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Modeling Banking, Sovereign, and Macro Risk in a CCA Global VAR

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Abstract

The purpose of this paper is to develop a model framework for the analysis of interactions between banking sector risk, sovereign risk, corporate sector risk, real economic activity, and credit growth for 15 European countries and the United States. It is an integrated macroeconomic systemic risk model framework that draws on the advantages of forward-looking contingent claims analysis (CCA) risk indicators for the banking systems in each country, forward-looking CCA risk indicators for sovereigns, and a GVAR model to combine the banking, the sovereign, and the macro sphere. The CCA indicators capture the nonlinearity of changes in bank assets, equity capital, credit spreads, and default probabilities. They capture the expected losses, spreads and default probability for sovereigns. Key to the framework is that sovereign credit spreads, banking system credit risk, corporate sector credit risk, economic growth, and credit variables are combined in a fully endogenous setting. Upon estimation and calibration of the global model, we simulate various negative and positive shock scenarios, particularly to bank and sovereign risk. The goal is to use this framework to analyze the impact and spillover of shocks and to help identify policies that would mitigate banking system, sovereign credit risk and recession risk—policies including bank capital increases, purchase of sovereign debt, and guarantees.

JEL Classification Numbers: **C51, G01, G13, G21, H63**

Keywords: contingent claims analysis (CCA), global vector autoregression (GVAR).

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I. INTRODUCTION AND OVERVIEW OF CCA-GVAR FRAMEWORK

A. Overview

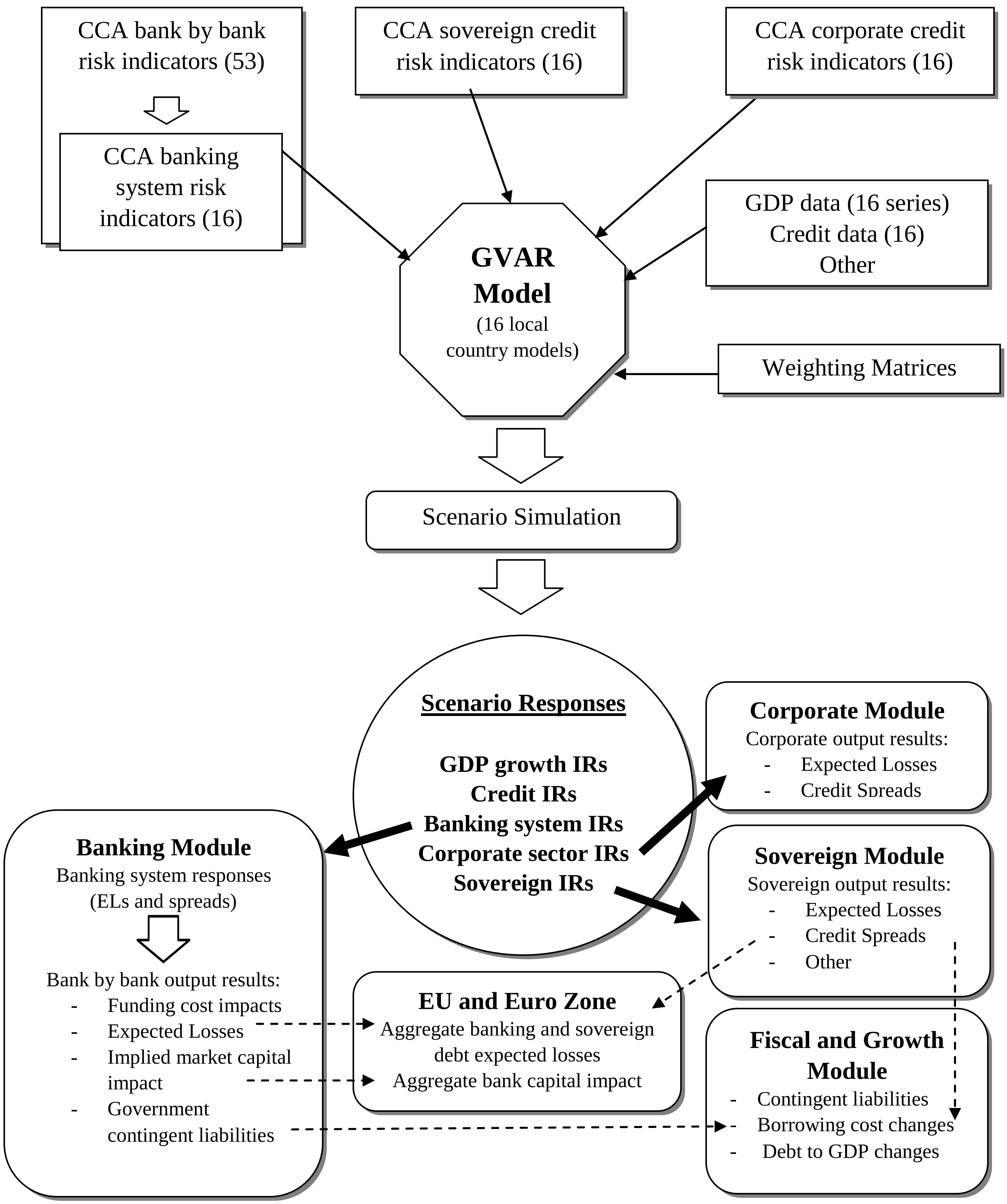
The goal of this paper is to develop a framework for the analysis of interactions between banking sector risk, sovereign risk, corporate sector risk, growth, and credit for a large sample of banks and countries. Contingent Claims Analysis (CCA) serves to construct risk indicators for banks, respectively for banking systems, sovereigns, and corporate sectors, which we combine with real GDP growth and credit growth in a global model, comprising 15 EU countries and the United States.

CCA indicators capture the nonlinearity of changes in bank assets, equity capital, bank credit spreads, and default probabilities that are derived from forward-looking equity market information in conjunction with balance sheet data. It captures the expected losses, spreads and default probability for sovereigns. A Global Vector Autoregressive (GVAR) model approach serves to combine sovereign credit risk, banking system credit risk, GDP growth, and credit growth in a way to allow all variables to interact fully endogenously. The goal is to use that framework to help identify policies that mitigate banking system, sovereign credit risk and recession risk—policies that include bank liquidity injections, bank capital increases, purchase of sovereign debt, guarantees of bank senior debt by sovereigns, guarantees of sovereigns by other public bodies, etc.

The first section of the paper will present an outline of Contingent Claims Analysis and how the key risk indicators for banks, banking systems, the corporate sector and sovereigns are estimated. A view into how the risk indicators evolve along with real activity shall help develop a first understanding of how sovereign/bank risks relate to business cycle dynamics. The GVAR model framework will then be presented, which is set up for 16 countries, 16 banking sectors which themselves are comprised of 53 individual banks (41 EU banks plus 12 U.S. banks). The five-variable version of the model includes banking system CCA risk indicators, sovereign risk indicators, corporate sector risk indicators, economic growth and credit to the private sector. The use of the GVAR model approach to combine these indicators can be motivated along many lines: cross-border linkages with regard to real activity (primarily via the trade channel) have been the rationale underlying most of the existing empirical GVAR literature as of yet. Regarding domestic credit, cross-border linkages matter to the extent that swings in credit supply from internationally active banks from abroad would spill over to other countries to which they have exposure. As to the linkages between sovereign and banking system risk, in particular, we will in later sections of the paper elaborate further on the rationale for cross-sector/cross-country linkages.

Figure 1 presents a schematic overview of the model framework, including the CCA components that serve as input to the GVAR and then the various sub-modules that receive as input the simulated scenario responses from the GVAR model.

Figure 1. CCA-GVAR Model Framework



We estimate and solve the global model based on a monthly sample covering the period from January 2002 to December 2012 (132 observations). We use the model to conduct scenario simulations, involving multiple shocks to selected sovereigns and banking systems. We consider both positive and negative shock scenarios. The output responses are inputs to banking/sovereign sub-modules which are used to compute aggregate loss estimates and changes in bank capital. We aim to use this framework as an analytical means for the analysis of shocks, spillovers and as well as a tool that helps assess tradeoffs among policy alternatives.

B. Motivation and Relationship to the Literature

Recent financial and sovereign crises have shown how financial sector distress is intimately related to government contingent liabilities and bailouts which affect sovereign credit risk. Financial sector and sovereign risks have important effects on credit growth, lending/borrowing rates, corporate and household finances, consumption, investment and economic growth. There are direct channels of risk transmission between banks, sovereigns, and borrowers within and between countries, as well as indirect channels which affect confidence and risk appetite within and between countries. There are many different ways to analyze these transmission channels, different data inputs and various levels of aggregation of the data. While a detailed literature review is not possible here, it is useful to touch on some key recent papers related to three areas, (i) banking sector and sovereign risk interactions; (ii) how financial risks relate to macroeconomic variables; and, (iii) ways to model macro and financial risk connections in a multi-country setting.

Financial sector risk and bailouts negatively impact sovereign credit risk (see Ejsing and Lemke 2009, and Acharya et al. 2011). Draghi et al. 2003 describe how large unanticipated risks can accumulate in the financial sector and on government balance sheets. Structural (CCA) models of banking and sovereign risk have been developed for individual countries which capture non-linear feedbacks between sovereign and banking sector risk (see Gapen et al. 2005, Gray et al. 2007, Gray and Malone 2012). These models are not tractable for a multi-country analysis as it would be difficult to calibrate such models for a multidimensional analysis across a large number of countries.

