of such outcomes is an indicator of health of the financial system (*FS)* given by the return of a portfolio of a set of systemically important financial firms less the return on the market. This indicator is germane to measures adopted in recent studies to construct systemic financial risk indicators (see Acharya et al., 2010, Brownlees and Engle, 2010, and the references therein). A measure of systemic *financial* risk is *FS-Expected Shortfall* (*FSES*), given by the expected loss in *FS* conditional on a given level of FS-at-Risk (*FSaR)*. *FSaR* is defined as the worst predicted realization of the *FS* indicator at a given (low) probability level.

We have chosen GDP growth and the *FS* indicator as measures of real activity and financial health for their relevance and simplicity. However, our modeling framework can be easily adapted to embed multiple measures of real or financial risk, both at aggregate and disaggregate levels. [6]

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[5] For an earlier contribution adopting a risk management approach as applied to banks, see Lehar (2005).

[6] Aggregate indicators may include unemployment and inflation measures, or indicators of financial market stress, such as the liquidity indicators introduced in De Nicolò and Ivaschenko (2009). Disaggregated indicators may include sectoral measures of real activity, or bank-specific measures of risk such as those based on CDS spreads introduced in Huang, Zhou and Zhu (2009 and 2010).

III. The Model: Estimation and Forecasting

Following Stock and Watson (2002, 2005), the dynamics of real GDP growth (denoted by $GDPG_t$) and the *FS* indicator (denoted by FS_t) are modeled with a Dynamic Factor Model (DFM) described by the following equations:

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

$$f_t = \Gamma(L) f_{t-1} + \eta_t \qquad (2)$$

$$GDPG_{t+1} = \lambda^R(L) f_t + \gamma_R(L) GDPG_t + u^1_{t+1} \qquad (3)$$

$$FS_{t+1} = \lambda^F(L) f_t + \gamma_F(L) FS_t + u^2_{t+1} \qquad (4)$$

The dynamics of N series (predictors) X_{it} (indexed by $i \in N$, with N large) is represented by the factor model (1), where f_t is a vector of *dynamic* factors. Equation (2) describes the dynamics of these factors through a VAR. Equations (3) and (4) describe the dynamics of $GDPG_t$ and FS_t, with factors as predictors.

Under the assumptions that factors and idiosyncratic errors u^1_{t+1}, u^2_{t+1}, and v_{it} are uncorrelated at all leads and lags, that dynamic factors have 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:*

$$X_{it} = \Lambda'_i F_t + v_{it} \qquad (5)$$

$$F_t = \Phi(L) F_{t-1} + G\eta_t \qquad (6)$$

$$GDPG_{t+1} = \Lambda^{R'} F_t + \gamma_R(L) GDPG_t + u^1_{t+1} \qquad (7)$$

$$FS_{t+1} = \Lambda^{F'} F_t + \gamma_F(L) FS_t + u^2_{t+1} \qquad (8)$$

Matrix $\Phi(L)$ 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, (6) is equivalent to (2). Equations (6)-(8) describe a version of a Factor-Augmented VAR (FAVAR) representation of the DFM akin to that adopted by Bernanke, Boivin, and Eliasz (2005).

A. Density Forecasts and Systemic Risk Measures

We construct density forecasts of $GDPG_t$ and FS_t by estimating quantile auto-regressions (Koenker, 2005) of the form (7) and (8), with estimates of the static factors F_t as conditioning variables. Denote with $\tau \in (0,1)$ a particular quantile, and with a "hat" estimated quantile coefficients. Initial quantile estimates of (7) and (8) for each $\tau \in \{1, 2, ...,99\}$ are:

$$GDPGQ_{t+1}(\tau) = \hat{\alpha}_1(\tau) + \hat{\Lambda}^{R\prime}(\tau)F_t + \hat{\gamma}_R(\tau)(L)GDPG_t \qquad (9)$$

$$FSQ_{t+1}(\tau) = \hat{\alpha}_2(\tau) + \hat{\Lambda}^{F\prime}(\tau)F_t + \hat{\gamma}_F(\tau)(L)FS_t \qquad (10)$$

Importantly, the quantile estimates of equations (9) and (10) are "raw" estimates, since we apply a "rearrangement" method to guarantee their consistency, as detailed below. For expositional purposes, however, in what follows we refer to (9) and (10) as our final quantile estimates.

For low values of $\tau \in (0,1)$, the VaR measures *GDPaR* and *FSaR* are the fitted values of $-GDPGQ_t(\tau)$ and $-FSQ_t(\tau)$. There are two well known limitations of VaR measures: (a) they not take into account the *size* of tail losses; and (b) they lack "coherence" in the sense of Artzner et al. (1999), since they do not satisfy the sub-additivity property required for consistent risk ordering.[7] A measure that overcomes these problems is given by the Expected Shortfall (*ES*). Given a random variable *X*, expected shortfall is defined as the expected downside loss at τ percent probability that *X* falls below quantile τ (see, e.g. Acerbi and Tasche, 2002).

In our context, expected shortfalls are conditional on a given state of the economy at a given date. Denoting with E_t the expectation operator conditional on information available at date *t,* for any given $\tau \in (0,1)$ our systemic risk indicators are defined as:

[7] Failing to account for the size of (conditional) losses is also a limitation of measures of distance-to-default and probability of default based on Black-Sholes-Merton-type models used in a large applied literature, as well as in many "vendor" models assessed by the Basel Committee on Banking Supervision (2010). For a recent review of this literature and an application of these measures, see Zambrana (2010).

$$GDPES_t(\tau) = -\mathrm{E}_t(GDPG_t \mid GDPG_t \leq GDPaR_t(\tau)) \quad (11)$$

$$FSES_t(\tau) = -\mathrm{E}_t(FS_t \mid FS_t \leq FSaR_t(\tau)) \quad (12)$$

B. Estimation and Forecasting

Estimation and forecasting are accomplished in four steps.

Number of factors and lags

In the first step, we compute *static* factors, and choose their number and the lags of the FAVAR (6)-(8) according to the following criterion. 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 the set of factors $\tilde{F} = \{(F_{r=1}),(F_1,F_{r=2}),....,(F_1,F_2,...,F_{r=R})\}$. Lastly, we choose the number of lags L and the number of static factors r that maximize the Bayesian Information Criterion (BIC) for FAVARs (6)-(8) estimated for each set of factors in $\tilde{F}$ and with one, two, three, and a maximum of four lags. In other words, the optimal number of lags L^* and the number of static factors r^* yield the maximum BIC criterion among 4 by R FAVAR specifications.

Quantile Estimation

In the second step, we use the optimal number of lags L^*, the number of static factors r^*, and the estimated factors to estimate quantile auto-regressions for $\tau = 1, 2....99$ specified as in (7) and (8).

Estimated quantile regressions may generally exhibit "crossings" of the conditional quantile functions. Such "crossing", if and when it occurs, implies that the key assumption that distribution functions are monotonically increasing is violated. As stressed by Koenker (2005, Ch. 8), this problem is likely to be more severe for quantile auto-regressions. Crossing can be the result of a mis-specification of the model, which in turn can adversely affect its forecasting performance.

We address this problem by adopting the "rearrangement" procedure introduced by Chernuzukhov, Fernandez-Val and Galichon (2010). They show that rearranging original quantile estimates into monotone quantile estimates, the resulting quantile curves are closer to the true quantile curves in finite samples and, by construction, these rearranged quantile curves do not exhibit crossing. To our knowledge, ours is the first implementation of a quantile rearrangement method in the context of macro-financial forecasting.

We implement this rearrangement procedure by re-ordering at each date the quantiles originally estimated via (7) and (8). These sorted quantiles are the final estimates used to construct conditional densities.

Density Estimates and Systemic Risk Indicators

In the third step, we construct estimates of conditional densities used to derive estimates of systemic risk indicators. Note that our quantile estimates provide *discrete* density estimates at each date, which can be represented by simple histograms. To obtain *continuous* densities and compute expected shortfalls, we proceed as follows.

Given a continuous probability distribution *F* of a random variable *X*, , the quantile corresponding to probability τ, denoted by $Q(\tau)$, is also equal to $Q(\tau) = F^{\leftarrow}(\tau)$, where $F^{\leftarrow}(\tau) \equiv \inf(x \mid F(x) \geq \tau)$ is the generalized inverse of *F*. Then, the expected shortfall of *X* can be expressed as:

$$ES(\tau) = -\frac{1}{\tau}\int_0^{\tau} F^{\leftarrow}(y)dy = -\frac{1}{\tau}\int_0^{\tau} Q(y)dy \qquad (13)$$

To obtain quantiles as continuous functions of $\tau \in (0,1]$, we regress the series of the 99 discrete quantiles at each date on a polynomial function of order *m*, obtaining $\hat{Q}_t(\tau) = \sum_{i=0}^{m} \hat{a}_i \tau^i$, where "hats" denote estimated coefficients. Then, expected shortfall estimates are given by:

$$ES_t(\tau) = -\frac{1}{\tau}\int_0^{\tau} \hat{Q}_t(y)dy = -\frac{1}{\tau}\int_0^{\tau} \sum_{i=0}^{m} \hat{a}_i y^i dy = -(\hat{a}_0 + \hat{a}_1 \frac{\tau}{2} + \hat{a}_2 \frac{\tau^2}{3} + \ldots + \hat{a}_m \frac{\tau^{m-1}}{m}) \qquad (14)$$

Our procedure is similar to several methods aimed at estimating tails of distributions based on extreme value theory (EVT). These methods estimate Hill indicators employing subsets of observations of the data relatively close to the tail of interest. The underlying assumptions are that unconditional densities are generated by a wide family of distributions with supports that are unbounded below. Our procedure differs from these methods in two ways: we do not impose distributional assumptions on conditional densities for our real and financial indicators, which have supports that are bounded below, and use information on the entire distribution of interest through the full range of quantile estimates.[8]

Forecasting

In the last step, we construct forecasts of conditional densities and of systemic risk indicators. Using the VAR of static factors described by equation (6), we compute dynamic forecasts of static factors k quarters ahead. Subsequently, these forecasts are used to obtain recursive forecasts of quantile estimates, which in turn provide discrete forecasts of the relevant density. Continuous density forecasts are obtained applying the procedure described previously. Forecasts of systemic risk indicators k quarters ahead are obtained as a by-product of this step.

IV. STRESS TESTING

We define stress testing as the measurement of size, persistence and impact of configurations of shocks on density estimates and systemic risk indicators. The resilience of the economy to these *unexpected* disturbances is gauged by assessing the sensitivity of densities and systemic risk indicators to different configurations of these shocks at a point in time and/or through time. We outline two complementary procedures. *Reduced-form* stress tests are based on historical shocks recovered from a statistical model of the dynamics of the *distribution* of the variables of interest. *Structural* stress tests are based on shocks derived from, and interpreted in light of, some set of theoretical models.

A. Reduced-Form Stress Testing

To retrieve the historical sequence of shocks to the distributions of GDP growth and the FS indicator, we assume that each quantile $\tau = 1, 2....99$ of these variables evolves according to the following AR(1) process:

$$GDPGQ_t(\tau) = a_R(\tau) + b_R(\tau) GDPGQ_{t-1}(\tau) + \eta_t^R(\tau) \qquad (15)$$

[8] In his recent review of tail estimates based on EVT, Le Baron (2009) advocates the use of the Hill estimators introduced by Huisman et al (2001). Comparing such estimates with ours is work in progress.

$$FSQ_t(\tau) = a_F(\tau) + b_F(\tau) GDPGQ_{t-1}(\tau) + \eta_t^F(\tau) \qquad (16)$$

The *steady state* density functions for GDP growth and the FS indicators can be view as determined indirectly by the "steady state" quantiles $GDPGQ(\tau) = a_R(\tau)/(1-b_R(\tau))$ and $FSQ(\tau) = a_F(\tau)/(1-b_F(\tau))$. [9] We estimate (15)-(16) with OLS to obtain the series of estimated residuals $\hat{\eta}_t^R(\tau)$ and $\hat{\eta}_{tt}^F(\tau)$ for each $\tau = 1, 2....99$ and each date $t \in [0,T]$, where T is the last date of the sample period. The series of estimated residuals is the historical sequence of "shocks" hitting each quantile of GDP growth and the *FS* indicator. Note that these are shocks to the entire distribution of these variables at each date t, quantile by quantile.

Denote with $GDPGQ_{T+H}(\tau)$ the quantile forecast at horizon $H \geq 0$. For any given *H*, we construct a time series of *stressed* quantiles by adding the series of estimated residuals $\hat{\eta}_t^R(\tau)$ and $\hat{\eta}_{tt}^F(\tau)$ for each quantile $\tau = 1, 2....99$ and each date $t \in [0,T]$ to the quantile forecasts at horizon *H.* Thus, these *stressed* quantile series are defined as:

$$SGDPGQ_{T+H,t}(\tau) = GDPGQ_{T+H}(\tau) + \eta_t^R(\tau) \qquad (17)$$

$$SFSQ_{T+H,t}(\tau) = FSQ_{T+H}(\tau) + \eta_t^F(\tau) \qquad (18)$$

Equations (17)-(18) measure what the current quantile forecasts at horizon *H* would be if they would be subject to the entire set of (*unexpected*) shocks to each quantile experienced at a given date *t* during the sample period.

The comparison between *stressed* densities for a given shock date *t* constructed on the basis of (17)-(18) and in-sample estimates at date *t* is what we term a *reduced-form* stress test. These tests can be equivalently viewed as a *historical* simulation. The stress test is *reduced-form,* since the "historical" shocks are not *identified* in the sense of being interpretable as shocks characterizing the stochastic structure of a specific theoretical model or class of models, since a shock experienced at a particular date *t* is just super-imposed on a particular density forecast.

[9] Comparing (15)-(16) with (9)-(10), we see that the estimated residuals $\hat{\eta}_t^R(\tau)$ and $\hat{\eta}_{tt}^F(\tau)$ capture the overall variation of the impact of factors on each quantile.

However, as we will show, stress tests statistics based on these "historical" shocks are informative as early warning signals about impending real and/or financial vulnerabilities.

One metric to evaluate the results of a stress test is constructed as follows. Note that for any value of $\tau \in (0,1)$, *stressed GDPaR* ($SGDPaR_t$) is $-SGDPGQ_{T+H}(\tau)$, and *stressed FSaR* (*SFSaR*) is $-SFSQ_{T+H,t}(\tau)$. Thus, for any given $\tau \in (0,1)$, *stressed* expected shortfalls are:

$$SGDPES_{T+H,t}(\tau) = -\mathrm{E}_t(GDPG_t \mid GDPG_t \leq SGDPaR_t(\tau)) \quad (19)$$

$$SFSES_{T+H,t}(\tau) = -\mathrm{E}_t(FS_t \mid FS_t \leq SFSaR_t(\tau)) \quad (20)$$

To compare these stressed shortfalls to the historical shortfalls, we define the *Expected Shortfall Stress-Test Deviation* (*ESSTD*) for any given $\tau \in (0,1)$ at each date as:

$$\Delta GDPES_t(\tau) = SGDPGES_{T+H,t}(\tau) - GDPES_t(\tau) \quad (21)$$

$$\Delta FSES_t(\tau) = SFSES_{T+H,t}(\tau) - FSES_t(\tau) \quad (22)$$

Equations (21) and (22) summarize the result of a stress test in terms of deviations of the stressed density from the historical density, evaluated for each date and each quantile. A positive (negative) deviation would indicate that stressed expected shortfalls are larger (smaller) than the historical estimate, signaling higher (lower) risk for each given quantile.

A summary statistics of these deviations is obtained by averaging deviations through time and reporting them for each quantile. This provides a natural risk metric to evaluate whether systemic risks at a current date are higher or lower *relative* to the historical experience. In our implementation of the model described below, we illustrate an example of the use of this risk metric.

B. Structural Stress Testing

To measure how systemic risk indicators respond to structural shocks in the economy, we use impulse responses to identified structural shocks through the FAVAR. These impulse responses can be viewed as an ideal vehicle to set up *stress test scenarios* for systemic risk indicators. Structural shocks derived from specific implications of theoretical models give economic content to the stress test in terms of their nature (technology, demand, etc.) and their possible source and their propagation. For these reasons, we term such stress testing procedure *structural*.

Structural stress testing is carried out in two stages: (a) identification; and (b) analysis of the sensitivity of impulse responses and variance decompositions of systemic risk indicators to different configurations of structural shocks.

Identification

As detailed in Stock and Watson (2005), we can obtain impulse responses of "factors" to their orthogonalized innovations obtained through the Factor VAR in equation (6). In turn, we can translate them into impulse responses of the quantiles of indicators of systemic risk via the estimated coefficients of the quantile regressions. This procedure is briefly explained as follows.

Inverting (6) yields the Moving Average (MA) representation of the factor VAR :

$$F_t = A(L)\eta_t \qquad \text{(6a),}$$

where $A(L) = (1-\Phi(L)L)^{-1}G$. Substituting (6a) in (7) and (8), we obtain:

$$GDPG_t = B^R(L)\eta_{t-1} + w_t^1 \qquad \text{(7a),}$$

$$FS_t = B^F(L)\eta_{t-1} + w_t^2 \qquad \text{(8a),}$$

where $B^R(L) = (1-\gamma_R(L)L)^{-1}\Lambda^{R\prime}A(L)$, $B^F(L) = (1-\gamma_F(L)L)^{-1}\Lambda^{F\prime}A(L)$, $w_t^1 = (1-\gamma_R(L)L)^{-1}u_t^1$ and $w_t^2 = (1-\gamma_F(L)L)^{-1}u_t^2$.

Likewise, quantiles (9) and (10) can be expressed as:

$$GDPGQ_t(\tau) = B^R(\tau)(L)\eta_{t-1} \qquad \text{(9a),}$$

$$FSQ_t(\tau) = B^F(\tau)(L)\eta_{t-1} \qquad \text{(10a),}$$

where $B^R(\tau)(L) = (1-\gamma_R^\tau(L)L)^{-1}\Lambda_\tau^{R\prime}A(L)$, $B^F(\tau)(L) = (1-\gamma_F^\tau(L)L)^{-1}\Lambda_\tau^{F\prime}A(L)$.

Structural identification in the DFM can be conducted using a variety of methods, as described in Stock and Watson (2005). However, our preferred identification strategy is based on the sign restriction methodology introduced by Canova and De Nicolò (2002). This strategy allows us to use in an informative way the implications of different theoretical constructs, as outlined next.

Note that orthogonal innovations extracted from the FAVAR do not have any "economic" interpretation, although they have the useful property of being contemporaneously and serially uncorrelated. These orthogonal innovations can be identified as economically interpretable *structural* shocks if the impulse responses of sets of observable variables to these innovations satisfy certain sign restrictions dictated by a model of class of models. As detailed in Canova (Ch. 4, 2007), identification through sign restrictions can be carried out through a variety of linearized DGSE models that have a VAR representation, and are also implementable in the context of Bayesian VARs (see Del Negro and Schorfheide, 2010). In practice, a theoretical model will impose sign restrictions on the responses of certain variables in equation (5) to shocks to factors. If the responses of these variables to a given orthogonalized shock from the factor VAR in equation (6) match the set of sign restrictions implied by the model, then this shock will be identified.

In this paper we adopt a variant of the procedure implemented by Canova and De Nicolò (2002), since the sign restrictions we consider are derived from *both* aggregate dynamic macroeconomic theory and a simple banking model.

The theoretical restrictions implied by a large class of 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.

To examine the implications of these theoretical responses for the demand and supply of bank credit, we use the simple partial equilibrium model in Boyd, De Nicolò and Loukoianova (2009). In this model, aggregate shocks can have an impact on both borrowers' demand for bank credit and banks' supply of funding.

The theoretical restrictions on the responses of bank credit growth and changes in loan rates implied by this banking model 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 the signs of these responses all 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 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 a partial equilibrium banking model:

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

Thus, identification of structural shocks is 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.

Impulse Responses as Stress Testing Devices

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 set of structural shocks provide a measure of changes in the *resilience* of an economy to these shocks. The responses of observable variables to structural shocks can be used to detect which sectors of the economy are most sensitive to a particular structural shock.

V. IMPLEMENTATION: ESTIMATION AND FORECASTING

Our modeling procedure is implemented using quarterly macroeconomic and financial series for the G-7 economies for the period 1980Q1-2010Q1. All series are taken from Datastream.

For each country, the vector of quarterly series X_t in equation (1) includes about 95 series, which are detailed in the Appendix. These series 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 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.

As shown in Table 1, there are significant variations in the first two moments of GDP growth and the *FS* indicator across countries. Two facts are worth noticing. First, 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 significantly different from zero 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. As per the last column of Table 1, note that the contemporaneous correlation between *GDPG* and *FS* is very small in five out of seven countries, being significantly positive only for the U.K. and Germany.

A. Estimation

We estimated static factors of each variable by principal components according to the procedures described in Stock and Watson (2002 and 2005), and chose their number and the lags according to the selection criterion described previously. This criterion selected only one lag for each country, and between 7 and 9 static factors depending on a country dataset. [10] We used these estimated factors as independent variables of quantile regressions specified with one lag. The resulting density estimates were used to obtain fitted values and forecasts of our systemic risk indicators.

Table 2 reports basic descriptive statistics of the systemic risk indicators at 10 percent probability ($\tau = 0.10$). As in Table 1, ranges as well as volatilities of both types of indicators differ markedly across countries, suggesting differential sensitivities of indicators of tail risk to underlying shocks. In addition, ranges and volatilities of expected shortfall measures all significantly higher than VaR measures. This indicates that VaR measures might not capture the actual extent of potential tail real and financial losses exactly when such assessment is needed most, namely, when adverse tail realizations are large. This evidence further reinforces the preference of expected shortfall measures over VaR measures as systemic risk indicators.

[10] As a cross-check, we also estimated the number of factors using the Bai and Ng (2002) criterions as applied to equation (2), obtaining a similar number of static factors for each country dataset.

B. Forecasting and Forecast Evaluation

As detailed in the previous section, density forecasts and systemic risk indicators eight quarters ahead were obtained projecting forward the factors through the VAR of equation (6) with all data available as of June 30, 2009, that is, at end-2010Q2.[11]

To illustrate, Figure 1 depicts density forecasts of GDP growth and the FS indicator for 2010Q3, compared to those estimated in the quarter including Lehman's collapse (2008Q3). Observe the fat left tail for both indicators in 2008Q3 (blue curve), compared to the current forecast (red curve).

Figure 1

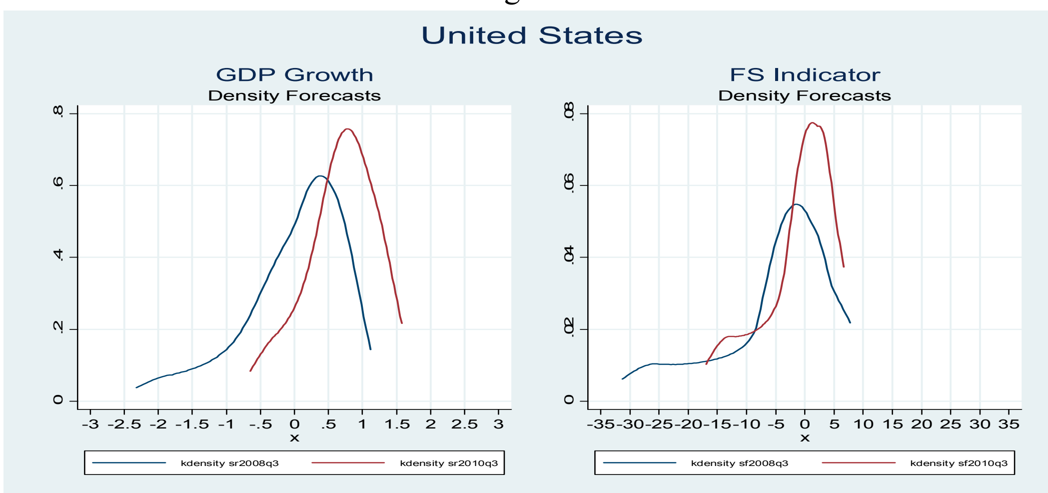

Figure 2 reports time series of estimated expected shortfalls for GDP growth and the FS indicator, and relevant forecasts as of 2010Q1 for the U.S., as measured by *GDPES* and *FSES* series at 20 and 5 percent probability levels. The forecasts of ES indicators at 20 and 5 percent probability depict *systemic risk fan charts*, which compactly summarize the range of expected tail real and financial prospects for a given probability range.

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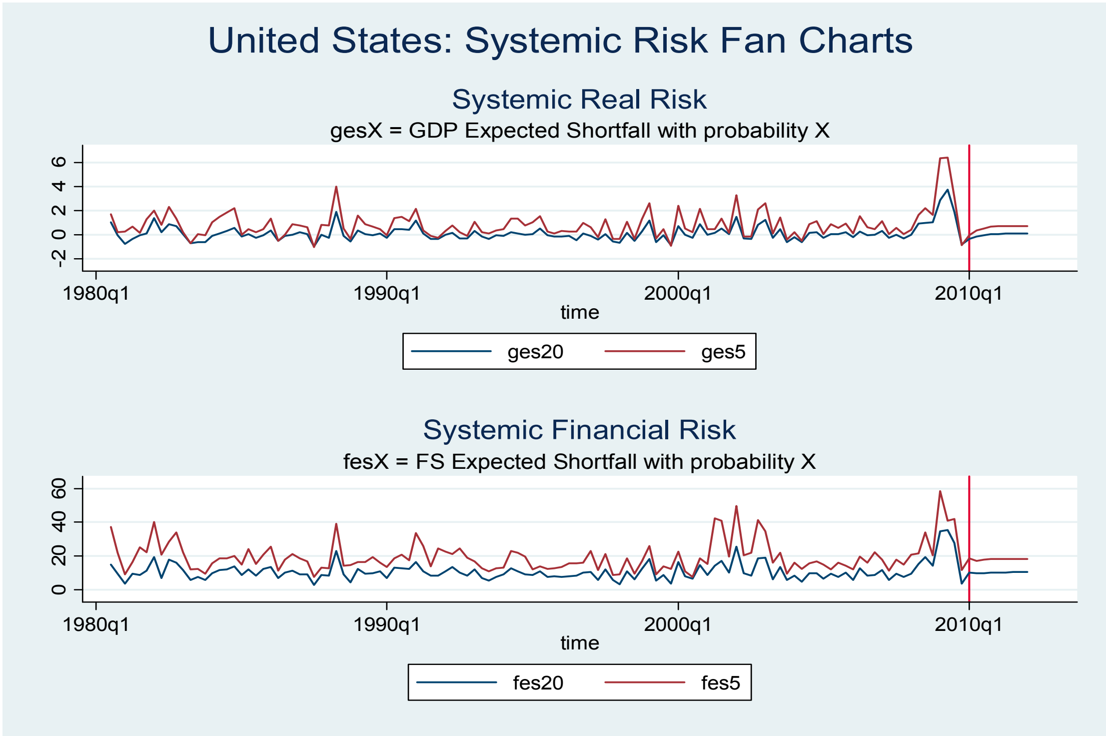
[11] Note, that in 2010Q2 actual real GDP was available only up to 2010Q1. Therefore, the first effective forecast date for the systemic real risk indicator is 2010Q2, and the estimated 2010Q2 GDP growth is a "nowcast".

Figure 2



Note that spikes in *GDPES* correspond to every recession episode, but their magnitude differs across episodes, with the spike in 2008Q4-2009Q1 being the largest experienced since the 1980s. Interestingly, spikes in *FSES* do not necessarily match spikes in *GDPES*, suggesting that the co-movements in the left tails of real activity and financial stress are time-varying and more complex than commonly believed. Perhaps most importantly, the *difference* between ES indicators at 5 percent and 20 percent probability track changes in the expected shortfalls associated with changes of the *size (or fatness) of the left tail*. Indeed, the size of the left tail increases at each spike, and the extent to which that occurs indicates that expected shortfalls are time-varying, and differ markedly for real activity and financial stress. These observations apply as well to the systemic risk fan charts of the other six countries reported in Appendix Figure Set 1.

Forecast Evaluation

We evaluate the accuracy of density forecasts both in-sample and out-of-sample. By implication, this evaluation is a test of the forecasting performance of our systemic risk indicators. We conduct this evaluation applying standard tests proposed in the literature and adapted to our model. Recall that our systemic risk indicators are constructed on the basis of full density estimates. Assessing the quality of forecasts therefore amounts to assessing whether the estimated density is "close" to the true unobserved density (for a survey of tests of accuracy of density forecasts, see Corradi and Swanson, 2006).

As shown in Diebold, Gunther and Rey (1998), a series of estimated quantiles accurately captures the actual distribution of a variable X_t if the series of Probability Integral Transforms (PIT) z_t, defined as the series of quantiles of the probability distribution that correspond to each observation in X_t, satisfies two properties: a) the series z_t is identically and independently distributed (*independence)*, and b) the series z_t is distributed uniformly over the unit interval (*uniformity).* To test these properties, we constructed PITs for both our real activity and FS indicators for each of the seven countries.

To check independence, we tested whether autocorrelations of these series up to eight lags were significantly different from 0 for each of the seven countries. We found that for all countries and both indicators these autocorrelations are not significantly different from 0 at standard confidence levels, suggesting that our model generates PITs consistent with the independence property.

To check uniformity, we followed Diebold, Gunther and Rey's (1998) suggestion to compare graphically our density estimates to a uniform density on the unit interval, and compute confidence intervals under the null of i.i.d. uniform distribution, decile by decile. For all countries, we found that uniformity was satisfied for most deciles, with few exceptions either in the tails or in the middle deciles. Overall, this evidence suggests that the quality of our density estimates is satisfactory, although there is room for improvements especially in the uniformity dimension.

A more fundamental set of tests concerns an assessment of densities' *in-sample* fit and, most importantly, their *out-of sample* fit. This latter test ultimately gauges the usefulness of our model as a risk monitoring tool. Given the relatively low number of observations in our application, we resorted to non-parametric methods. Specifically, we used standard "goodness-of-fit" test for categorical data based on the Pearson's Q statistics. For small samples, the

Pearson's Q statistics is approximately distributed as a chi-square with *k-1* degrees of freedom, where *k* is the number of categories or partitions of the data.[12]

To test in-sample fit, we partitioned the unit interval in regions delimited by two specific quantile ranges, where we used (in-sample) quantile estimates. The first partition includes 4 regions delimited by the estimated quantiles: [<Q5,Q5-Q10,Q10-Q20,>Q20]. This partition is designed to test whether the fraction of actual realizations of *GDPG* and *FS* are close to the *left-tail* of the actual (unobserved) distribution. A perfect matching of the estimated and the actual distribution would result in 5 percent of observations falling in the first region (<Q5), 5 percent in the second region (Q5-Q10), 10 percent in the third region (Q10-Q20), and 20 percent in the fourth region. In this case, a Q statistics not greater than the .95 percentile of the chi-square distribution with 3 degrees of freedom (equal to 7.815) would lead to not reject (or to accept) the null that the fit is good. The second partition includes 6 regions delimited by the estimated quantiles: [<Q10,Q10-Q25,Q25-Q50,Q50-Q75,Q75-Q90,>Q90]. This partition is designed to test whether the fraction of actual realizations of *GDPG* and *FS* are close to the entire actual (unobserved) distribution. A perfect matching of the estimated and the actual distribution would result in 10 percent of observations falling in the first region (<Q10) and the last region (>Q90), 15 percent in regions Q10-Q25 and Q75-Q90, and 25 percent in regions Q25-Q50 and Q50-Q75. In this case, a Q statistics not greater than the .95 percentile of the chi-square distribution with 5 degrees of freedom (equal to 11.07) would lead to accept the null that the fit is good.

As illustrated in Table 3, the tests of in-sample goodness of fit show that for *all* countries, for *both* real and financial indicators, and for *both tests* for the tail and the entire distribution, the model delivers (in-sample) density estimates with a good fit.

To assess out-of sample fit, the limited number of observations compelled us to limit the partition of the unit interval into two regions: [<Q20,>Q20]. Thus, our tests focus on out-of-sample goodness of fit on the left-tail. We considered four forecasting horizons, from one quarter to four quarters ahead. Recursive forecasts of quantiles were computed in "simulated" real-time, starting in 1999Q1. In each forecasting quarter, up to quarter 2008Q4, we re-

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[12] For details on these tests, see for example De Groot and Schervish (2002). For a review of applications in financial risk management, see Campbell (2005).

estimated the entire model using only observations up to that quarter, but kept the selection of the number of factors and lags fixed. In this case, a Q statistics not greater than the .95 percentile of the chi-square distribution with one degree of freedom (equal to 3.84) would lead to accept the null that the prediction is accurate.[13]

As shown in Table 4, out-of sample predictions are generally satisfactory. For two countries, the U.S. and the U.K., predictions are good for both variables and all forecasting horizons. For *GDPG*, there is only one rejection at some horizon for Canada, Japan and France, and two for Italy. By contrast, there is only one rejection for *FS* (Germany).

Overall, the fit of our density forecasts, both in-sample and out-of-sample, provide support for the ability of our systemic risk indicators to forecast actual systemic real and financial risk realizations satisfactorily.

VI. Implementing Stress Testing

We illustrate our stress-testing procedures with real-time simulations. These tests gauge whether the model generates early warning signals of enhanced systemic risks. In essence, these tests can be viewed as a risk monitoring tool complementary to the forecasts of systemic risk indicators, as summarized, for example, by the systemic risk charts.

We report perhaps the most demanding evaluation of the model's ability to serve as a risk monitoring tool: we assess if the model signals increased systemic risks *prior* to historical declines in real activity and increased financial stress during certain periods of the 2007-2008 crisis.