There are different approaches on how financial risks relate to macroeconomic variables. First there are asset pricing approaches which relate asset price declines to changes in risk premiums—equity risk, interest rate, and risk appetite (pricing kernel/market price of risk) and macroeconomic variables (see Gabaix 2008). There are econometric models linking financial sector risk indicators to macro variables (Gray and Walsh 2008) and can be incorporated in monetary policy models (Garcia et al. 2011). Economy-wide risk transmission using interlinked structural balance sheets for sectors show how credit risk can be amplified in a crisis and how it affects output (Gray et al. 2002, 2008, and 2010). There are many ways to model macro and financial risk connections in a multi-country setting. Global VAR models are well suited to analysis of macroeconomic interrelationships and can include financial risk indicators (as in Chen et al. 2010, Chudik and Fratzscher 2011, Eickmeier and Ng 2011 and others). Structural financial sector risk indicators and sovereign risk were used in a multi-country setting using a Factor Augmented VAR approach by Gray, Jobst and Malone 2011. Network models can be used in a multi-country analysis of links between individual banks, insurers and sovereigns using CCA risk indicators (e.g., Merton 2013 and Billio et al. forthcoming) but are not tractable or as useful when the interest is in examining macroeconomic impacts.

The analysis in this paper integrates the advantages of Global VAR models to measure the interconnectedness of *sector* level CCA risk indicators and GDP and credit "flow" variables in a multi-country setting. Using data at the sector level keeps the model size manageable. The advantages of the CCA sector risk indicators are: (i) they are forward-looking measures of risk (unlike backward looking accounting ratios); (ii) they combine together leverage, asset volatility, and risk appetite into a single indicator; and (iii) they can be transformed into a credit spread (at the sector or individual entity level), which are intuitive to understand.

II. Contingent Claims Analysis for Banks, Banking Systems, Corporate Sector and Sovereigns

Contingent claims analysis (CCA) is a risk-adjusted balance sheet framework. In CCA the value of liabilities is derived from the value of assets and assets are uncertain. The value of assets equals the value of equity plus risky debt, where risky debt is default-free value of debt minus the expected loss due to default. CCA balance sheets are very useful as they incorporate forward-looking credit risk, which is non-linear, and can analyze risk transmission between banks, corporates, and sovereigns and the real economy. CCA balance sheets are calibrated using the value and volatility of equity plus accounting information on debt in an option-theoretic framework.

CCA originated with the Merton model[1] and it provides a methodology to construct risk-adjusted balance sheets using market and balance sheet information. It is used to derive a set of credit risk indicators for individual firms and financial institutions and can also be aggregated at the sector level to analyze financial, corporate, and sovereign risk interactions. For an individual financial institution or firm an estimate of the market value of assets and asset volatility is needed. However, the market value of assets is not directly observable because many of the assets on the balance sheet of a financial institution are not traded. CCA imputes the value and volatility of assets indirectly using the market value of equity from stock price data, equity volatility (from equity data and/or equity options), and the book value of short- and long-term debt obligations. This is then used to calculate risk indicators such as the probability of default, credit spreads, or other risk indicators (Bohn, 2000, Crouhy et al. 2000).

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[1] See Merton (1973, 1974, 1977, 1992), Gray, Merton, and Bodie (2008), and Gray and Malone (2008).

On the CCA balance sheet the total market value of assets, *A*, is equal to the sum of its equity market value, *E*, and its risky debt, *D*. The asset value is stochastic and may fall below the value of the debt default barrier at time horizon *T*. Equity and risky debt derive their value from the uncertain assets; equity value is the value of an implicit call option on the assets, with an exercise price equal to default barrier, B. The value of risky debt is equal to default-free debt minus the present value of expected loss due to default. The expected loss due to default can be calculated as the value of an implicit put option on the assets, A, with an exercise price equal to the default-free value of debt, *B*, over time horizon T, risk-free rate r, and asset volatility σ_A. The implicit put option value will be called the *expected loss value,* ELV. Risky Debt = Default-free Debt − Expected loss due to default

(1) $$D = Be^{-rT} - ELV$$

Equity values are consensus views of market participants and thus provide forward-looking information. The calibration of the model for banks and corporates uses the value of equity, the volatility of equity, the distress barrier as inputs into two equations in order to calculate the implied asset value and implied asset volatility. The implied asset value and volatility can then be used with the other parameters to calculate risk indicators such as the spreads, the expected loss value, default probabilities, and other risk indicators. There are a variety of techniques that can be used to calibrate the CCA parameters. See Appendix I for details on the CCA framework.

From the CCA model, the yield to maturity on the risky debt, *y*, is defined as:

(2) $$y = \frac{\ln\left(B/D\right)}{T}$$

where $D = Be^{-yT}$ is the risky debt and *B* the default barrier. The credit spread, s, can be written as:

(3) $$s = y - r = \frac{\ln\left(B/D\right)}{T} - r = -\frac{1}{T}\ln(1 - \frac{ELV}{Be^{-rT}})$$

The expected loss ratio[2] (defined as EL) is the expected loss value per unit of default-free debt and it is equal to:

(4) $$1 - \exp(-sT) = \frac{ELV}{Be^{-rT}} \equiv EL$$

[2] The expected loss ratio can be shown to also equal to the risk neutral default probability (RNDP) times Loss Given Default (LGD). This is described in detail in Appendix I.

A. Expected Loss Ratios for Banks and Non-Financial Corporations

In order to incorporate the banking system risk indicators in the GVAR model we need risk indicators for the individual banks in a country, which will be used to construct a national banking system risk indicator. In principle there are a variety of CCA calibration techniques that could be used to calculate bank-by-bank CCA parameters and calculate the implicit put option (expected loss value), spreads and expected loss ratios.

For the calibration of implied assets and volatility the following inputs are used: Market capitalization values and volatility, historical or estimated or derived from equity options, default barrier estimates from promised payments on debt, the risk free rate, a time horizon, etc. However, also models could be used that incorporate not just the volatility of the asset return process but higher moments as well (e.g., jump diffusion, Gram-Charlier, or other process as described in Backus et al., 2004, and Jobst and Gray, 2013). After the calibration of the asset process the expected loss value (i.e. implicit put option value) can be calculated which in turn is used to calculate credit spreads; we will call this spread a "fair value spread," which is the credit spread from the CCA model derived from equity and balance sheet information.

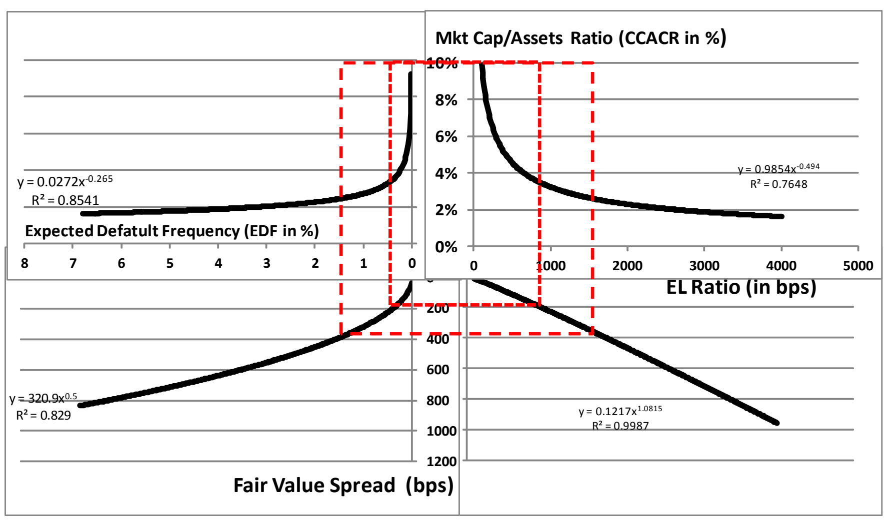
Strong evidence supports the claim that implicit and explicit government backing for banks depresses bank CDS spreads to levels below where they would be in the absence of government support. Bank creditors are the beneficiaries of implicit and explicit government guarantees, but equity holders are not. Several studies have shown that for banks during the crisis in 2008–2009 when the CCA model is used (based on equity market and balance sheet data) the resulting fair value spreads are higher than the observed market CDS spreads in many cases (see Gray et al. 2008, Gapen 2009, Moody's Analytics 2011, Gray and Jobst 2011, Schweikhard and Tsemelidakis 2012). The observed CDS spreads of banks are *lower* than fair value spreads because of the effect of implicit and explicit government guarantees on observed CDS, especially in times of crisis, and thus the bank CDS is distorted. Also, it is observed that for banks in countries with very high sovereign spreads, the observed bank CDS is frequently *higher* than the bank fair value spread.