A. An Example of Reduced-Form Stress Testing

After a surge experienced in March 2008, during the entire second quarter of 2008 most financial risk indicators (such as CDS spreads) in advanced economies returned to levels witnessed on the onset of the crisis in the summer of 2007 (see BIS, 2008, pp.1-2). On the real side, global growth was projected to slow down moderately, with the U.S. predicted to "tip into

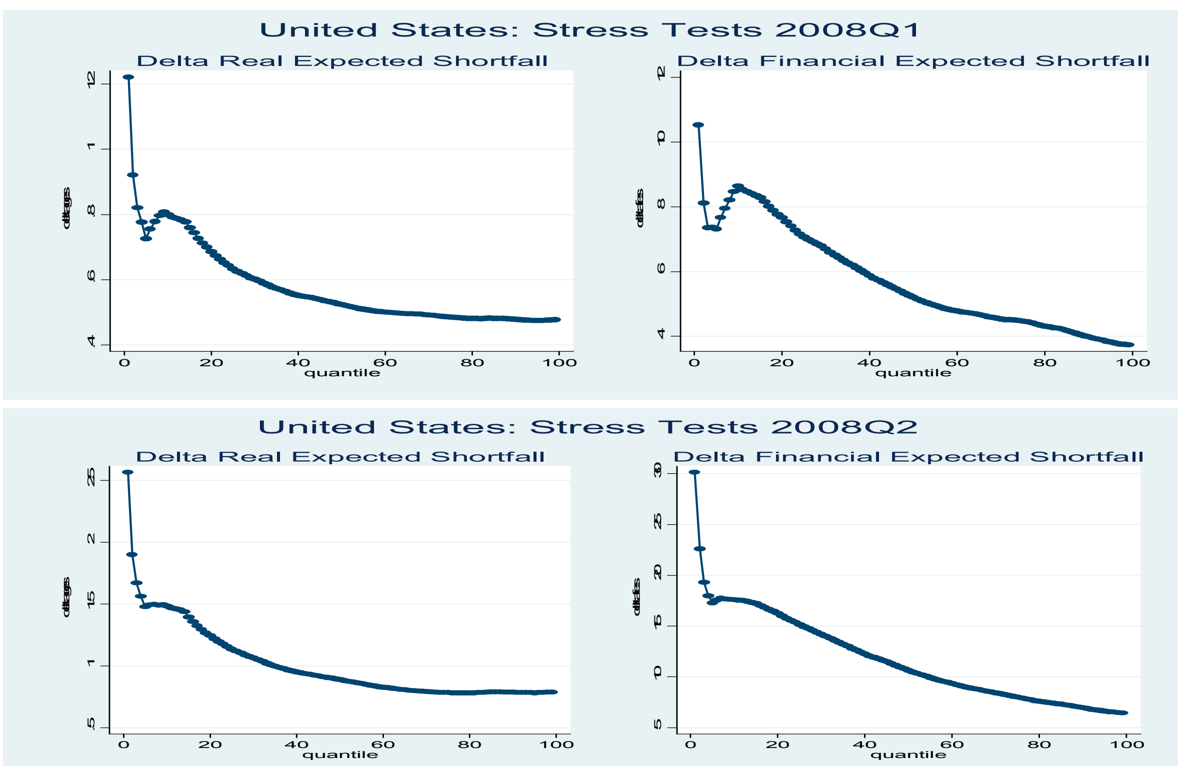
[13] Following West (2006), we plan to implement alternative forecasting schemes based on rolling windows to check whether out-of-sample forecasting accuracy could be improved by capturing time variation in estimated parameters.

a mild recession in 2008.....before starting a modest recovery in 2009" (IMF World Economic Outlook, 2008, Executive Summary, p. XV). In sum, as of the end of the second quarter of 2008, the substantial ease in risk indicators in the financial sector suggested a decline in systemic financial risk, whereas growth prospects, although revised downward, were not generally judged as implying imminent systemic real risk.

By contrast, a very different picture would have emerged from reduced-form stress tests conducted at that time. Recall that a *positive* (negative) *ESSTD* indicates expected shortfalls *larger* (smaller) than those of the distribution of reference, indicating higher vulnerability. When the positive (negative) values of the *ESSTD* concentrate on the lower quartiles, this is an indication of higher (lower) systemic risk.

Using only data available as of end of the first and second quarter of 2008, Figure 3 illustrates for the U.S. the *average ESSTD* for GDP growth and the FS indicator *at each quantile* for the entire sequence of shocks experienced since 1980Q1, applied to the quantile estimates in 2008Q1, and a quarter later, in 2008Q2.

Figure 3



Note that the 2008Q2 average *ESSTD* for GDP growth is about *double* the size of that in 2008Q1 across *all* quantiles, but particularly for the lowest 20 quantiles. Similarly, the 2008Q2

ESSTD for the FS indicator is almost *three times larger* than that recorded in 2008Q1 for all quantiles, but again, the difference is greater for the lowest 20 quantiles. Similar patterns are recorded for Japan, Germany and France, as shown in Figure Set 2 in the Appendix.

Thus, these stress tests would have given strong early warnings of systemic real and financial risks also in 2008Q2, when such warnings could not be inferred by looking simply at market developments and real data releases. As it is well known, what happened in 2008Q3-Q4 confirmed the prediction of heightened systemic real and financial risks. We view these results as evidence of the ability of reduced-form stress tests to serve as a useful risk monitoring tool.

B. Structural Stress Testing

Assessing to what extent real and financial sectors are primarily hit by common shocks, or spillovers from one sector to the other dominate is important, especially during periods of both real and financial instability. Whether the 2007-2008 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 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.

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 started to decelerate in September 2008. This may suggest that the contraction in bank lending growth reflects primarily the sharp decline in the demand for bank credit resulting from the severe contraction in consumption growth and investment.[14] Identification is essential to address these issues.

[14] 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 (2010).

Identification

Recall that the number of static factors estimated for each country dataset ranges from seven to nine. Given the relatively short time dimension of our dataset, we restricted the number of factors in the VAR of equation (3) to be equal to the number of dynamic factors estimated as principal components of the residuals of each variable in equation (7) and (8). We estimated five dynamic factors for the U.S., and between 4 and 6 dynamic factors for the other countries. For simplicity, for each country dataset we treated the first five estimated static factors as equal to the number of dynamic factors, essentially assuming $F_t = f_t$, so that in equation (8) $G = I$.

The identification procedure outlined previously was implemented following three steps. First, we selected an orthogonal decomposition of the MA representation (9a). Second, for each country, we computed impulse responses of FAVARs for GDP Growth, Inflation, Bank Lending Growth and first differences in Loan Rates.[15] Lastly, we checked whether the joint signs of the responses of these variables conformed to the signs predicted for different shocks by the basic macroeconomic and banking models summarized in Table A.

As a benchmark orthogonalization, we chose 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, these covariance matrices are approximately diagonal: this suggests that our results may be robust to other orthogonal decompositions— not

[15] Recall that these FAVARs involve nine variables: the selected five factors plus the four observable variables used for identification

necessarily recursive—that can be extracted applying the systematic statistical search implemented by Canova and De Nicolò (2002).

Figure Set 3 in the Appendix 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 non negative (in few cases).[16] Hence, according to Table A, *under the assumed 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 consistent with 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 non-recursive orthogonalizations of the VAR of each country. Our results are also consistent with recent work by Arouba and Diebold (2010), who find demand shocks as the dominant source of aggregate fluctuations in the U.S.

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 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 detailed evidence by Berrospide and Edge (2010) for the U.S. is consistent with our results. [17]

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 4, the variance decompositions

[16] 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 A, and thus results unidentified under the chosen decomposition.

[17] Interestingly, similar results are obtained by Bherens, Corcos and Mion (2010) with regard to international trade patterns.

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.[18]

Similar results are obtained when we look at the impulse responses and variance decompositions of *GDPES* and *FSES* measures. As shown in Figure Set 2, the sign of the impact of each shock on *GDPES* and FSES is qualitatively very similar in each country, although magnitude and persistence of these shocks differ markedly. As shown in Table 5, the relevant variance decompositions indicate the importance of each of the identified shocks for the systemic risk indicators in each country, as these decompositions are significant in magnitude for each shock.

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 appears robust to alternative sets of orthogonal innovations in the FAVAR.

An Example of Structural Stress Testing

Recall that a *stress-test* is the impulse response of the density function of the indicators of real and financial activity to a particular selection of structural shocks. Changes in the impulse response function of the density of our real and financial indicators to given sizes of structural shocks, or comparisons of impulse responses at different point in time, can give a measure of resilience of the real and financial sides of the economy.

We illustrate this stress-testing procedure with a simple example. Specifically, we gauge weather our stress tests signal lower resilience to structural shocks in the G-7 economies *prior* to the 2007Q3, which is the quarter during which the 2007-2008 crisis began.

Table 7 shows the *difference* of the cumulative impact of the impulse response functions of *GDPES* and *FSES* to each structural shock up to 8 quarters estimated for the whole sample period before the crisis (1980Q1-2007Q2), and since the mid 1990s (1993Q2-2007Q2) A positive difference would indicate a larger cumulative adverse impact in the last sub-period compared to the whole sample period.

[18] These results echo the findings of an increased impact of sectoral shocks on aggregate industrial production indexes documented recently by Foerster, Sarte and Watson (2008)

This table summarizes two pieces of information that could have been useful for policymakers in 2007Q2. First, in *all* countries the first two shocks become predominant in the latest sub-period, compared with the full sample. This is true for *both GDPES* and *FSES* indicators. This can be viewed as a signal of increased risk concentrations in these economies on both the real and financial sides. Second, the U.S. economy is the only country that exhibits a *positive* difference in the cumulative impact of impulse responses for both *GDPES* and *FSES* indicators. In 2007Q2, this signaled that the U.S. economy had increased its vulnerability to shocks both on the real and financial sides, in absolute terms as well as relative to the other G-7 economies.

Structural stress testing can be also designed to detect where identified structural shocks are likely to originate, and to which other sectors of the economy they are transmitted. This can be accomplished using impulse responses and variance decompositions of selected key observable variables. In terms of Figure A of the introduction, we can associate certain observable variables to each box. The size of the impulse response of these observable variables at impact may indicate where a particular shock hits most severely, and such a shock is transmitted between "boxes". Tracing these impulse responses across variables in each box may provide a *risk map* at a point in time. Comparisons of risk maps at different points in time can be useful to gauge how the sensitivity of an economy to given structural shock evolves. Detailing these risk maps and designing structural stress tests as comparisons of risk maps across time is our work in progress.

VII. Conclusion

Building on our previous effort, this paper has presented a modeling framework that can be used as a positive tool as well as a *systemic risk monitoring system* implementable in real time. The model delivers real-time density forecasts of indicators of real activity and financial health, and systemic real and financial risk indicators constructed on these density forecasts. In addition, the proposed stress testing procedures make it feasible to gauge the resilience of the real and financial sectors of economies to systemic risk realizations, measured by the sensitivity of the systemic risk indicators to both reduced-form and structural shocks.

We believe that further developments and extensions of this modeling framework are likely to yield increasing returns. The model 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 an increasingly powerful monitoring tool available to policy-makers.

Two developments are already part of our research agenda. The first is an extension of our framework to the simultaneous modeling of countries and regions of the world. This would allow us to expand the set of positive questions that the model can address, and provide risk monitoring tools of systemic risk interdependencies across countries. The second development would use more disaggregated data, together with a richer set of theoretical constructs as identification tools, to construct more detailed risk maps.

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Tables and Figures

Table 1. Descriptive Statistics of Real GDP Growth (GDPG) and the Financial Stress Indicator (FS)
(Significance at 5% confidence level in **boldface**)

	GDPG				FS				
	Mean	**Std. Dev**	**Min**	**Max**	**Mean**	**Std. Dev**	**Min**	**Max**	**corr. GDPG/FS**
United States	0.68	0.75	-2.07	2.22	-0.23	8.61	-33.50	38.34	0.11
Canada	0.62	0.77	-1.82	2.47	0.51	6.92	-17.56	25.06	-0.04
Japan	0.54	1.04	-4.30	3.11	-0.35	10.20	-29.09	56.07	0.15
U.K.	0.53	0.70	-2.64	2.17	-0.17	8.68	-38.68	19.52	**0.21**
France	0.45	0.50	-1.64	1.45	0.33	9.72	-41.30	29.16	0.15
Germany	0.32	0.72	-3.60	1.80	-0.72	6.94	-34.26	19.66	**0.37**
Italy	0.35	0.65	-2.76	2.19	-0.28	7.67	-17.69	29.27	0.02
Average	0.50	0.73	-2.69	2.20	-0.13	8.39	-30.30	31.01	0.14

Table 2. Descriptive Statistics of Systemic Risk Indicators ($\tau = 0.10$)

	REAL					FINANCIAL			
	Mean	**Std. Dev.**	**Min**	**Max**		**Mean**	**Std. Dev.**	**Min**	**Max**
U. S.									
GDPaR(10)	0.07	0.62	-1.02	3.60	*FSaR(10)*	9.17	4.80	0.95	33.50
GDPES(10)	0.45	0.79	-0.87	4.66	*FSES(10)*	13.92	6.08	4.91	40.04
Canada									
GDPaR(10)	0.07	0.60	-1.05	2.79	*FSaR(10)*	7.66	2.40	0.81	17.02
GDPES(10)	0.41	0.60	-0.72	3.06	*FSES(10)*	11.28	3.23	3.96	23.36
Japan									
GDPaR(10)	0.63	0.50	-1.14	2.93	*FSaR(10)*	10.59	4.01	0.15	23.03
GDPES(10)	1.24	0.70	-0.44	3.97	*FSES(10)*	16.21	5.61	4.04	37.42
U.K									
GDPaR(10)	0.07	0.54	-0.99	2.10	*FSaR(10)*	10.21	4.84	-0.62	30.45
GDPES(10)	0.43	0.92	-6.93	2.97	*FSES(10)*	14.83	6.11	0.70	37.68
France									
GDPaR(10)	0.71	0.36	-0.70	2.22	*FSaR(10)*	9.98	4.18	-0.44	28.30
GDPES(10)	0.35	0.43	-0.48	2.65	*FSES(10)*	17.90	7.65	2.17	44.66
Germany									
GDPaR(10)	0.50	0.45	-0.26	2.87	*FSaR(10)*	7.64	2.55	1.91	15.33
GDPES(10)	0.82	0.61	-0.20	3.62	*FSES(10)*	12.30	4.82	2.75	31.13
Italy									
GDPaR(10)	0.29	0.44	-0.73	1.97	*FSaR(10)*	8.83	2.29	2.55	15.79
GDPES(10)	0.62	0.54	-0.40	3.14	*FSES(10)*	12.51	1.71	7.73	18.21

Table 3. In–Sample Goodness-of-Fit

Each column reports the fraction of observations falling in the region delimited by each estimated quantile. Significance of the Q- statistics at a 5 percent confidence level is reported in **boldface**.

Left-Tail

GDPG	**<Q5**	**Q5-Q10**	**Q10-Q20**	**>Q20**	**Qstat**
United States	2.24	2.99	11.94	72.39	**4.61**
Canada	3.73	4.48	8.21	72.39	**1.90**
Japan	2.24	5.22	9.70	73.88	**2.70**
U.K.	2.99	5.22	10.45	72.38	**2.09**
France	2.99	4.48	10.45	73.13	**1.96**
Germany	2.98	4.48	11.19	73.13	**2.14**
Italy	2.99	5.97	7.46	71.64	**3.37**
FS					
United States	3.73	4.48	8.21	73.88	**1.56**
Canada	3.73	5.22	8.96	72.39	**1.56**
Japan	2.23	5.97	7.46	72.39	**4.13**
U.K.	3.73	3.73	10.45	71.64	**2.06**
France	3.73	3.73	10.45	71.64	**2.06**
Germany	3.73	3.73	9.70	73.13	**1.66**
Italy	5.22	4.48	9.70	69.40	**1.98**

Distribution

GDPG	**<Q10**	**Q10-Q25**	**Q25-Q50**	**Q50-Q75**	**Q75-Q90**	**>Q90**	**Qstat**
United States	5.22	17.16	18.66	22.39	11.94	14.18	**8.39**
Canada	8.21	14.93	19.40	20.15	13.43	12.69	**4.23**
Japan	7.46	15.67	18.67	20.15	15.67	13.43	**5.41**
U.K.	8.21	14.18	17.91	22.39	14.93	13.43	**4.60**
France	7.46	14.93	17.16	23.13	13.43	14.18	**6.12**
Germany	7.46	15.67	21.64	20.15	12.69	12.69	**3.89**
Italy	8.96	12.69	18.66	20.90	14.93	11.19	**3.81**
FS							
United States	8.21	14.18	17.91	22.39	14.18	12.69	**4.25**
Canada	8.96	13.43	20.90	20.15	14.93	11.94	**2.87**
Japan	8.21	13.43	23.13	19.40	13.43	11.94	**3.07**
U.K.	7.46	15.67	20.15	21.64	13.43	11.19	**3.12**
France	7.46	14.18	22.39	20.15	14.18	11.19	**2.74**
Germany	7.46	15.67	21.64	20.15	11.19	11.94	**4.40**
Italy	9.70	16.42	18.66	19.40	14.93	10.45	**4.05**

Table 4. Out-of–Sample Goodness of Fit

Each column reports the Q statistics corresponding to the forecast horizon k (in quarters). Significance of the Q- statistics at a 5 percent confidence level is reported in **boldface**.