There is a database from Moody's CreditEdge that provides a long time series of risk indicators, calculated in a consistent manner, which can be used to calculate what Moody's CreditEdge refers to as the Fair Value CDS spread (FVCDS). This FVCDS is a good proxy for the fair value spread we need, so we can use it to obtain the bank-by-bank expected loss ratio, EL_b, and corporate expected loss ratio, EL_c (described in detail in Appendix I). These expected loss ratios have a five year horizon (T=5), monthly frequency, and are expressed in basis points. The FVCDS and its associated expected loss ratio, EL_b, are not distorted in a major way by the effect of government guarantees (situations where FVCDS > CDS) or from spillovers from high sovereign spreads (situations where CDS > FVCDS) and thus are a "purer" forward-looking measure of bank risk. Box 1 shows the nonlinear relationships between the CCA capital ratio, EDF, FVCDS and the EL for a typical bank.[3]

Box 1. Relationships between CCA Capital Ratio, EDF, FVCDS and Expected Loss Ratio for a Typical Bank

It is useful to understand the nonlinear relationships between the ratio of market capital to assets, the CCA Capital Ratio (CCACR), the Expected Default Frequency (EDF), the spread (FVCDS spread), and the Expected Loss ratio (shown in the graphs as a fraction), as illustrated in Figure 2. This is the typical pattern for a bank which has experienced periods of distress and non-distress. It is compiled from a data sample covering approximately three years that is taken from the CreditEdgePlus database (Moody's). If the CCACR is high, 0.8 to 0.9 (8 or 9 percent), EDF is very low, the EL is low (around 0.05, or 500 bps), credit spreads are low (around 100 bps). In distress periods, when the CCACR falls from 0.3 to 0.1, the EDF is very high (6 to 7 percent), spreads reach about 700 to 900 bps, and the EL is 0.3 to 0.4 (equal to 3000 to 4000 bps). Once the capital ratio starts moving below 3 percent, the EDF increases over 1 percent, spreads start exceeding a 250 bps "threshold" and EL is higher than 1000 bps there is increasing risk of negative shocks leading to sharply higher spreads and EDFs. The dynamics are non-linear.

Figure 2. Relationships between CCA Capital Ratio, EDF, FVCDS and EL for a Typical Bank



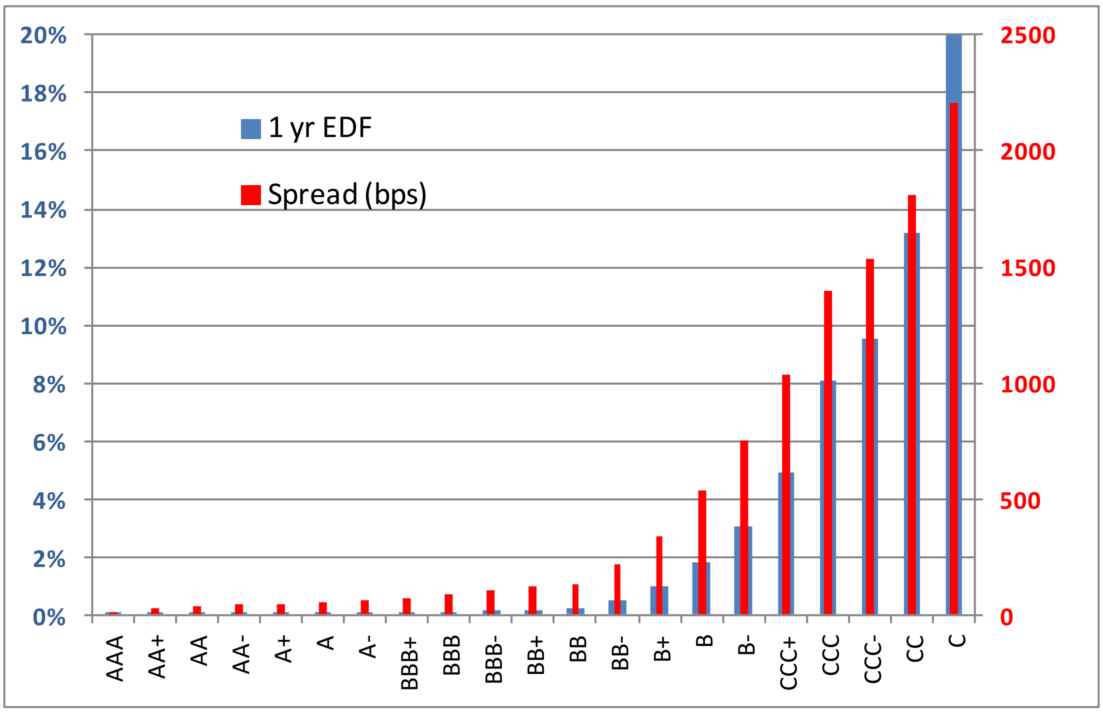
Source: Moody's CreditEdge data and author estimates

The red square in the center of Figure 2 is the safest zone, investment grade and above. CCACR 3 percent and above, EL of 1000 bps or less, spreads less than 200 bps, and EDF of less than 0.5 percent. The slightly larger safe zone, just below investment grade, in Figure 2 is the zone where EDFs are less than 1.5 percent, spreads are 400 bps or less, EL is less than 2000 bps and CCACR is above 2.5 percent.

[3] See Merton et al. 2013 and Billio et al. 2013 for application of these CCA risk indicators in network models.

The relationship between Moody's ratings, one-year EDFs, and fair-value spreads is shown in Figure 3. Investment grade is defined as ratings BBB- and higher. Spreads of 400 bps or less corresponds to EDFs of about 1.5–2 percent and ratings of B or higher. The sharp increase in spreads and EDFs at rating below B shows significant non-linearity. The comparison of ratings spreads, and EDFs is shown in Figure 3. Once the rating becomes sub-investment grade, the spreads and default probabilities increase sharply as ratings decline further.

Figure 3. Comparison of Ratings, Spreads and EDFs



Source: Moody's CreditEdge data and author estimates.

One of the benefits of using the EL in the GVAR is that the shocks to EL can be related to shocks to the CCA capital ratio, EDF and spreads, and the output responses from the model can be transformed from EL to the corresponding change in capital ratios, EDFs, and spreads. One can think of the "safe zone" as a target zone that one would like to reach using combinations of policies (capital injections, increasing the level and lowering asset volatility, and risk transfer policies described in more detail later).

B. Aggregating Expected Loss Ratios for Banking Systems and the Non-Financial Corporate Sector

For the purpose of aggregating individual banks' and non-financial corporations' risk indicators that belong to country *j* we compute a weighted average of the expected loss ratios of major banks in the country (weighted respectively by bank or corporate asset size, i.e., the market value of assets). The banking system expected loss ratio is $EL_{bs,j}$, and the corporate sector expected loss ratio is $EL_{cs,j}$ in country *j*.

(5) $$EL_{bs,j} = \sum_{1}^{x} \omega_i EL_{b,i}$$

(6) $$EL_{cs,j} = \sum_{1}^{x} \omega_i EL_{c,i}$$

The monthly banking and corporate sector aggregate EL ratios for each country are then used in the GVAR model. The output responses for the sectors as a whole can be transformed back into the EL for the individual banks and corporates (using the weights that were initially used to construct the sector EL). In particular for the individual banks, the EL responses can be related to changes in capital, EDF, spreads (and the Expected Loss Value, which is the implicit put option described earlier).[4]

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[4] It would be desirable to include household EL related to mortgage and other debt but data are not available for all countries (see Gray et al. 2008 and 2010 for more information on the household balance sheet).

C. Sovereign CCA Expected Loss Ratio

For the sovereigns, we do not have equity values, so we use actual market sovereign CDS spreads because we assume there is no one guaranteeing their debt and CDS should reflect the sovereign credit risk (see Merton et al. 2013).[5] A recent analysis of sovereign CDS (IMF, 2013) shows that the sovereign CDS market is not prone to speculative excesses, nor leading to higher sovereign funding costs and this market does not appear to be more prone to high volatility than other financial markets.[6] The CDS spread for a sovereign (as well as banks and corporate) is a function of the time horizon and the expected loss ratio. The formula for the sovereign CDS, expressed in basis points, is:

$$CDS_{sov} = 10000 * [-\tfrac{1}{T}\ln(1 - EL_{sov})] \quad (7)$$

Solving for the expected loss ratio for the sovereign as a function of time horizon and sovereign CDS value would give the following formula.

$$EL_{sov} = 1 - \exp(-(CDS_{Sov} / 10000)T) \quad (8)$$

For sovereigns, the five-year CDS is used since, as with bank and corporate CDS, the five-year CDS is the most liquid. There are numerous channels through which the sovereign and the banks interact. The mark-to-market fall in the value of sovereign bonds held by banks reduces bank assets. This can increase bank-funding costs and if the sovereign is strongly distressed, the value of official support (guarantees) will be eroded leading to knock-on and contagion effects. In some situations, this vicious cycle can spiral out of control, resulting in the inability of the government to provide sufficient guarantees to banks and leading to a systemic financial crisis and a sovereign debt crisis. In such cases, the relationship of ELs of sovereigns, ELs of banking systems, and GDP are inter-related in a way subject to costly destabilization processes. If funds for a banking sector recapitalization come from increased sovereign borrowing, this increases sovereign risk (more details on the sovereign CCA framework and risk transmission to banking systems can be found in Appendix I).

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[5] If the European Stability Mechanism (ESM) or another entity outside of certain country were to explicitly guarantee sovereign debt then it might be possible to measure the effect on the sovereign CDS. The potential ECB Outright Monetary Transactions (OMT) purchases of sovereign debt in the Euro area is not a guarantee but rather more like rollover financing and thus sovereigns risk would decrease and the sovereign CDS would be expected to decline.

[6] The IMF 2013 results do not support the need for a ban on “naked” sovereign CDS protection buying, which went into effect in the European Union in November 2012 and there is some evidence that liquidity in some of the smaller countries has decreased since the ban went into effect.

III. GVAR Model

At the heart of our model framework for integrating the CCA risk indicators with macroeconomic variables lays the GVAR methodology as initially proposed by Pesaran, Schuermann and Weiner (2004). The methodology has been developed further and been applied empirically since then, for instance to model macroeconomic dynamics and credit risk in Pesaran, Schuermann, Treutler and Weinter (2006), or to consider a counterfactual analysis to evaluate what the effects would have been if the UK or Sweden had joined the euro area in 1999 (Pesaran, Smith, and Smith (2007)). The out-of-sample forecast performance of GVAR models was the subject in Pesaran, Schuermann and Smith (2009). Other, more recent empirical contributions include e.g. Chudik and Fratzscher (2011) who study the dynamics of the 2007-2009 financial crisis and Eickmeier and Ng (2011) who analyze how supply shocks propagate internationally.