	GDPG				FS			
	k=1	k=2	k=3	k=4	k=1	k=2	k=3	k=4
U.S.	**0.03**	**2.19**	**1.14**	**3.57**	**0.43**	**2.19**	**2.19**	**0.43**
Canada	**2.19**	**2.19**	**2.19**	7.36	**2.19**	**0.33**	**0.33**	**0.03**
Japan	5.30	**1.14**	**1.14**	**1.14**	**1.14**	**1.14**	**0.43**	**0.43**
France	**2.19**	**3.57**	5.30	**1.14**	**0.06**	**0.06**	**0.03**	**0.03**
Germany	**2.19**	**1.14**	**1.14**	**1.14**	7.36	**2.19**	**0.43**	**0.43**
Italy	**1.14**	**1.14**	5.30	7.36	**0.97**	**0.97**	**1.95**	**1.95**
U.K.	**2.19**	**0.03**	**0.06**	**1.14**	**2.19**	**0.43**	**0.43**	**0.43**

Table 5. 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	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
	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
U.K	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
Germany	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

N.B.: Boldfaced values denote estimates significantly different from 0 at 5 percent confidence levels.

Table 6. Variance Decomposition of GDPES and FSES
to Identified Aggregate Demand and Bank Credit Demand Shocks

		Shock 1	Shock2	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
U.K	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

N.B.: Boldfaced values denote estimates significantly different from 0 at 5 percent confidence levels.

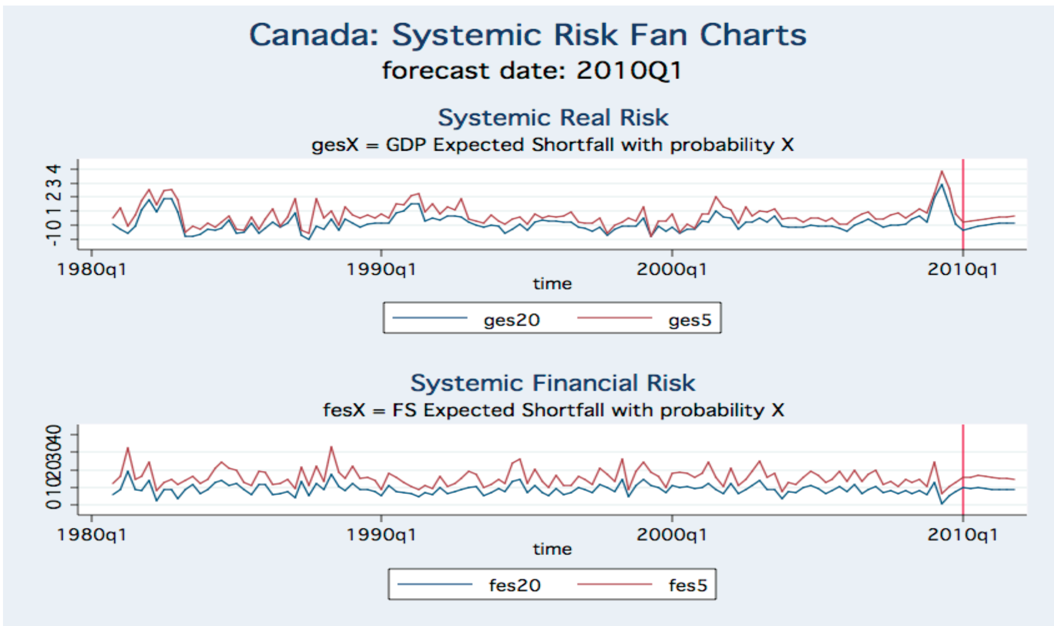
Table 7. Structural Stress Test: An Example

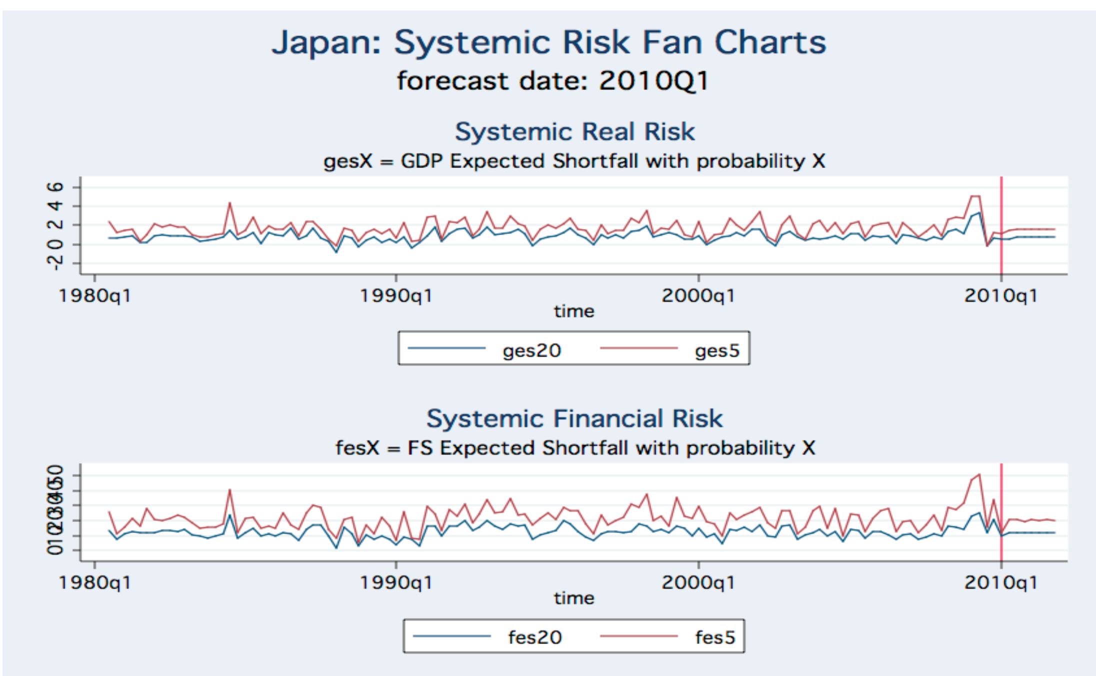
The table reports the *difference* of Impulse Response Functions (IRF) and Variance Decompositions (VD) for GDP growth (*Real*) and the FS Indicator (*Financial*) between the latest sub-sample (1993Q1-2007Q2) and the entire sample (1980Q1-2007Q2).

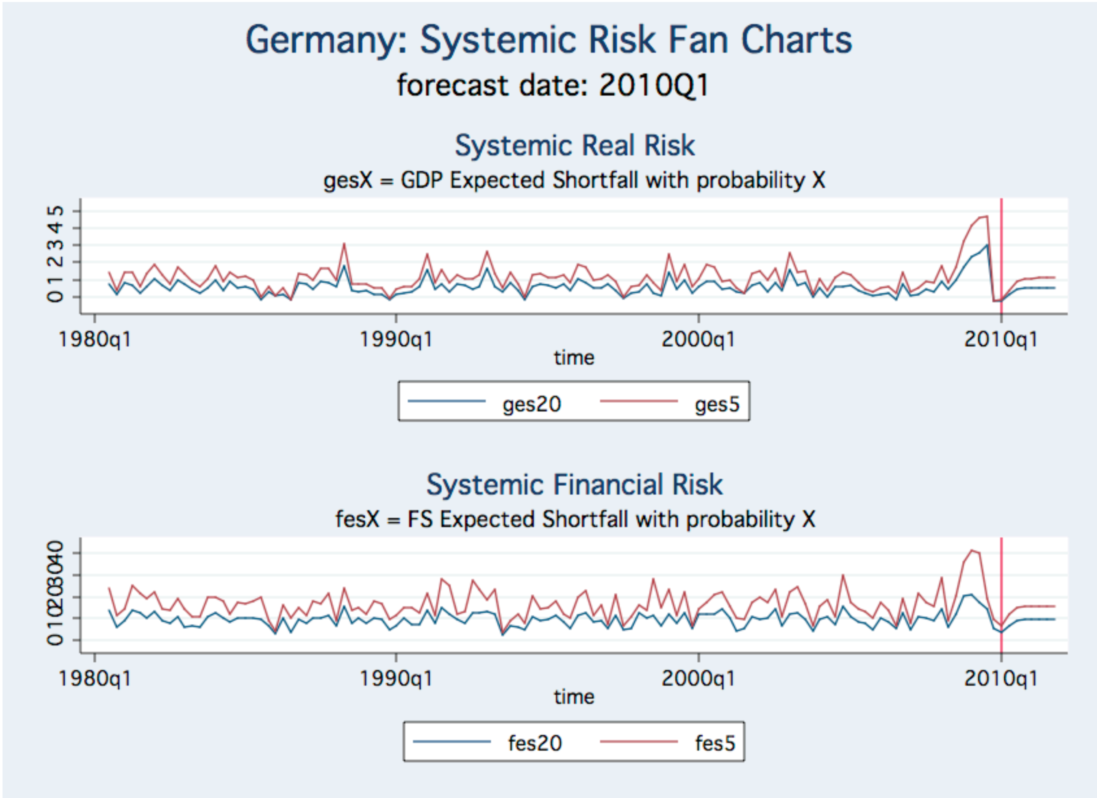
		SUM	Shock 1		Shock2		Shock 3		Shock 4		Shock 5	
		IRF*VD	*IRF*	*VD*	*IRF*	*VD*	*IRF*	*VD*	*IRF*	*VD*	*IRF*	*VD*
United States	*Real*	**0.17**	0.01	0.08	0.72	0.22	-0.98	-0.07	-0.26	-0.05	-0.78	-0.05
	Financial	**0.55**	2.99	0.01	7.60	0.13	-6.80	-0.09	-1.96	-0.04	-0.78	-0.05
Canada	*Real*	-0.15	-0.09	-0.04	0.12	0.03	-0.74	-0.01	-0.23	-0.03	-0.78	-0.05
	Financial	-0.79	-0.83	0.01	-3.03	0.16	-0.42	-0.08	-0.79	-0.04	-0.78	-0.05
Japan	*Real*	-0.09	-1.42	0.11	0.27	0.13	0.22	-0.24	0.31	0.04	-0.78	-0.05
	Financial	-0.09	-1.42	0.11	0.27	0.13	0.22	-0.24	0.31	0.04	-0.78	-0.05
U.K	*Real*	-0.38	0.31	0.09	0.45	0.15	-1.41	-0.31	-0.70	0.03	-0.78	-0.05
	Financial	-0.11	6.96	0.06	-1.38	0.14	-6.94	-0.03	-3.24	0.09	-0.78	-0.05
France	*Real*	**0.11**	0.22	0.11	0.12	0.08	-0.78	-0.09	0.22	0.19	-0.78	-0.05
	Financial	-1.11	-3.30	-0.07	-5.33	0.16	-0.36	-0.06	-0.79	-0.04	-0.78	-0.05
Germany	*Real*	-0.54	-0.73	0.07	-0.21	-0.04	-1.05	-0.17	-1.31	0.09	-0.78	-0.05
	Financial	**4.82**	-1.50	0.03	-2.54	0.04	-0.39	0.03	14.28	0.30	-0.78	-0.05
Italy	*Real*	-0.05	0.19	0.09	0.17	0.07	-0.78	-0.11	-0.43	0.01	-0.78	-0.05
	Financial	-0.08	0.10	0.00	-0.09	-0.06	2.25	-0.02	0.26	0.00	-0.78	-0.05

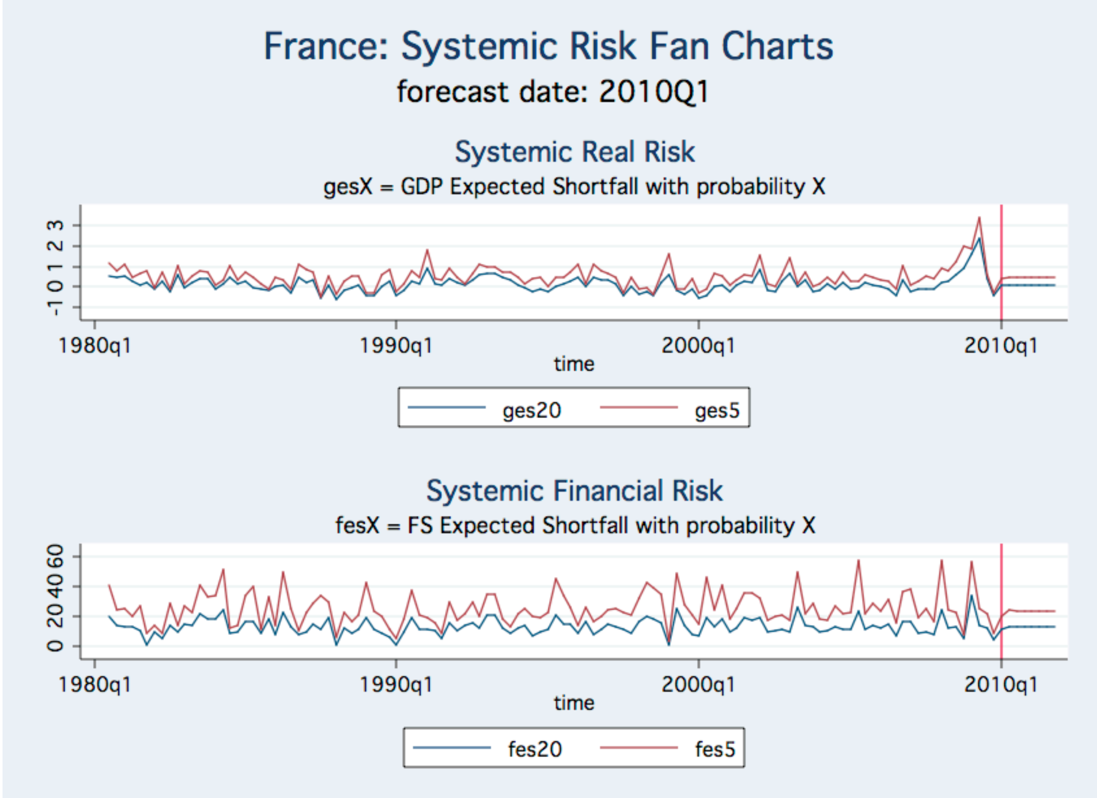
Appendix

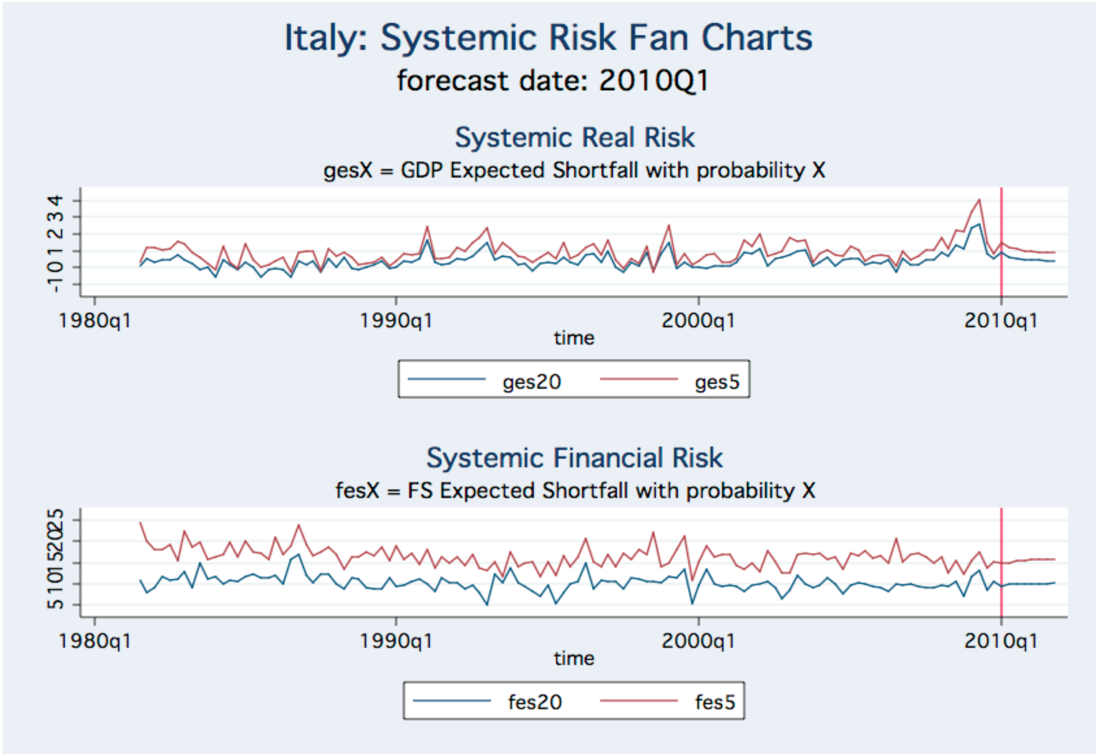
Figure Set 1. Systemic Risk Fan Charts






Germany: Systemic Risk Fan Charts
forecast date: 2010Q1
Systemic Real Risk
gesX = GDP Expected Shortfall with probability X
0 1 2 3 4 5
1980q1
1990q1
2000q1
2010q1
time
ges20
ges5
Systemic Financial Risk
fesX = FS Expected Shortfall with probability X
1980q1
1990q1
2000q1
2010q1
time
fes20
fes5