A. Local Models

The following outline of the GVAR methodology follows by and large the model framework proposed by Pesaran et al. (2004). We assume that the global model comprises *N*+1 countries that are indexed by *i*=0,…,*N*. A set of country-specific endogenous variables are collected in a $k_i \times 1$vector y_{it} which is related to a number of autoregressive lags up to *P*, and a $k_i^* \times 1$ vector of weighted foreign variables y_{it}^* that enters the model time-contemporaneously and with a number of lags up to *Q*, that is,

$$(9) \qquad y_{it} = a_{i0} + a_{i1}t + \sum_{p=1}^{P} \Phi_{ip} y_{i,t-p} + \sum_{q=0}^{Q} \Lambda_{iq} y_{i,t-q}^* + \Psi d_t + \varepsilon_{it}$$

where a_{i0}, a_{i1}, Φ_{ip}, Λ_{iq}, and Ψ are coefficient matrices of size $k_i \times 1$, $k_i \times 1$, $k_i \times k_i$, and $d_i \times 1$ respectively. The vector d_t contains global weakly exogenous variables. We shall assume that the idiosyncratic error vector ε_{it} is i.i.d. and has zero mean and covariance matrix Σ_{ii}.

B. Weight Matrices

For estimating the local models of the GVAR model, the tradition has been to construct weights based on external data sources (trade, financial asset exposures and other sources). The weights are needed to compute the foreign variable vectors y_{it}^* in equation (9) and to later solve the model (see Section C). For the GVAR model that we aim to develop in this paper, we refrain however from referring to external data sources and instead estimate the weights along with the other GVAR parameters, following a method suggested by Gross

(2013). The rationale for estimating the weights in particular for the application at hand is that there is no obvious choice for the weights that would link the sovereigns, the banks, and the corporate sectors. For GDP and credit growth, trade-based weights might be an option; estimated weights and the accompanying error bounds, however, suggested significant deviations from trade-based weights for about 75–80 percent of the weights.[7] In order to not to induce any biases, we therefore estimate all weights for the five variables in the model separately.[8] The estimated weighting matrices that we employ are presented in Appendix II.

C. Global Solution of the Model

For solving the global model, we define a country-specific $\left(k_i + k_i^*\right)\times 1$ vector z_{it} as follows.

(10) $$z_{it} = \begin{bmatrix} y_{it} \\ y_{it}^* \end{bmatrix}$$

The local models in equation (9) can then be reformulated.

(11) $$A_{i0} z_{it} = a_{i0} + a_{i1} t + A_{i1} z_{i,t-1} + ... + A_{iP_i} z_{i,t-P} + \varepsilon_{it}$$

where we assume for ease of notation in the following that P=Q and the global exogenous variable vector d_t to be empty. The A_{ip} coefficient matrices are all of size $k_i \times \left(k_i + k_i^*\right)$ and have the following form.

(12) $$\begin{aligned} &A_{i0} = \left(I_{k_i}, -\Lambda_{i0}\right) \\ &A_{i1} = \left(\Phi_{i1}, \Lambda_{i1}\right) \\ &... \\ &A_{iP} = \left(\Phi_{iP}, \Lambda_{iP}\right) \end{aligned}$$

The endogenous variables across countries are stacked in one global vector y_t which is of size $k \times 1$ where $k = \sum_{i=0}^{N} k_i$. Here, we need to map the local variable vectors z_{it} to the

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[7] We do not report the error bounds in this paper. They are available from the authors upon request.

[8] Estimating the weights comes at the cost of higher uncertainty that surrounds the estimated coefficients of the model.

global endogenous variable vector y_t which is accomplished via $(k_i \times k_i^*) \times k$ link matrices W_i. With $z_{it} = W_i y_t$ we can rewrite the model once more.

(13) $$A_{i0} W_i y_t = a_{i0} + a_{i1} t + A_{i1} W_i y_{t-1} + ... + A_{iP_i} W_i y_{t-P} + \varepsilon_t$$

We move from country-specific models to the global model by stacking the former in one global system, that is,

(14) $$G_0 y_t = a_0 + a_1 t + G_1 y_{t-1} + ... + G_P y_{t-P} + \varepsilon_t$$

The $k \times k$ matrices G have the following format.

(15) $$(G_0,...,.G_P) = \begin{pmatrix} A_{11}W_1 & & A_{1P}W_1 \\ A_{21}W_2 & & A_{2P}W_2 \\ ... & ,..., & ... \\ A_{N1}W_N & & A_{NP}W_N \end{pmatrix}$$

Finally, we obtain a reduced form of the global model by pre-multiplying the system with the inverse of G_0.

(16) $$y_t = G_0^{-1} a_0 + G_0^{-1} a_1 t + G_0^{-1} G_1 y_{t-1} + ... + G_0^{-1} G_P y_{t-P} + G_0^{-1} \varepsilon_t$$

For shock simulation purposes, standard impulse response techniques could be employed, e.g., of a ‘generalized’ type (see Pesaran and Shin, 1998) in order to account for correlation among shocks right upon arrival of a shock. Generalized impulse responses are often used with GVAR models because a causal ordering that would be needed to design an orthogonalized impulse response profile can hardly be meaningfully set up for such large-scale models that easily involve up to 100 or more equations (the present model consists of 80 equations).

An alternative concept that we employ for generating shock profiles is motivated by the fact that we aim to apply *multiple* shocks, while not wanting to neglect an instantaneous, correlated shock response on impact to other variables, which for instance a simple non-factorized, multiple shock would imply. The generalized impulse response concept is not useful here because it would allow considering only single shock origins. Instead, we operate with the global model’s residual matrix and proceed in two steps. First, their joint, multivariate distribution is simulated so as to obtain a bootstrap replicate, which is accomplished without assuming any concrete functional form for the copula, that, together with the marginal distributions of the residual series, constitute the joint distribution of the residuals.[9] The bootstrap is therefore entirely nonparametric in nature.[10] Second, we then condition the bootstrap replicate on an assumption for a number (a multiple) of variables and retain only those simulated bootstrap samples that are conform to these assumptions. Assumptions are formulated as inequalities, for instance by hypothesizing that Spain's sovereign and banking risk indicators (their expected loss ratios) increase at least by 100 bps or more. The simulated bootstrap paths that let the two shock origins move beyond the self-set thresholds would be retained and a shortfall measure, i.e., an average (or in principle any other moment) of the truncated distribution for all equations' residuals be computed. To motivate the thresholds for conducting this shortfall estimation conditional on a scenario assumption we take an unconditional quantile of the marginal distribution of the respective shock origins' residuals at a pre-set probability level (e.g., at 1 percent).[11]

For deriving error bounds around the simulated dynamic responses from the GVAR, we simulate a large number of pseudo-datasets from the initial model calibration upon which we re-estimate and simulate the impulse responses from the model. From the resulting distribution we compute selected percentiles from their tails. The resampling procedure for generating pseudo-data samples is again nonparametric in nature, i.e., we refrain from imposing a concrete parametric assumption on the joint and the marginal distributions for the model residuals.

IV. Macro and CCA Data Inputs

The CCA-GVAR model variables are real GDP, credit to the private sector, sovereign EL, national banking system EL, and corporate sector EL. The data sample has a monthly frequency and ranges from January 2002 to December 2012 (132 observations). Our sample covers 16 countries (13 EU countries plus Norway, Switzerland and the U.S.). GDP is interpolated from quarterly to monthly by means of a quadratic match sum conversion method. With five endogenous model variables and 16 countries, the global model has 80 equations in total. All variables are modeled in first (i.e., monthly) differences of

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[9] A 'simple' bootstrap is employed here (see Davidson and McKinnon 2005 for a general introduction to bootstrapping methods). There is no need for a block bootstrap because the model residuals shall be sufficiently free of serial correlation.