France: Systemic Risk Fan Charts
forecast date: 2010Q1
Systemic Real Risk
gesX = GDP Expected Shortfall with probability X
-1 0 1 2 3
1980q1
1990q1
2000q1
2010q1
time
ges20
ges5
Systemic Financial Risk
fesX = FS Expected Shortfall with probability X
0 20 40 60
1980q1
1990q1
2000q1
2010q1
time
fes20
fes5


Italy: Systemic Risk Fan Charts
forecast date: 2010Q1
Systemic Real Risk
gesX = GDP Expected Shortfall with probability X
-1 0 1 2 3 4
1980q1
1990q1
2000q1
2010q1
time
ges20
ges5
Systemic Financial Risk
fesX = FS Expected Shortfall with probability X
5 10 15 20 25
1980q1
1990q1
2000q1
2010q1
time
fes20
fes5

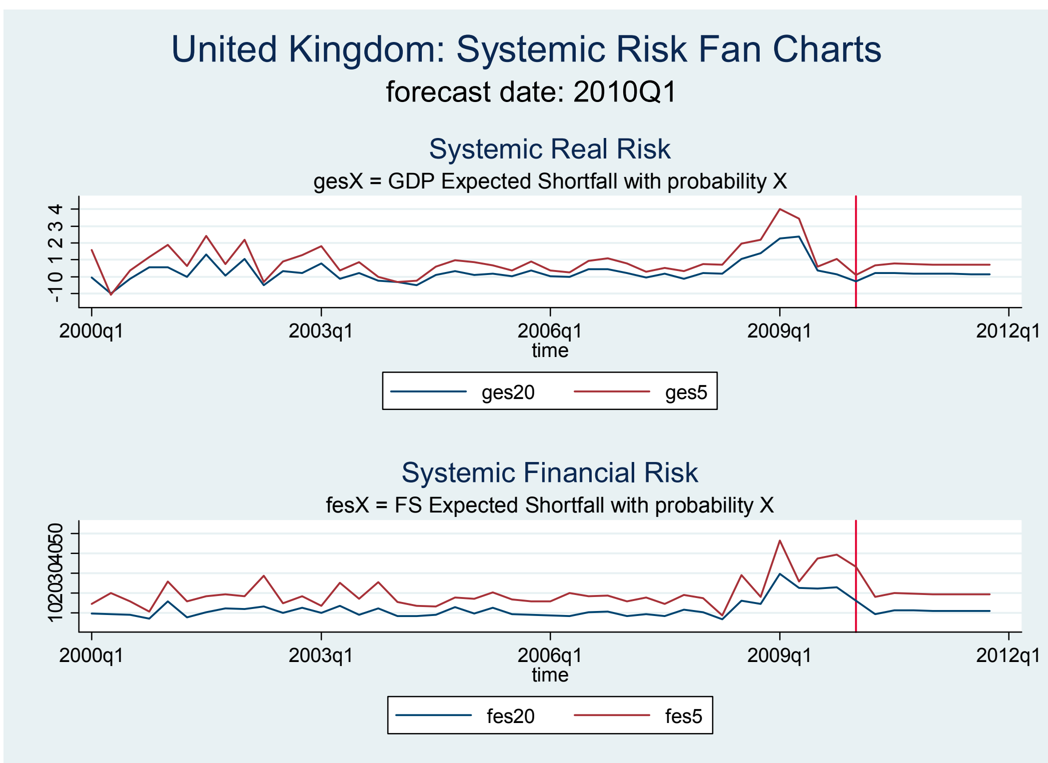
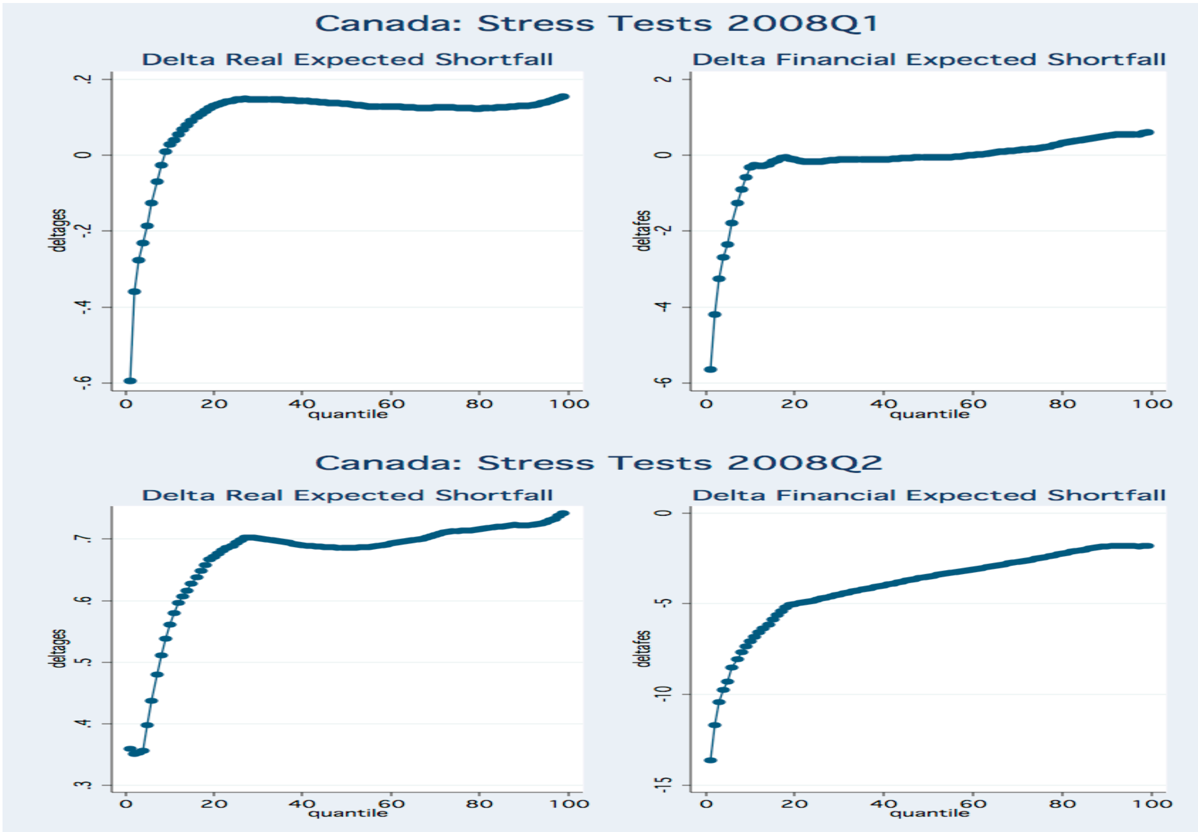
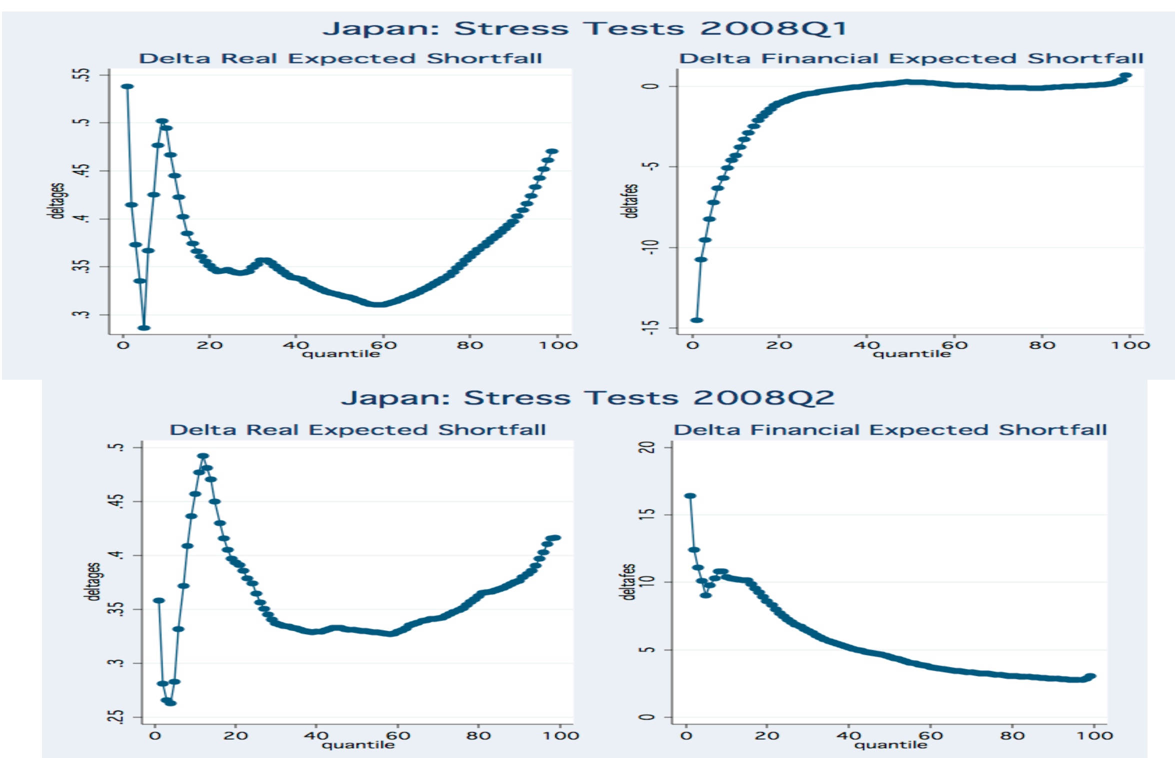
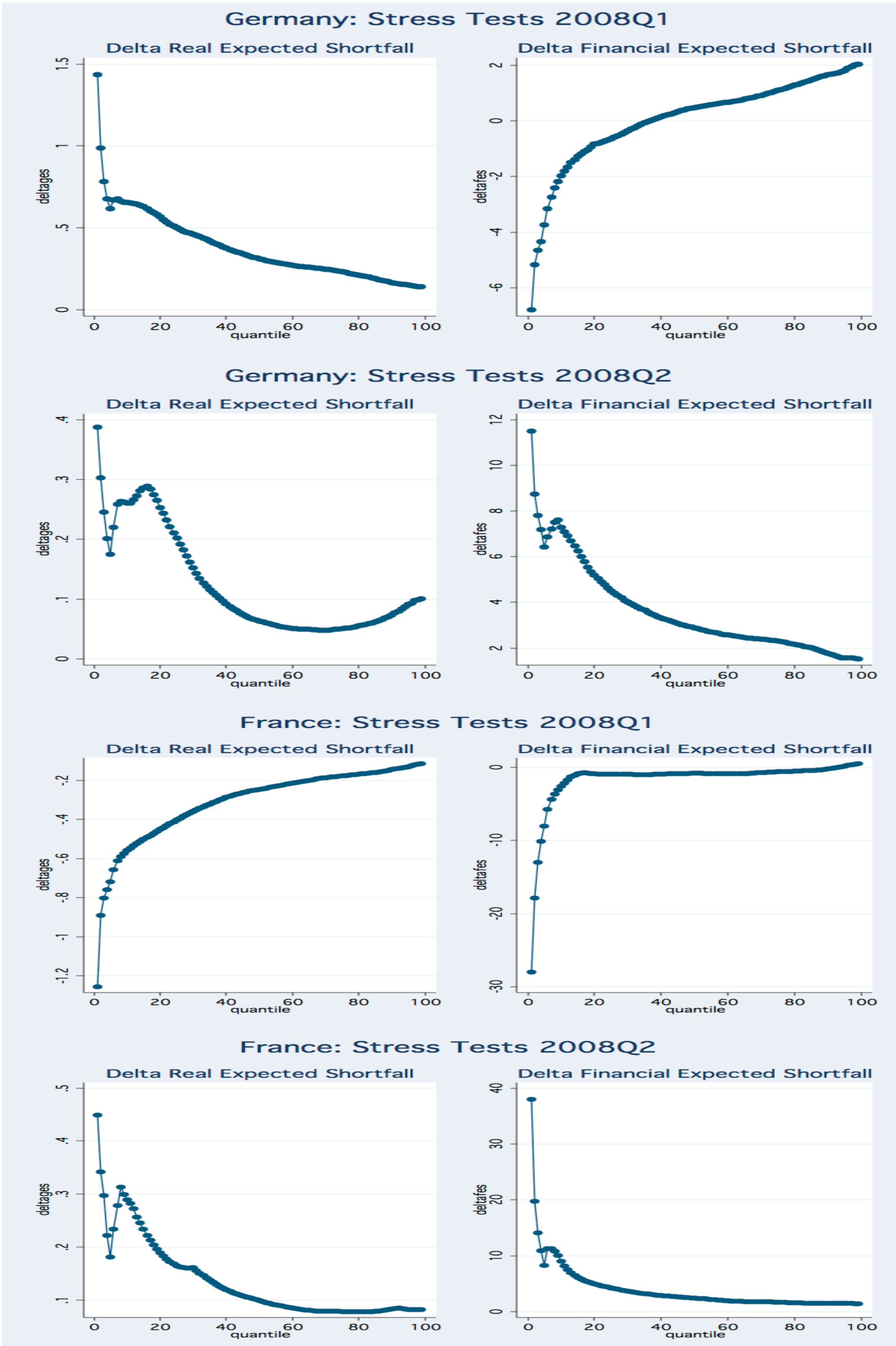

United Kingdom: Systemic Risk Fan Charts
forecast date: 2010Q1
Systemic Real Risk
gesX = GDP Expected Shortfall with probability X
-1 0 1 2 3 4
2000q1
2003q1
2006q1
2009q1
2012q1
time
ges20
ges5
Systemic Financial Risk
fesX = FS Expected Shortfall with probability X
10 20 30 40 50
2000q1
2003q1
2006q1
2009q1
2012q1
time
fes20
fes5

Figure Set 2. Reduced-Form Stress Tests






Germany: Stress Tests 2008Q1
Delta Real Expected Shortfall
Delta Financial Expected Shortfall
Germany: Stress Tests 2008Q2
Delta Real Expected Shortfall
Delta Financial Expected Shortfall
France: Stress Tests 2008Q1
Delta Real Expected Shortfall
Delta Financial Expected Shortfall
France: Stress Tests 2008Q2
Delta Real Expected Shortfall
Delta Financial Expected Shortfall
deltages
deltafes
quantile
0
20
40
60
80
100

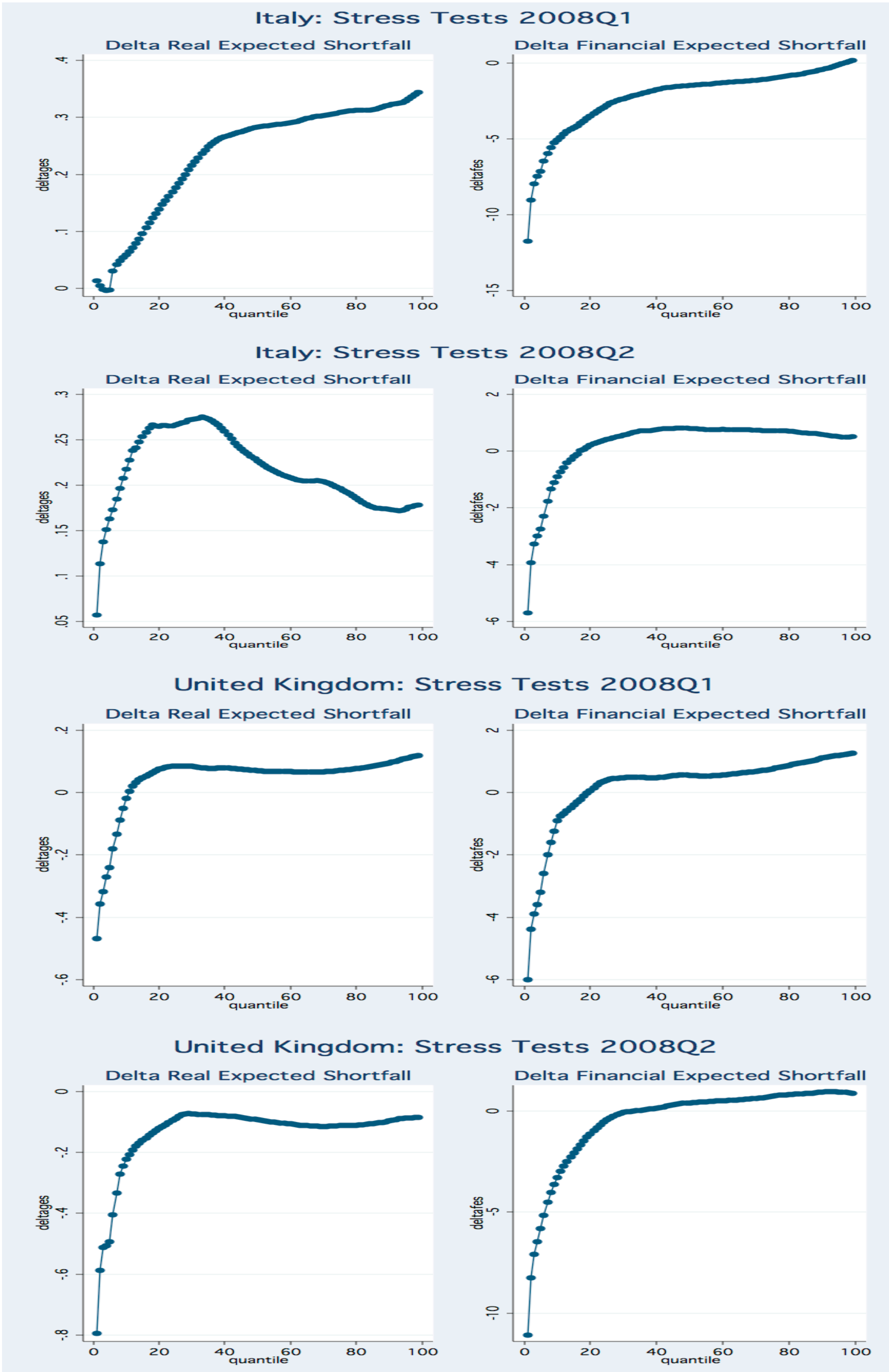
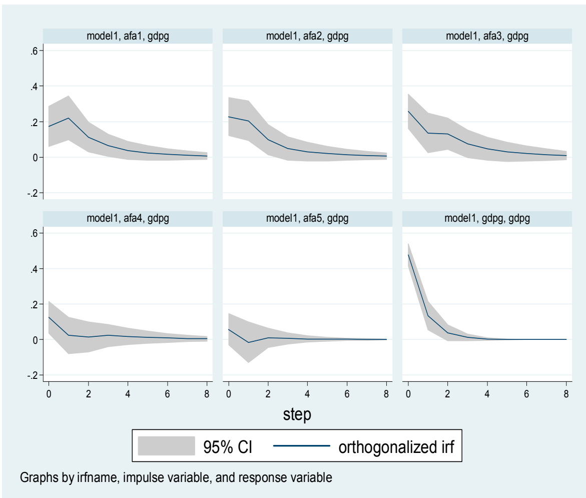

Italy: Stress Tests 2008Q1
Delta Real Expected Shortfall
deltages
0
.1
.2
.3
.4
0
20
40
60
80
100
quantile
Delta Financial Expected Shortfall
deltafes
-15
-10
-5
0
0
20
40
60
80
100
quantile
Italy: Stress Tests 2008Q2
Delta Real Expected Shortfall
deltages
.05
.1
.15
.2
.25
.3
0
20
40
60
80
100
quantile
Delta Financial Expected Shortfall
deltafes
-6
-4
-2
0
2
0
20
40
60
80
100
quantile
United Kingdom: Stress Tests 2008Q1
Delta Real Expected Shortfall
deltages
-.6
-.4
-.2
0
.2
0
20
40
60
80
100
quantile
Delta Financial Expected Shortfall
deltafes
-6
-4
-2
0
2
0
20
40
60
80
100
quantile
United Kingdom: Stress Tests 2008Q2
Delta Real Expected Shortfall
deltages
-.8
-.6
-.4
-.2
0
0
20
40
60
80
100
quantile
Delta Financial Expected Shortfall
deltafes
-10
-5
0
0
20
40
60
80
100
quantile

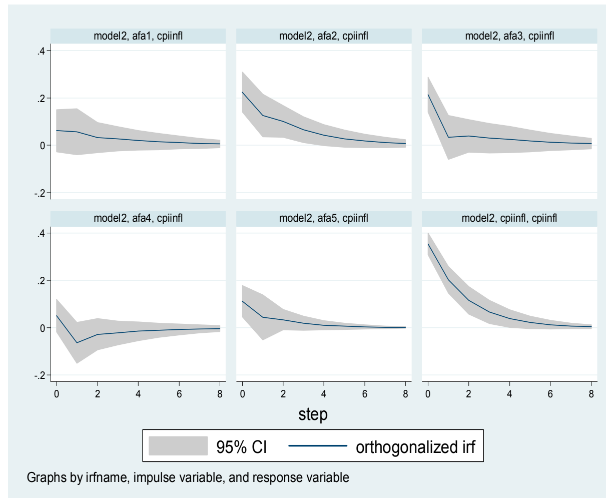
Figure Set 3. Impulse Responses of GDP Growth, Inflation, Bank Lending Growth and Change in Lending Rates to Shocks to Factors and Own Shock

United States

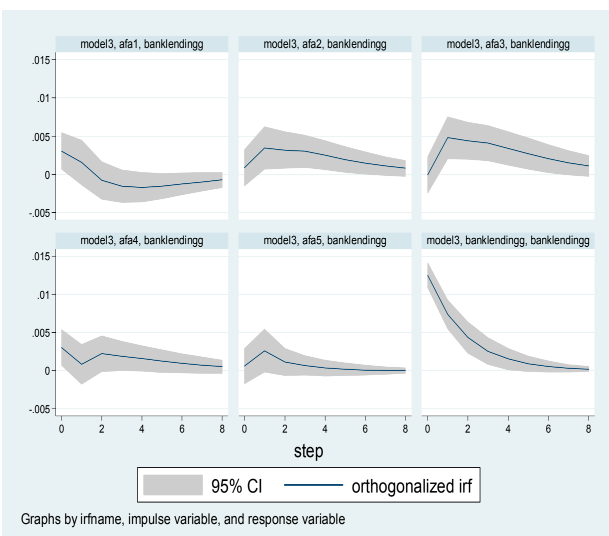
GDP Growth



Inflation



Bank Lending Growth



Δ Loan Rate

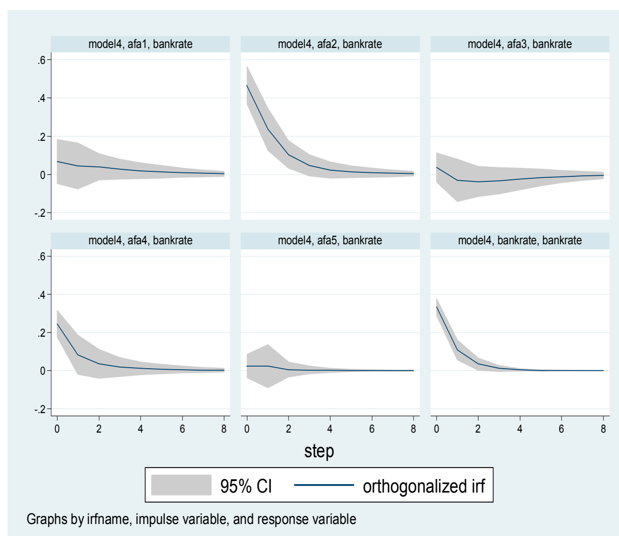
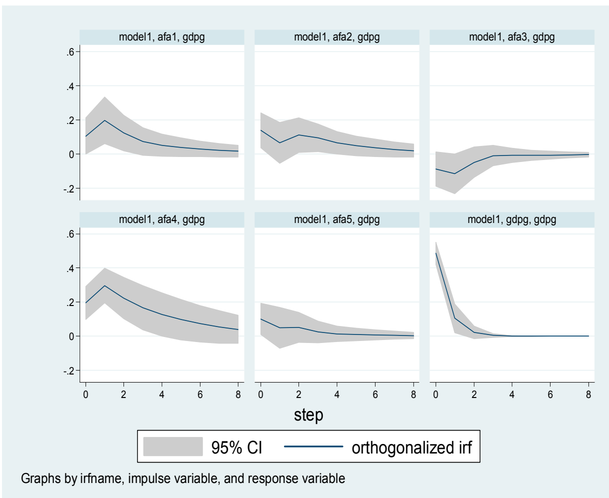


Figure Set 3 (cont…)

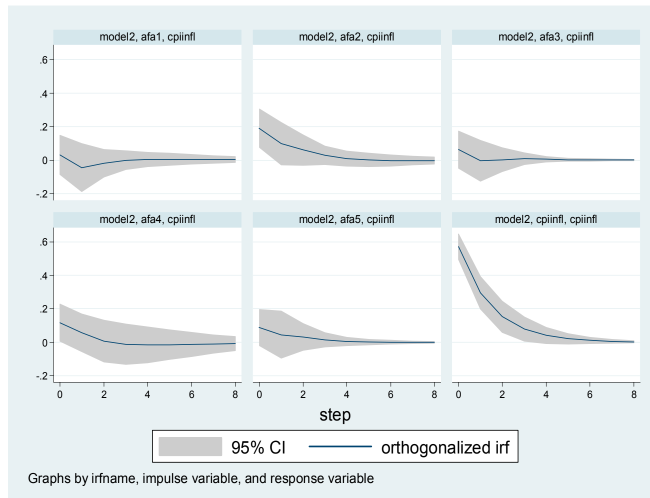
Impulse Responses of GDP Growth, Inflation, Bank Lending Growth
and Change in Lending Rate to Shocks to Factors and Own Shock

Canada

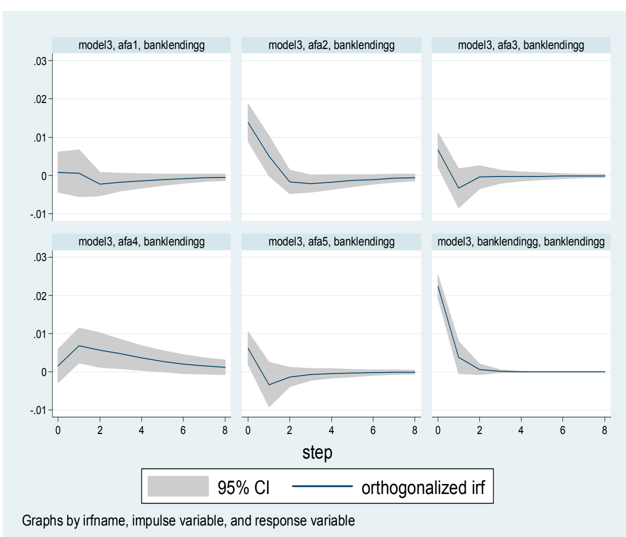
GDP Growth



Inflation



Bank Lending Growth



Δ Loan Rate

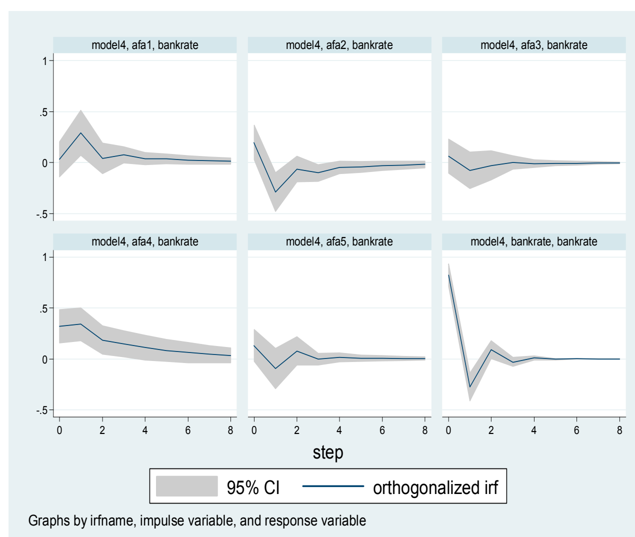
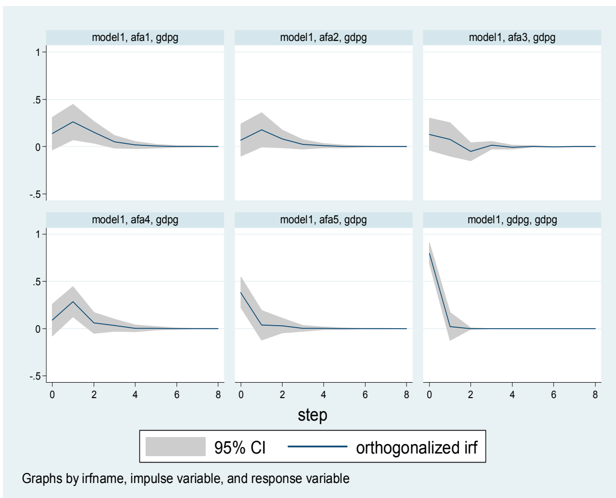


Figure Set 3 (cont.)

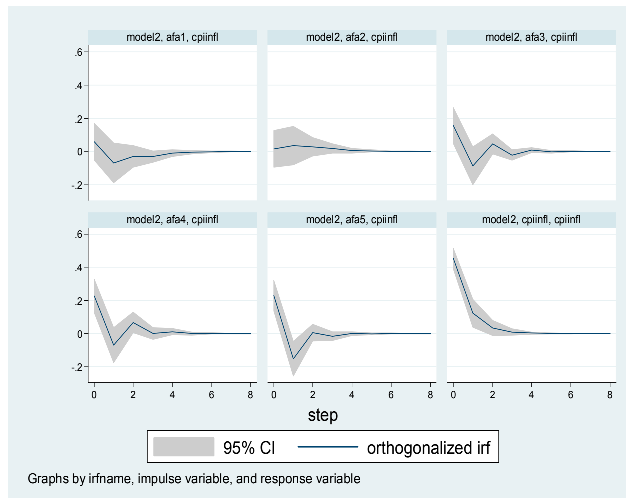
Impulse Responses of GDP Growth, Inflation, Bank Lending Growth
and Change in Lending Rate to Shocks to Factors and Own Shock

Japan

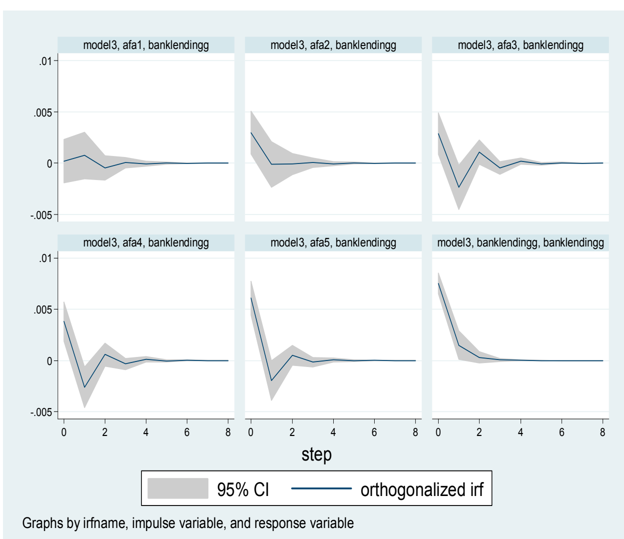
GDP Growth



Inflation



Bank Lending Growth



Δ Loan Rate

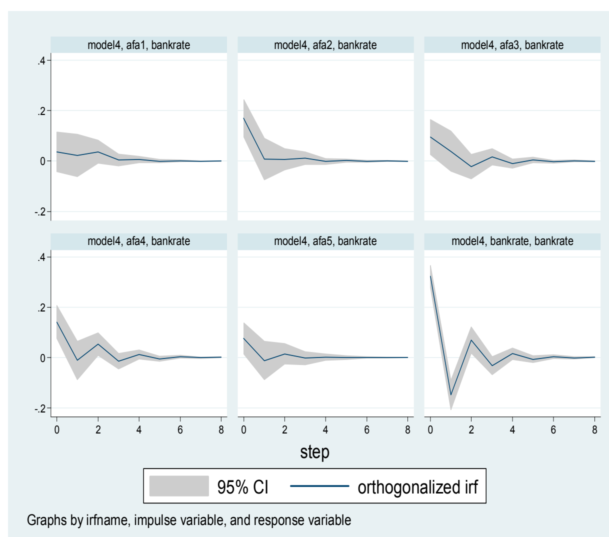
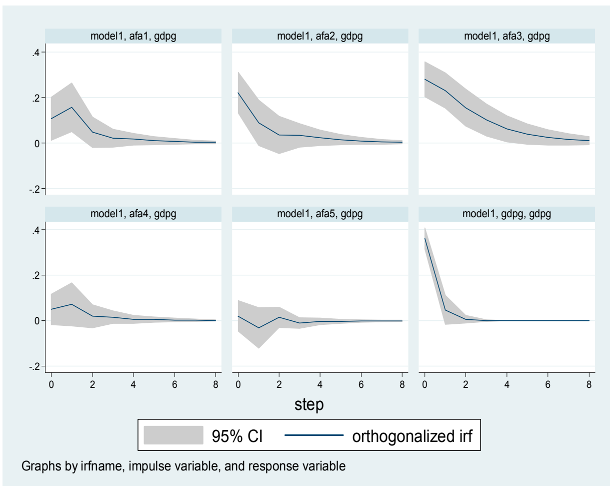