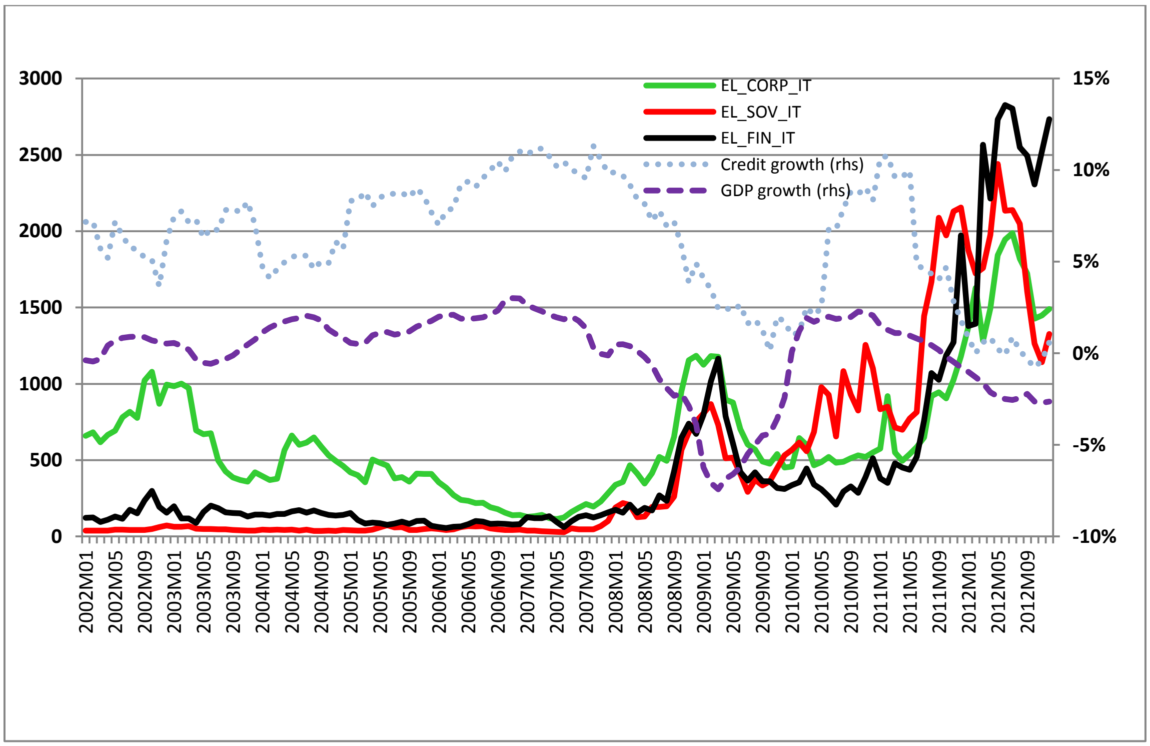
[10] A parametric assumption for the joint residual distribution could be employed, under which the truncated distribution and resulting shortfall measures conditional on some scenario assumption could be computed. Experimentation with our model residuals, however, suggested that shock responses from the nonparametric simulation tended to be somewhat more adverse, suggesting that the joint Normal assumption would tend to underestimate tail risk. We do not present the parametric (joint Normal) shock profiles and the resulting dynamic responses in the following, nor do we aim to scrutinize in much detail the precise shape of the joint distribution. The nonparametric approach to simulation is meant to ensure that we do not underestimate, nor distort the tail dependence structure of the shocks.

[11] Note that as a result of the nonparametric treatment of the multivariate shock distribution, a positive and negative shock scenario with otherwise equal shock origins and tail probabilities (e.g. at 1 percent) might imply different shock sizes in absolute terms.

logarithmic levels. The first differences of the variables are stationary at conventional levels of significance for all countries and banking systems.

Figure 4 shows for the case of Italy the evolution of the EL ratios for the sovereign, banking system, and corporate sector, all expressed in basis points along with real GDP and credit growth, here expressed in year-on-year growth rates. ELs are the expected loss ratio at a five year horizon. Note how the banking sector expected loss ratio spikes when real activity sharply dropped over the 2008–2009 period. The banking and sovereign risk indicators have recently been rising. In Appendix III, we collect the same graphs with all input variables for all 16 countries that our model comprises.

Figure 4. Italy: Sovereign, Banking System, and Corporate Sector EL, Real GDP Growth, and Credit Growth



Source: Moody's CreditEdge, Eurostat, and author estimates.

V. Shock Scenario Analysis

This section describes the responses of sovereigns, the financial sectors, the corporate sectors, GDP growth and credit growth to four different shock scenarios.[12] The features of four scenarios that we consider are summarized in Table 1 below.

[12] A summary of the CCA-GVAR model and results are presented in ECB, Financial Stability Review, May 2013.

Table 1. Shock Scenarios

Scenario / Shock origins	Marginal shock probabilities	Joint shock probability	Implied shock sizes at T=1 (EL relative)		Implied shock sizes at T=1 (EL absolute in basis points)	
			ES	IT	ES	IT
Adverse shock to Spanish (ES) and Italian (IT) sovereigns	5%	0.7%	18.4%	19.6%	253	260
Adverse shock to Spanish (ES) and Italian (IT) banking systems	5%	0.8%	15.0%	24.3%	275	665
Positive shock to Spanish (ES) and Italian (IT) sovereigns	5%	1.6%	-23.7%	-21.8%	-325	-290
Positive shock to Spanish (ES) and Italian (IT) banking systems	5%	0.8%	-31.5%	-64.9%	-576	-1,774

For assessing the impact of the four scenarios we follow three approaches: First, we examine the shock profiles on impact, i.e., referring to period T=1 when the hypothesized shocks arrive. Spillovers to countries and variables that were not shocked are allowed for time T=1 (by design of the simulation method described in the previous sub-section). Detailed shock profiles on impact for all scenarios and variables are collected in Appendix IV. Second, we report dynamic impulse responses to the initial shocks for a two-year horizon, results for which are collected in Appendix V. Third, we aim to further compress the information contained in the dynamic impulse responses by referring to only the most adverse cumulative deviation over the two-year simulation horizon, i.e., for EL variables the maximum, and for GDP and credit growth the minimum cumulative responses. The maximum/minimum cumulative deviations are an interesting summary measure as they tell how much each variable moves cumulatively from the outset of the scenario horizon. Detailed results for the minimum/maximum cumulative deviations for all scenarios are collected in Appendix VI. As regards the significance of shock scenario responses, we also aim to compress the information, by reporting the *p*-values only referring to the maximum or minimum along the simulation horizon. For the CCA risk indicators, the *p*-values refer to the hypothesis that responses are positive (adverse in that sense); for GDP and credit they refer to the hypothesis that responses be negative. For the positive scenarios that we consider, the orientation is the opposite. The table in Annex VII indicates whether responses where significant at the 1 percent, 5 percent, or 10 percent levels. Overall, not too many of the responses are significant at these levels, which partly owes to the fact that the weight estimation scheme that we employ increases parameter uncertainty and thereby tends to render error bounds relatively wide.[13]

Since all variables are modeled in first differences of logarithmic levels, the simulated raw model responses, including those for ELs for banks, sovereigns, and the corporate sectors are to be understood as logarithmic percentage point deviations. For the ELs in Appendix IV, we transform the relative changes back to absolute EL basis point changes by chaining the relative changes implied by the scenario to end-sample (December 2012) EL

[13] As hinted to earlier, we accept that responses tend to be somewhat less significant for the sake of mitigating the risks arising from possible mis-specification when employing fix weights that would not correspond to the true weights. Gross (2013) has demonstrated that the weights do matter in small samples.

ratios, to then compute the absolute shock responses in EL basis points. We should keep in mind that a ranking of severity of responses based on the absolute EL measures is therefore partly reflective of the start point levels of EL that we take as a reference. For the responses in Appendix VI (maximum/minimum cumulative deviations) we convert the relative EL responses into absolute fair value credit spread responses. Here, too, the reference point for credit spread levels has been set to December 2012.

A. Shock Scenario One—Adverse Shock to Sovereigns in Italy and Spain

The adverse shocks to the sovereign EL, with marginal shock probabilities set to 5 percent (resulting in a joint probability of 0.7 percent), let the ELs for the two countries increase by about 250–260 basis points on impact of the scenario (see Appendix IV). The model-implied response at T=1 for Greece suggests an approximate 700 basis point increase for the Greek sovereign EL ratio. Responses are pronounced for other stressed European economies such as Portugal and Ireland.

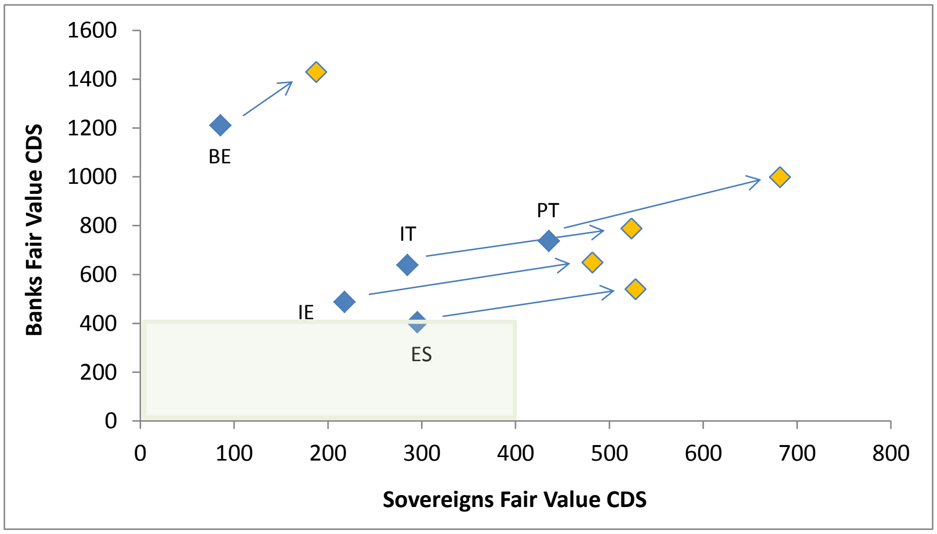
Spillovers to banking system ELs are notable for Ireland, Spain, Greece, Italy and Portugal, with EL responses ranging between 160–370 basis points. The corporate sector EL shock profile at T=1 shows smaller effects, yet suggests a rather similar ranking of countries, with Portugal, Spain, Greece, and Ireland attaining the highest ranks with respect to corporate sector EL deviations. They range between 46–150 basis points.

With respect to GDP and credit, T=1 impact rankings suggest strong effects for Greece, Ireland, and Spain, with their GDPs falling by between -0.6 percent (Spain) and -1.4 percent (Greece) in the first month of the simulation horizon. Credit to the private sector, for the first five most strongly affected countries would be contracting by -0.5 percent (Greece) and -1.4 percent (Italy) in the first month.

Turning to the dynamic responses (see Appendix V) and the corresponding maximum cumulative deviations (Appendix VI), we find the same set of stressed European economies attaining the highest ranks.[14] Figure 5 below takes the small subset of countries that appear to be particularly strongly affected and scatters the sovereign against the banks' fair value spread at the end-sample position (December 2012) and the shock scenario. The underlying deviations correspond to the results presented in Appendix VI.

[14] Focus will in the following lie on the maximum cumulative responses presented in Appendix VI. Appendix V is left for the reader's information.

Figure 5. Shock Scenario One—Sovereign Versus Banks' Maximum Cumulative Fair-Value Spread Responses



Source: Author estimates.

For the Greek sovereign, the maximum cumulative fair-value CDS would move beyond 10,000 basis points; it is not included in Figure 5 for that reason. For Ireland and Portugal, the simulated sovereign fair value CDS responses equal about 250 basis points. The Italian and Spanish banking systems, where shocks were set for the respective sovereigns, rank only sixth and seventh, with cumulative maximum responses yet ranging around 140 basis points. Corporate sector responses appear less pronounced in magnitudes, with the responses for Greece equaling 210 basis points. Maximum deviations for GDP and credit can again be observed for several stressed European economies. Greece's GDP contracts by -1.9 percent cumulatively. Ireland's credit to the private sector contracts by -5.1 percent. Overall, the scenario thus implies sizable adverse responses for risk across sovereigns, banks, and the corporate sector. Real activity and credit contract markedly.

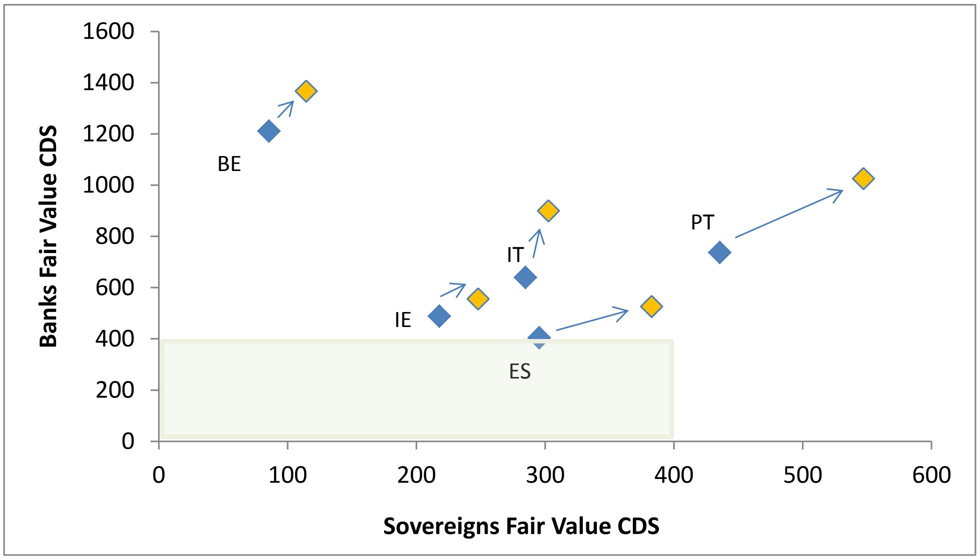
B. Shock Scenario Two—Adverse Shock to Banking Systems in Italy and Spain

The adverse shocks to banking systems in Italy and Spain, with marginal probabilities set to 5 percent (resulting in a joint probability of 0.8 percent) imply shock sizes to the EL ratios for the two countries of 665 and 275 basis points, respectively.

The shock profiles at T=1, in particular for sovereign and bank ELs, suggest that peripheral countries are strongly affected, while the EL indicators for selected countries such as Sweden, Norway, Austria, France and Germany would fall on impact; for the French sovereign EL for instance by about 70 basis points. For Portugal, the simulated response at T=1 is stronger than for the shock originating banking systems in Spain and Italy, both on the sovereign (+370 basis points) and the banking system side (+690 basis points). See Figure 6.

With regard to the corporate sector ELs, vulnerable appear Italy, where the shock originated, and further Portugal, France and Greece, with shocks ranging between 90 and 175 basis points. Most adverse cumulative deviations are again summarized for a smaller subset of strongly affected countries.

Figure 6. Shock Scenario Two—Sovereign Versus Banks' Maximum Cumulative Fair-Value Spread Responses



Source: Author estimates.

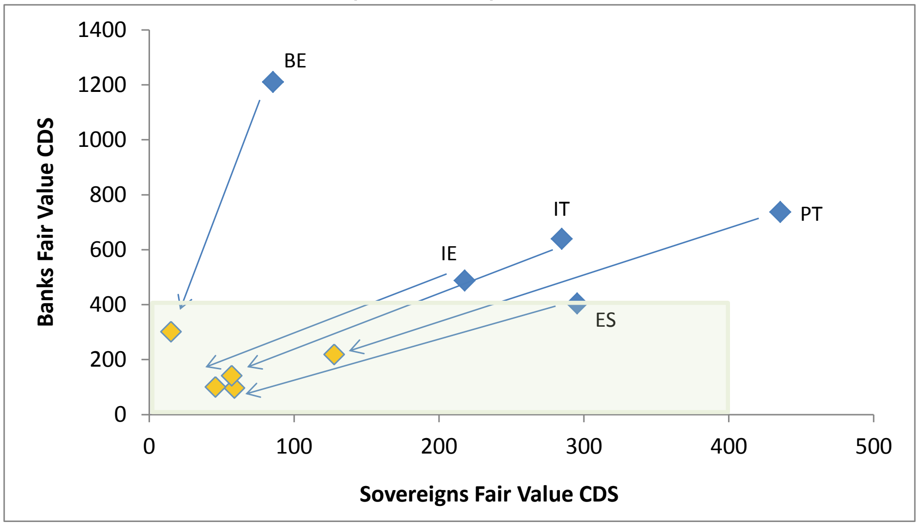
In comparison to the sovereign shock scenario (see previous subsection and in particular Figure 5), it can be seen that responses are now more pronounced along the bank EL dimension, and relatively less along the sovereign dimension. Cumulative deviations away from the start point fair value CDS for the sovereign shown in Figure 6 range between 30 basis points for Belgium and 110 basis points for Portugal. Deviations for the banking systems range between 160 basis points for Belgium and 290 basis points for Portugal. Corporate sector responses approach 90 basis points for Portugal. The scenario, furthermore, implies a cumulative contraction of GDPs up to -0.5 percent for Italy, and let credit to the private sector contract by close to -2.5 percent for Spain.

C. Shock Scenario Three—Positive Shock to Sovereigns in Italy and Spain

The positive shocks to the sovereigns, with marginal shock probabilities set to 5 percent (resulting in a joint probability of 1.6 percent), let the ELs for Italy and Spain fall by about 290–352 basis points on impact of the scenario (see Appendix IV). The Greek sovereign EL response at T=1 would be relatively pronounced in absolute terms, with the EL ratio falling by about 700 basis points. With respect to the banking systems, Belgium reacts most strongly at T=1 with its EL ratio decreasing by almost 1,000 basis points. On the corporate sector side, responses are sizable, too, ranging between -35 basis points for Portugal and -350 basis points for Spain.

Turning again to cumulative responses to assess how much deviation the scenario implies for along the horizon (Appendix VI), Figure 7 scatters sovereign and bank fair value spread deviations for a small subset of countries.

Figure 7. Shock Scenario Three—Sovereign Versus Banks' Minimum Cumulative Fair-Value Spread Responses



Source: Author estimates.

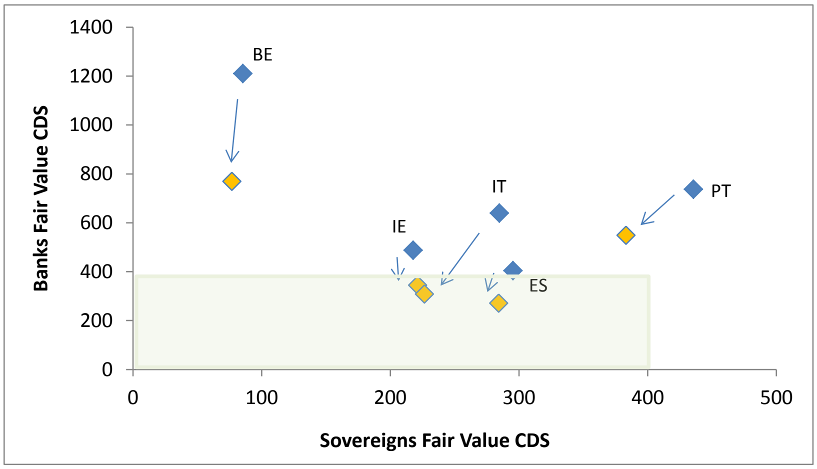
For the countries contained in Figure 7, all sovereign and banking system fair value spreads would move back into the 'safe zone' comprising the less than 400 basis point area. For the sovereigns, fair value spreads would fall by between -70 basis points for Belgium and -310 basis points for Portugal. For the banking systems, the cumulative deviations range between -500 and -900 basis points for Italy and Belgium, respectively. The simulated corporate sector responses for the median of the countries range between -65 basis points for Belgium and -400 basis points for Greece. With respect to GDP and credit growth, the scenario implies relatively strong positive cumulative reactions for all countries. The cumulative most positive impact on Greece's GDP for instance has been estimated to equal 5.5 percent. Cumulative credit growth would even surpass 8 percent for Ireland.