Figure Set 3 (cont…)

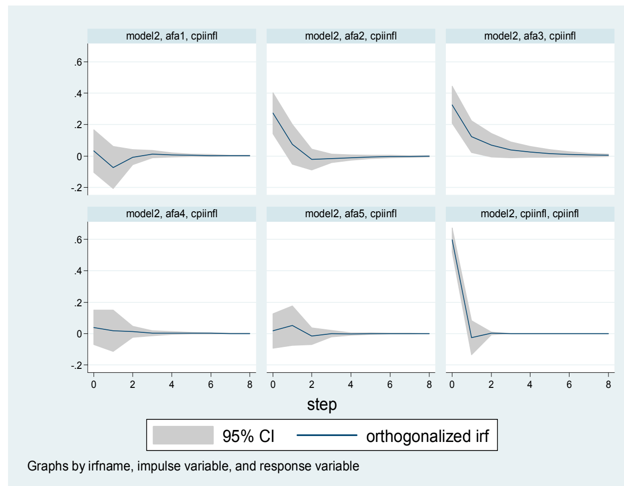
Impulse Responses of GDP Growth, Inflation, Bank Lending Growth
and Change in Lending Rate to Shocks to Factors and Own Shock

United Kingdom

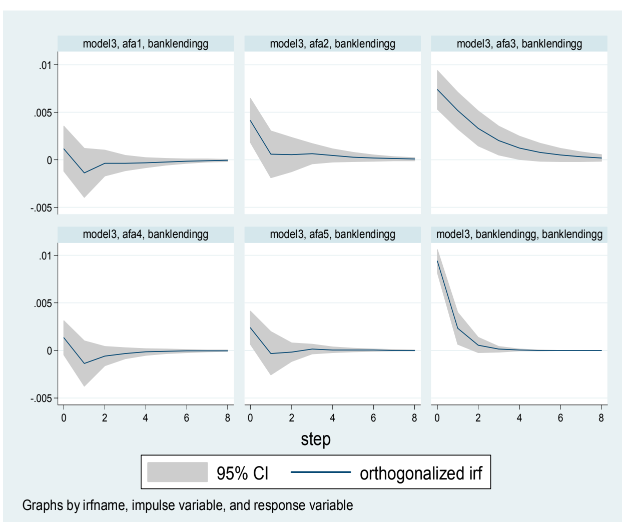
GDP Growth



Inflation



Bank Lending Growth



Δ Loan Rate

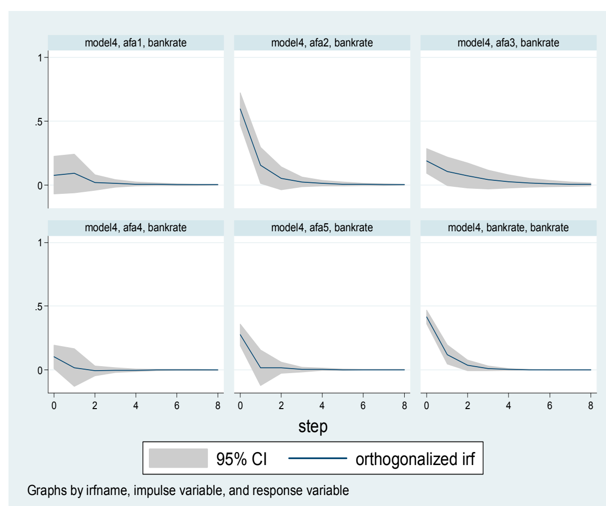
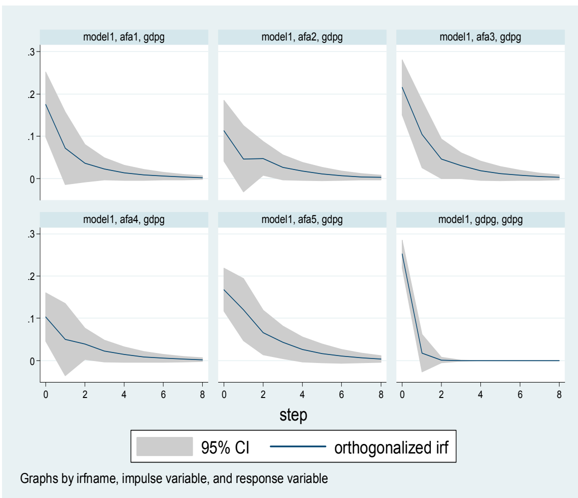


Figure Set 3 (cont…)

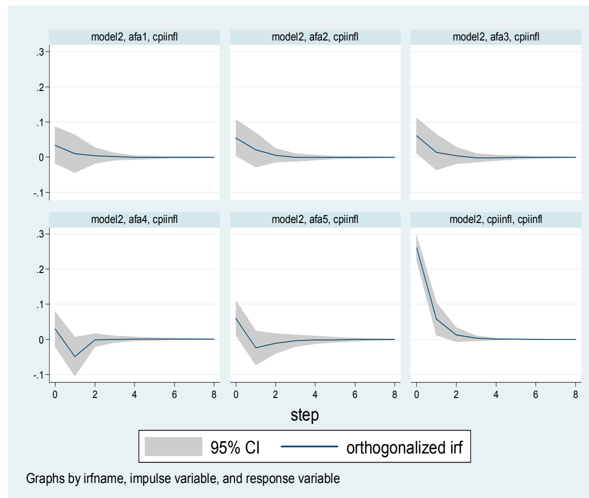
Impulse Responses of GDP Growth, Inflation, Bank Lending Growth and Change in Lending Rate to Shocks to Factors and Own Shock

France

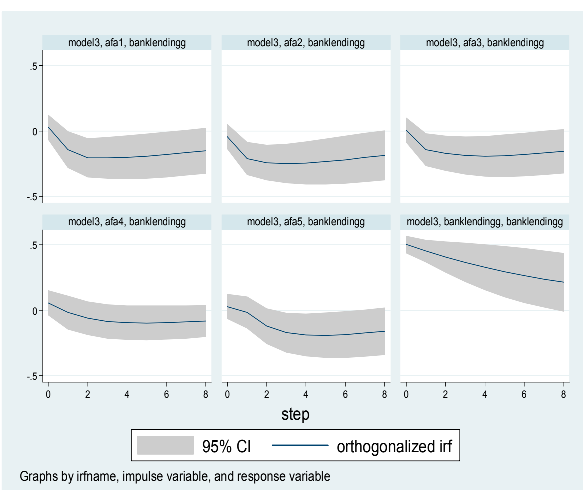
GDP Growth



Inflation



Bank Lending Growth



Δ Loan Rate

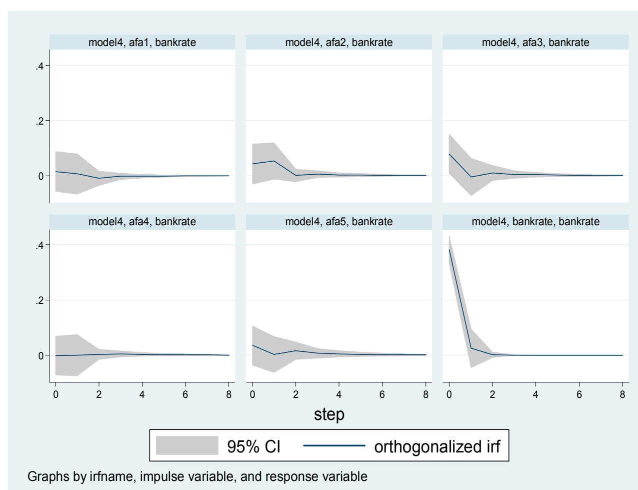
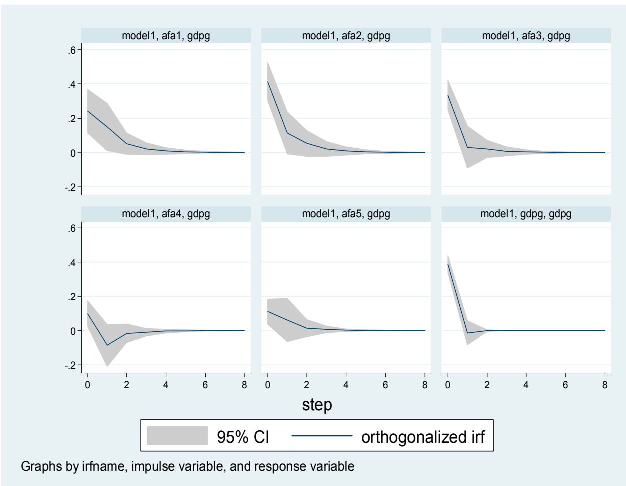


Figure Set 3 (cont...)

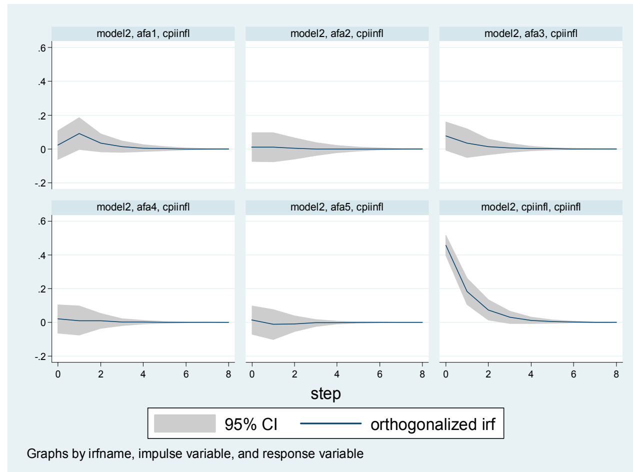
Impulse Responses of GDP Growth, Inflation, Bank Lending Growth and Change in Lending Rate to Shocks to Factors and Own Shock

Germany

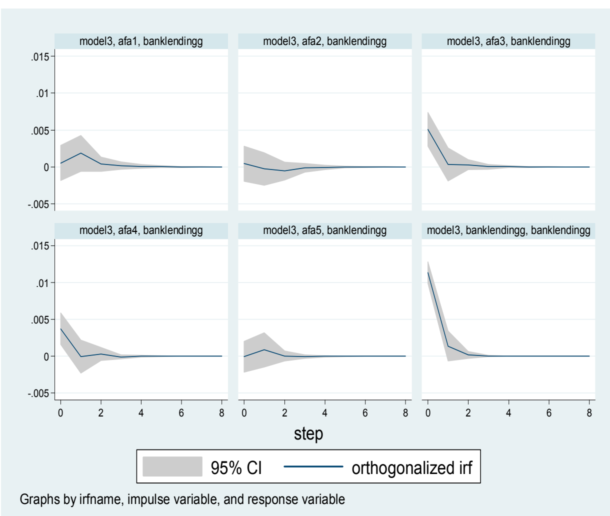
GDP Growth



Inflation



Bank Lending Growth



Δ Loan Rate

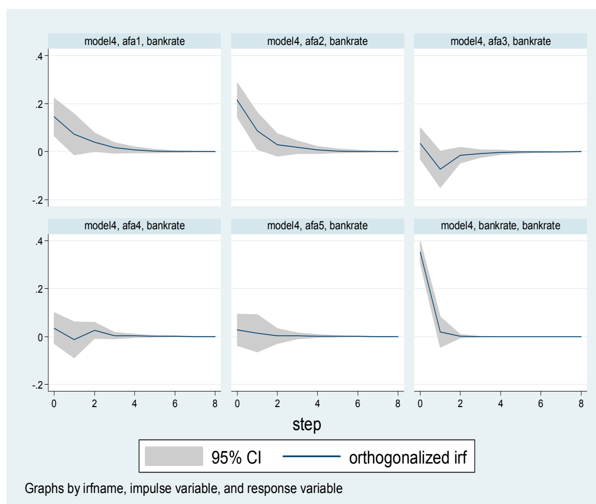
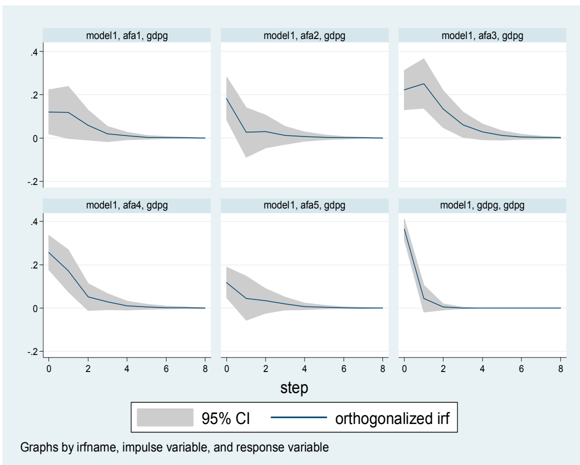


Figure Set 3 (cont...)

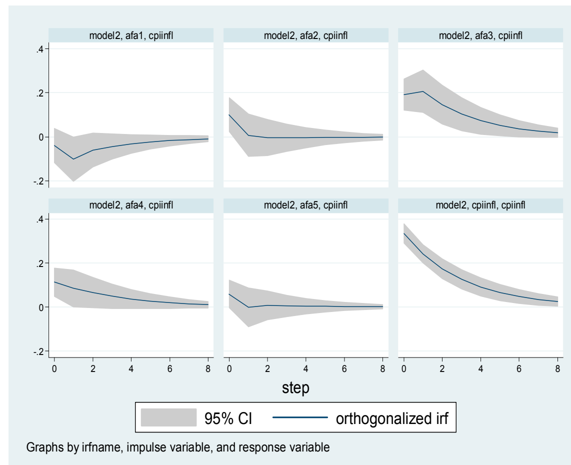
Impulse Responses of GDP Growth, Inflation, Bank Lending Growth
and Change in Lending Rate to Shocks to Factors and Own Shock

Italy

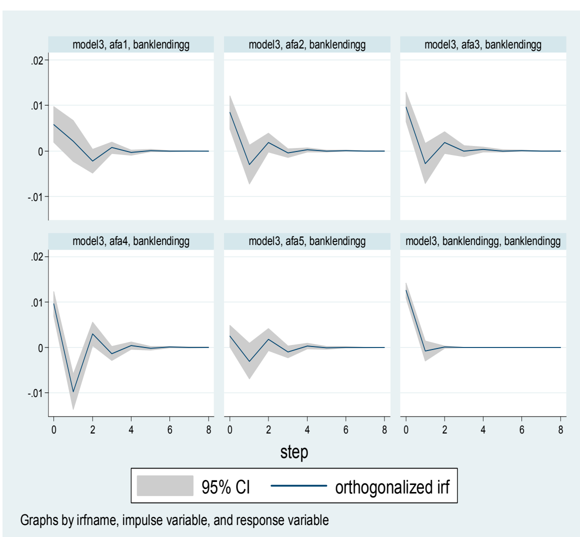
GDP Growth



Inflation



Bank Lending Growth



Δ Loan Rate

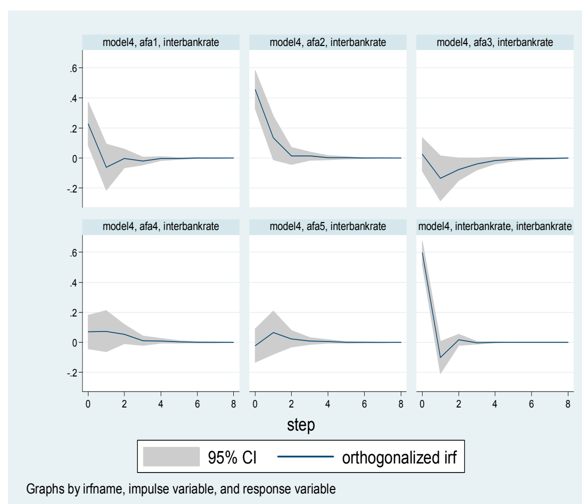
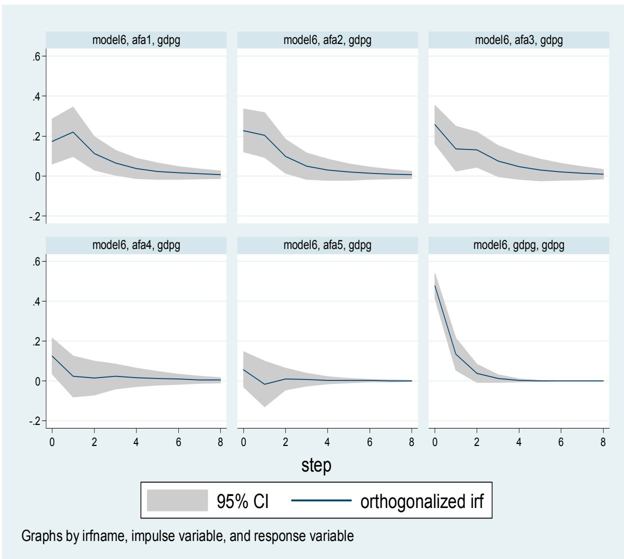
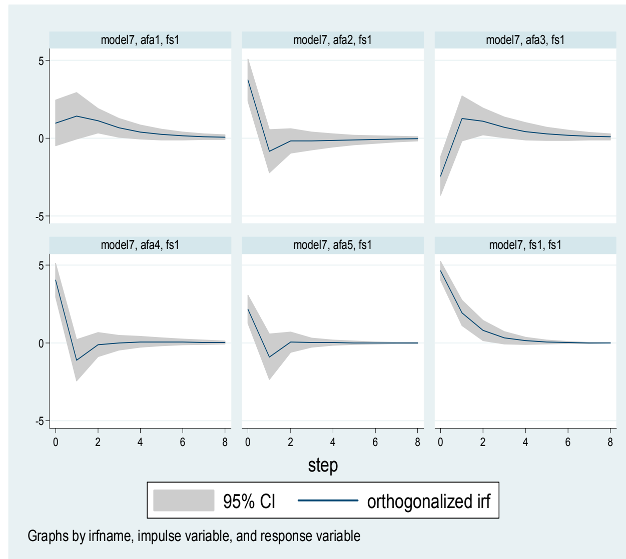


Figure Set 4. Impulse Responses of GDPES(5) and FSES(5) to Identified Aggregate Demand and Bank Credit Demand Shocks and Own Shock

United States

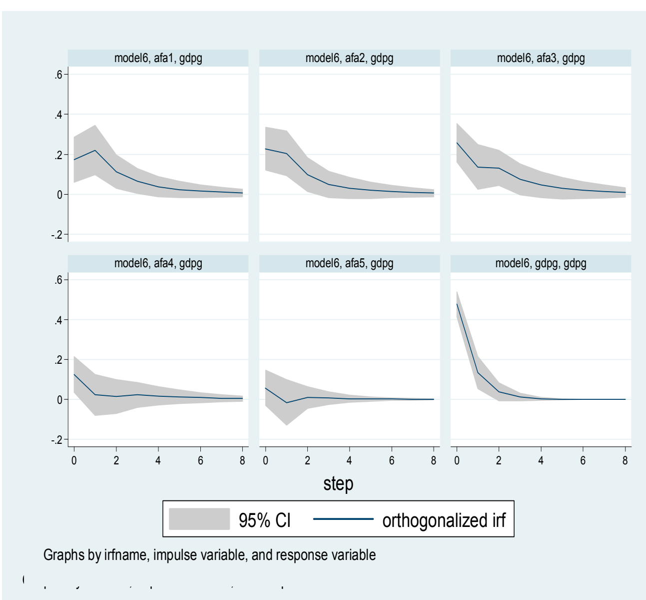
GDPES(5) **FSES(5)**





Canada

GDPES(5) **FSES(5)**



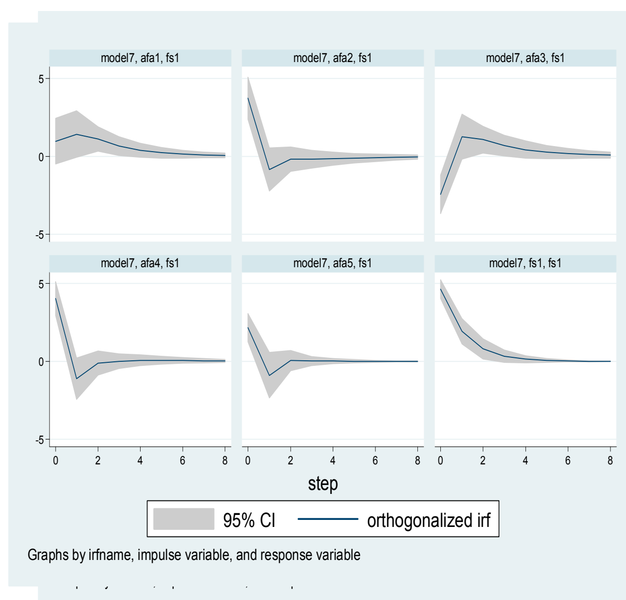
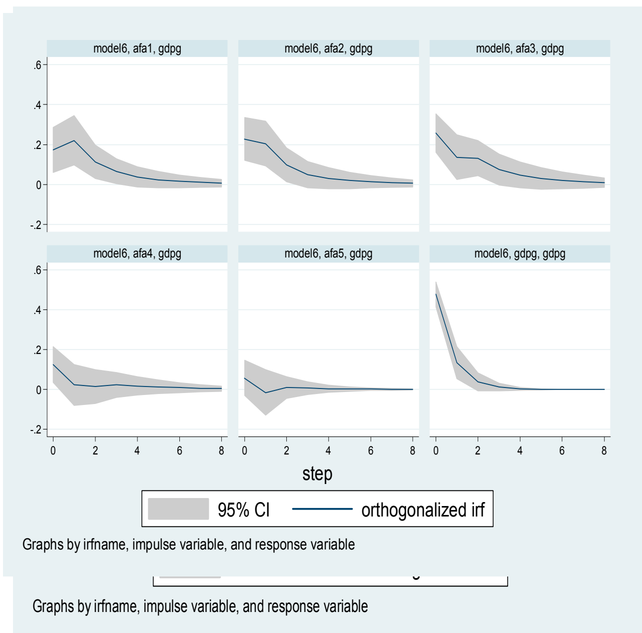


Figure Set 4 (cont…)

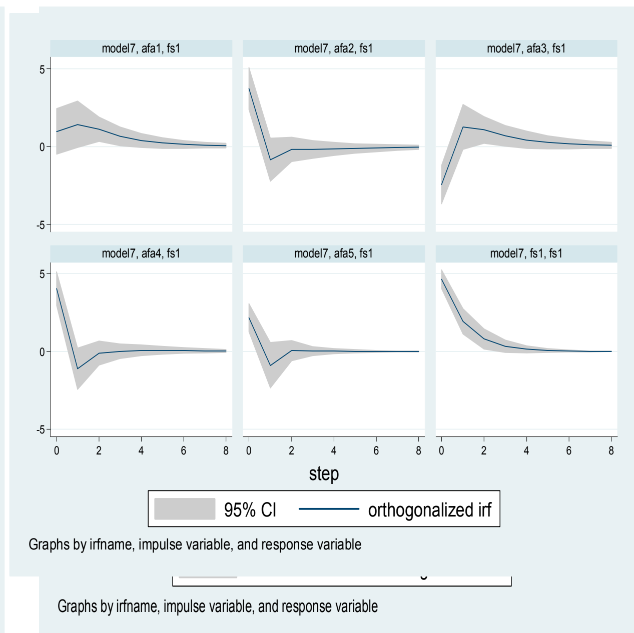
Impulse Responses of GDPaR and FSaR to Identified Aggregate Demand and Bank Credit Demand Shocks and Own Shock

Japan

GDPES(5)

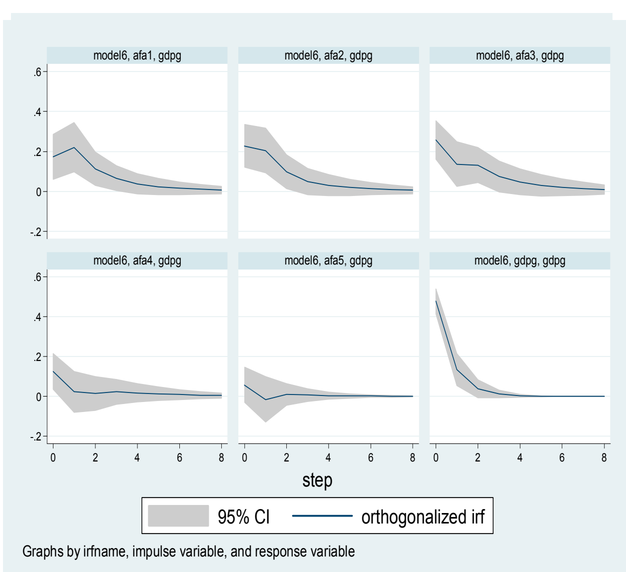


FSES(5)



United Kingdom

GDPES(5)



FSES(5)

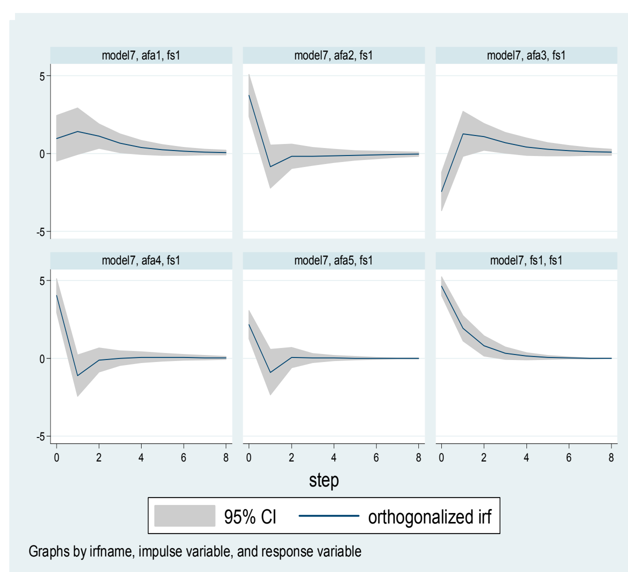
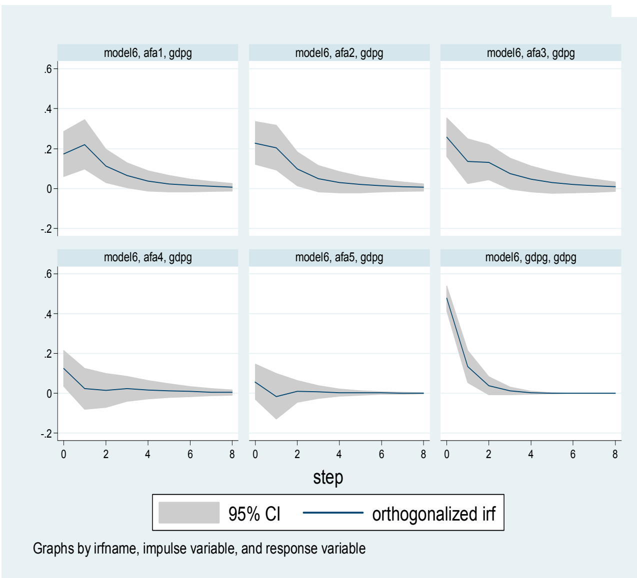


Figure Set 4 (cont…)

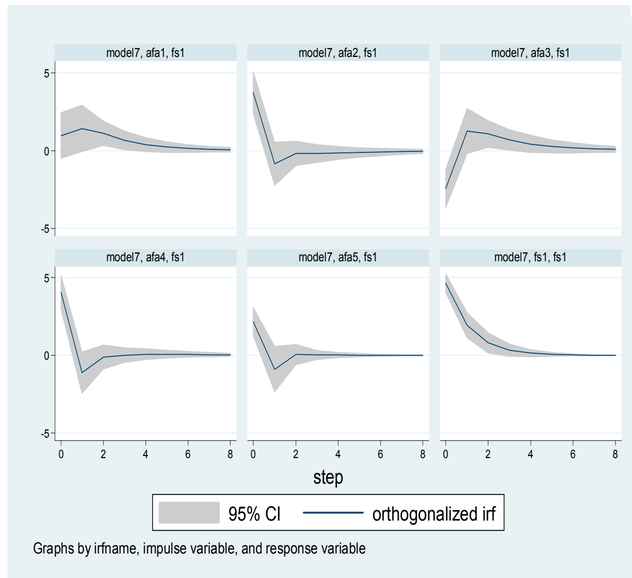
Impulse Responses of GDPaR and FSaR to Identified Aggregate Demand and Bank Credit Demand Shocks and Own Shock

France

GDPES(5)

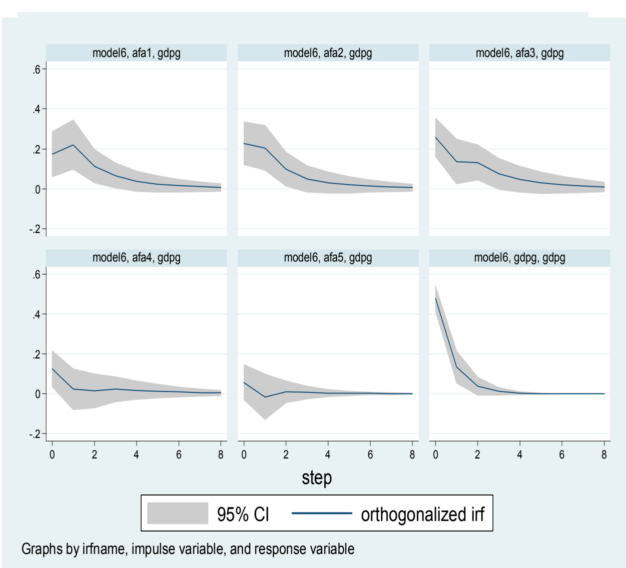


FSES(5)



Germany

GDPES(5)



FSES(5)

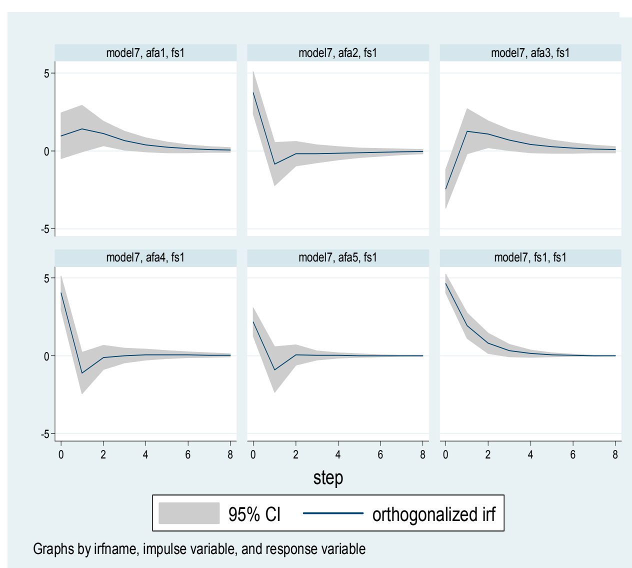
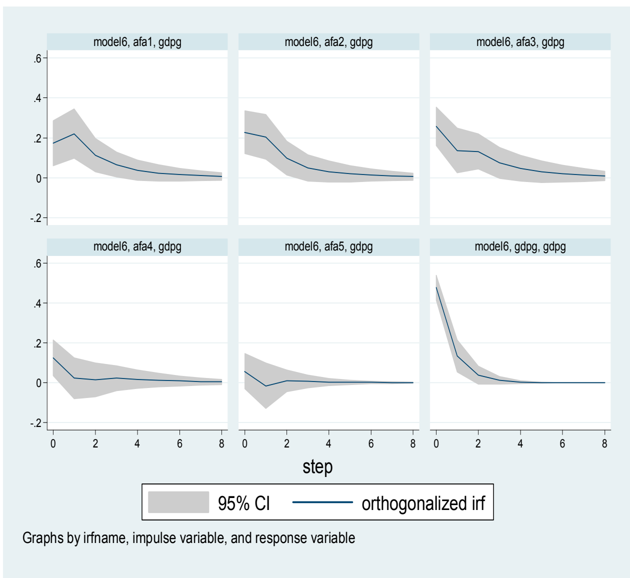


Figure Set 4 (cont…)

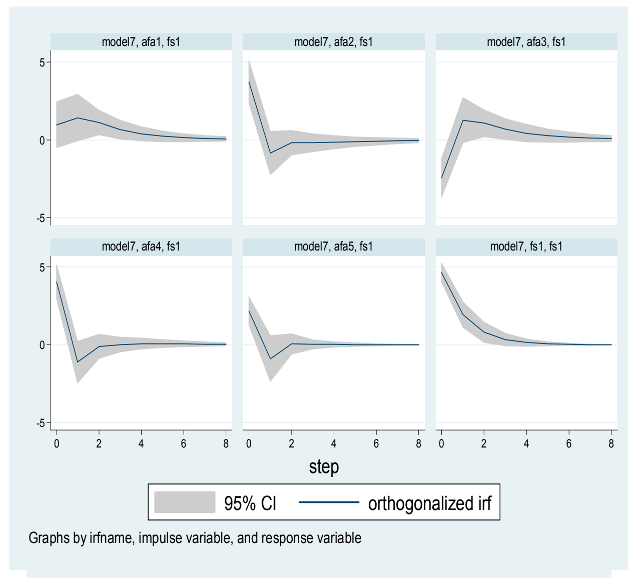
Impulse Responses of GDPaR and FSaR to Identified Aggregate
Demand and Bank Credit Demand Shocks and Own Shock

Italy

GDPES(5)



FSES(5)



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