D. Shock Scenario Four—Positive Shock to Banking Systems in Italy and Spain

The positive shocks to the banking systems, with marginal shock probabilities set to 5 percent (resulting in a joint probability of 0.8 percent), let the ELs for banks in Italy and Spain fall by about 1,700–580 basis points on impact of the scenario (see Appendix IV). Italy's end-sample EL ratio of 2,730 basis points would fall by 65 percent. The scenario therefore envisages a sizable positive impulse to the two banking systems.

In parallel to the T=1 impulses of the shock origins themselves, sovereigns and banks in Greece, Belgium, and Portugal appear to benefit the most. Sovereign EL fall by -230 basis points for Portugal and -800 basis points for Greece. Banking system ELs decrease by close to 800 basis points for Belgium and -2,300 for Greece. The set of countries whose corporate sectors benefit the most include again Italy, Portugal, Spain and Greece, with EL responses ranging between -135 and -180 basis points. Real GDP responses at T=1 are somewhat less pronounced compared to Scenario Three, with the most positive response being recorded for Spain's GDP that would rise by +0.9 percent upon arrival of the shock. Credit growth responses on the other hand are somewhat more pronounced on average compared to Scenario Three, with credit in Spain for instance growing by 2.7 percent. Figure 8 presents the most positive cumulative responses along the simulation horizon again for the sub-sample of countries for which responses are most pronounced.

Figure 8. Shock Scenario Four—Sovereign Versus Banks' Minimum Cumulative Fair-Value Spread Responses



Source: Author estimates.

Despite the banking systems (in Italy and Spain) having been the shock origins in Scenario Four, it is Portugal's and Belgium's sovereigns that move back into the safe zone that is delineated by the 400 basis point threshold for the fair value spreads; Their banking system fair value spreads remain at elevated levels, at 770 basis points for Belgium and 550 basis points for Portugal. To the extent that Scenarios Three and Four are comparable in terms of severity in a probabilistic sense (5 percent marginal shock probabilities), the simulation results suggest that positive impulses to sovereign risk have more potential to compress jointly banks' and sovereigns' risk, as measured by their fair value credit spreads.

VI. Further Extensions and Applications

The framework presented in this paper is a first attempt to link forward-looking CCA risk indicators in a multi-country GVAR framework. Further extensions of this analysis are numerous.

The CCA risk indicators' drivers are asset value and volatility, default barrier, and leverage. They relate bank market capital to assets level and volatility as well as default probability and credit spreads. As such, it is a particularly valuable framework for comparing the impact of different risk mitigation policies, both on balance sheet changes and risk transfer-type instruments and policies, as shown in Table 2 below.

Table 2. Risk Mitigation Policies

On-Balance Sheet Adjustment Policies to Mitigate Risk to:			**Risk Transfer-Type Instruments and Policies to Mitigate Risk to:**		
Banks		**Sovereign**	**Banks**	**Sovereign**	**Corporates**
Increase market capital	Increase regulatory capital; Increase solvency ratio	Reduce or increase maturity of debt	Guarantees on bank senior debt; asset protection guarantees	Guarantees or insurance or selling CDS protection on sovereign debt	Incentives for banks to lend to corporates
Increase assets, change asset composition and lower asset volatility	Pillar 2 measures Macro-prudential policies, including ones that affect credit growth	Increase assets, change asset composition and lower asset volatility	EU wide deposit insurance	Debt purchases by banks (e.g., LTRO) Debt purchases by public entity (SMP/OMT, EFSF/ESM, other)	Corporate debt (or equity) across the board purchases by government or central bank
Debt equity conversion/ Bail-in		Extending debt maturity or restructuring	EU wide bank resolution	Mutualize, socialize existing and/or new sovereign debt	

Ways to mitigate risk (lower the EL and reduce spreads) are to increase bank capital or debt to equity conversion (see Box 1 and Figure 2 for magnitudes of changes in EL). Guarantees on bank debt or toxic ring-fenced asset guarantees will lower spreads and reduce risk. For sovereigns, ways to mitigate risk include increasing debt maturity, having debt roll-over backstops from supra national organizations, and credible long-term fiscal policies. Sovereign debt purchases or explicit guarantees by a public entity (ECB, the European Stability Mechanism, ESM, or other entity) help lower sovereign spreads. Other policies such as Outright Monetary Transactions (OMT), or potential for OMT purchases of sovereign debt, can lower sovereign spreads, lower risk, and have positive growth impacts.

The framework developed here may be a tool to assess the combinations of policies that reduce risk for banking systems and sovereigns while increasing real GDP growth. Going forward there are several extensions and refinements to the framework described in this paper. One is to consider alternative thresholds/criteria for defining the boundaries of the 'low risk zone'. This framework could be adapted for conditional/unconditional forecasting of CCA-GVAR model variables. Also additional fiscal variables could be included in the model. A regime-switching GVAR could be employed to allow for the relation between model variables to be regime-dependent. Simulated shock scenarios would become state-dependent, i.e. depend on whether the outset for the shock simulation horizon is chosen to be a crisis or non-crisis regime.[15]

The framework could be extended to evaluate changes in FVCDS spreads on the market capital and CCA capital ratio for banking systems and individual banks as well as to more explicitly analyze the impact of changes in FVCDS on observed CDS spreads (which are affected by implicit and explicit guarantees).

The CCA-GVAR model framework can be used to further explore the role of conventional and in particular unconventional policy measures, or as well to account more explicitly for the fact that some countries that the global model comprises entered EU/IMF programs, to then simulate counterfactual scenarios while assuming unconventional policy be active or inactive, or the program status of countries be activated or deactivated.

Finally, the out-of-sample forecast performance of the CCA-GVAR shall be assessed in future work. The aim would be to take the CCA-GVAR as a reference, and then switch various sectorial linkages off, e.g. the sovereign-bank channel, the sovereign to GDP and credit channel, etc. to then examine which channels contribute the most to enhancing the conditional out-of-sample forecast accuracy.

VII. CONCLUSIONS

While the global financial crisis has seen many phases, a main feature has been the interplay of risks across various economic and financial sectors, even culminating in outright risk transfer in some cases. Prominent examples have included the spillover of fragilities from the financial sector to the broader economy and from the banking sector to the sovereign sector. Understanding 'macro-financial' linkages, i.e. the interplay between financial institutions, and also markets, and the real economy, has become a topic of growing interest since the recent sovereign debt crisis for academics, market participants and policy makers.

[15] See Binder and Gross 2013 for the regime-switching Global VAR methodology.

In particular for policy makers, there is a need to have tools producing reliable information as well as instruments at hand that allow them to take efficient and effective policy actions. The goal is to use the framework presented in this paper to help identify policies that mitigate banking system, sovereign credit risk and recession risk—policies could include bank liquidity injections, bank capital increases, purchase of sovereign debt, guarantees of bank senior debt by sovereigns, guarantees of sovereigns by other public bodies, etc.

In monitoring the propensity for the above mentioned spillover to occur and in evaluating their impact, direct (i.e., accounting) linkages tend to understate risks. Earlier and more robust signals of the possibility for cross-sectoral linkages to cause systemic stress can be obtained via contingent claims analysis (CCA), which augments cross-sectoral linkages on the basis of the main tenets of financial option pricing. This paper applies such a methodology to the joint dynamics among three sectors that are key in crisis propagation (the banking, sovereign and corporate sectors), along with real economic activity and credit growth in a Global Vector Autoregressive (GVAR) model.

The advantage of the CCA-GVAR approach is that it allows for an endogenous interaction of all sectors and risk measures that the model comprises. Moreover, integrating macroeconomic and financial variables in one framework, while using for some variables CCA indicators instead of accounting measures, we see as an improvement compared to the existing empirical work in the literature.

The analysis relies on three forward-looking risk indicators derived from CCA: (i) fair-value spreads, which pool multiple sources of default risk, including the market price of risk; (ii) loss given default; and (iii) the expected default frequency. CCA indicators capture the nonlinearity of changes in bank assets, equity capital, bank credit spreads, and default probabilities that are derived from forward-looking equity market information in conjunction with balance sheet data. It also captures the expected losses, spreads and default probability for sovereigns and the corporate sector.

A key feature of the CCA-GVAR framework is that it operates with broad balance sheet items (i.e., assets, liabilities and equity capital) aggregated at the country level. In that sense, it has a “macro” perspective to the balance sheet, instead of the “micro” view that, for instance, a solvency analysis takes, which involves specific models for various bank balance sheet components (such as interest income, interest expense, loan losses, mark-to-market valuation losses, etc.) that are then applied at a bank-by-bank level.

Our global model has been set up for 13 EU countries as well as Norway, Switzerland, and the United States and has been estimated based on a sample period from January 2002 to December 2012. As an empirical example, the paper presents the model responses to a negative and a positive shock to (i) the sovereigns and (ii) the banking systems in Italy and Spain. With regard to the adverse scenarios, the results suggest that a negative shock to the sovereigns in Italy and Spain is more potent than a negative shock to their banking systems to induce sizable adverse responses for risk across sovereigns, banks, and the corporate sector. Real activity and credit contract markedly under the adverse shocks to sovereign risk.

To the extent that the positive shock scenarios are comparable in terms of severity in a probabilistic sense, the simulation results suggest that positive impulses to sovereign risk have more potential to compress jointly banks' and sovereigns' risk, as measured by their fair value credit spreads. Moreover, it is striking that across all scenarios credit spread responses for banks are more pronounced than the sovereign risk measures, while the corporate sector appears generally as the least affected.

APPENDIX I. CONTINGENT CLAIMS ANALYSIS

The market value of assets is key to understanding credit risk and crisis probabilities. Default happens when assets cannot service debt payments, that is, when assets fall below a distress barrier (typically defined as all short-term debt plus a fraction of long-term debt). Thus, default risk is driven by uncertain changes in the future asset value, relative to promised payments on debt. The market value of a bank's asset is stochastic and may decline below the point where it can cover its scheduled debt payments on scheduled dates. Once the market value of assets and asset volatility are estimated the default probabilities can be calculated.

A. Contingent Claims Analysis: Merton Model

We can use this basic idea to construct risk-adjusted balance sheets, i.e., CCA balance sheets where the total market value of assets, *A*, at any time, *T*, is equal to the sum of its equity market value, *E*, and its risky debt, *D*. The asset value is stochastic and may fall below the value of outstanding liabilities. Equity and debt derive their value from the uncertain assets. As pointed out by Merton (1973) equity value is the value of an implicit call option on the assets, with an exercise price equal to default barrier, *B*. The value of risky debt is equal to default-free debt minus the present value of expected loss due to default. The firm's outstanding liabilities constitute the bankruptcy level. The expected loss due to default can be calculated as the value of a put option on the assets, A, with an exercise price equal to *B*, time horizon *T*, risk-free rate r, and**,** asset volatility σ_A. The value of the implicit put option will be called the Expected Loss Value (ELV).

Risky Debt = Default-free Debt − Expected Loss Value

$$D = Be^{-rT} - ELV \tag{17}$$

The calibration of the model uses the value of equity, the volatility of equity, the distress barrier as inputs into two equations in order to calculate the implied asset value and implied asset volatility.[16] Equity and equity volatility are consensus forecasts of market participants and this provide forward-looking information. The value of assets is unobservable, but it can be implied using CCA. In the Merton Model for firms, banks and non-bank financials with traded equity use equity, *E*, and equity volatility, σ_E, and the distress barrier in the following two equations (equations 18 and 19) to solve for the two unknowns A, asset value, and σ_A**,** asset volatility. $N(\cdot)$ is the cumulative standard normal distribution.

[16] See Merton (1973, 1974, 1977, 1992), Gray, Merton, and Bodie (2008), and Gray and Malone (2008).

(18) $$E = A\mathrm{N}(d_1) - Be^{-rT}\mathrm{N}(d_2)$$

(19) $$E\sigma_E = A\sigma_A N(d_1)$$

(20) $$d_1 = \frac{\ln\left(\frac{A}{B}\right) + \left(r + \frac{\sigma_A^2}{2}\right)T}{\sigma_A\sqrt{T}} \text{ and } d_2 = \frac{\ln\left(\frac{A}{B}\right) + \left(r - \frac{\sigma_A^2}{2}\right)T}{\sigma_A\sqrt{T}}$$

Once the asset value, asset volatility are known, together with the default barrier, time horizon, and r, the values of the ELV (implicit put option) are calculated from:

(21) $$ELV = Be^{-rT}N(-d_2) - A_0 N(-d_1)$$

Risk-neutral probability of default is $N(-d_2)$.

The formula for the credit spread is:

(22) $$s = -\tfrac{1}{T}\ln(1 - EL) \text{ and the } EL = \frac{ELV}{Be^{-rT}} = N(-d_2) * LGD$$

B. Moody's Model Overview

In the 1990s a company called KMV adapted Merton's approach for commercial applications. They used information from the equity market for firms, along with book value information of liabilities to get estimates of distance-to-distress, which were used with a large database of actual defaults to estimate Expected Default Probabilities (EDF™). KMV was purchased by Moody's in 2002. The exact methodology is confidential, but general descriptions can be found in Bohn (2000), and Crouhy et al. (2000). The latest version is Moody's CreditEdge which provide daily data on EDFs, market value of assets, risk indicators etc. for tens of thousands of financial institutions and corporations worldwide. The EDF credit measure is calculated using an iterative procedure to solve for the asset volatility. It uses and initial guess of volatility to determine asset value and de-lever the equity returns. The volatility of the asset returns are used as an input into the next iteration of asset values and asset returns until a convergence is obtained. In essence, the model used equity return volatility, equity values, distress barrier from book value of liabilities, and time horizon to get a distance-to-distress. This distance-to-distress was then mapped to actual default probabilities, called EDFs (expected default probabilities), using a database of detailed real world default probabilities for many firms.

Moody's CreditEdge initially estimates the "actual" default probabilities. The EDF credit measure is calculated daily for 35,000 corporations and financial institutions in

55 countries (see MKMV 2001 and 2003). Robustness checks prove the model to be quite accurate and a leading indicator for default.[17]

The standard Merton-type default probability is the "risk-neutral" (also referred to as the "risk-adjusted") default probability, $N(-d_2)$. In reality, there are two types of distance-to-distress, d_2 : (i) the *risk-neutral* distance-to-default with an asset drift of the risk-free rate (r) and its corresponding risk-neutral default probability $N(-d_2)$; and (ii) the *real-world* distance-to-default, $d_{2,\mu}$, with an asset drift of μ_A and its corresponding "actual" default probability, $N(d_{2,\mu})$. These two risk indicators are related by the *market price of risk*, λ:

(23) $$N(-d_{2,\mu}) = N(-d_2 - \lambda\sqrt{t})$$

The market price of risk reflects investors' risk aversion and can be measured in several ways. Moody's CreditEdge uses a two moment CAPM to derive λ and show that is can be estimated as:

(24) $$\lambda = \frac{\mu_A - r}{\sigma_A} = \rho_{A,M} SR$$

where $\rho_{A,M}$ is the correlation of the bank's or corporate's asset return with the market and *SR*, the market Sharpe Ratio. According to CreditEdge data, $\rho_{A,M}$ has fluctuated around 0.5 to 0.7 and SR was 0.6 before the crisis and reached a high of 1.2 at the peak of the 2008–09 crisis.

To get the risk neutral default EDF, first, a one-year EDF is converted to a cumulative five-year EDF as follows:

(25) $$CEDF_{5-yr} = 1-(1-EDF_{1-yr})^5$$

The formula for the cumulative risk-neutral EDF is:

(26) $$CEDF_{risk-neutral} = N(N^{-1}\left(CEDF_T\right) + \rho_{A,M} SR\sqrt{T})$$

Moody's CreditEdge calculates the Fair Value CDS (FVCDS), which is calculated using an LGD that is the average LGD for the banking sector as a whole (Dwyer et al. 2007). For corporate the LGD is the respective corporate sector LGD.

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[17] See Dwyer, Douglas and Irina Korablev (2007), and Korablev and Qu (2009).

(27) $$FVCDS = -\frac{1}{T}\ln\left(1 - CEDF_{risk-neutral} LGD\right)$$

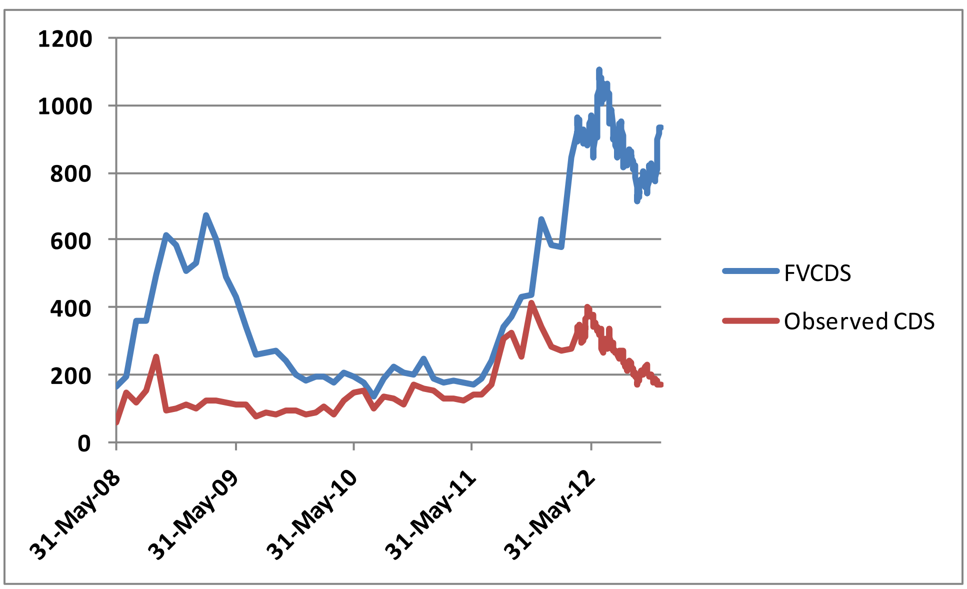
The expected loss ratio is thus:

(28) $$CEDF_{risk-neutral} LGD = EL$$

In normal (non-distress) periods, the observed CDS and FVCDS are equal or quite close to equal. However, during the 2008–2009 financial crisis period, explicit and implicit government guarantees on bank debt depressed the observed CDS resulting in the FVCDS being significantly higher. The difference between the two can be seen as an estimate of the "market implied" government contingent liabilities (Gray et al., 2008, Moody's Analytics, 2011, Gray and Malone 2012, Schweikhard and Tsesmelidakis, 2012).

Below in Figure 9 is an example of a large bank in France. The FVCDS is much higher than the observed (Markit) CDS in the 2008–2009 period and November 2011 to May 2012 period.

Figure 9. Example Bank FVCDS, and Markit CDS (bps)

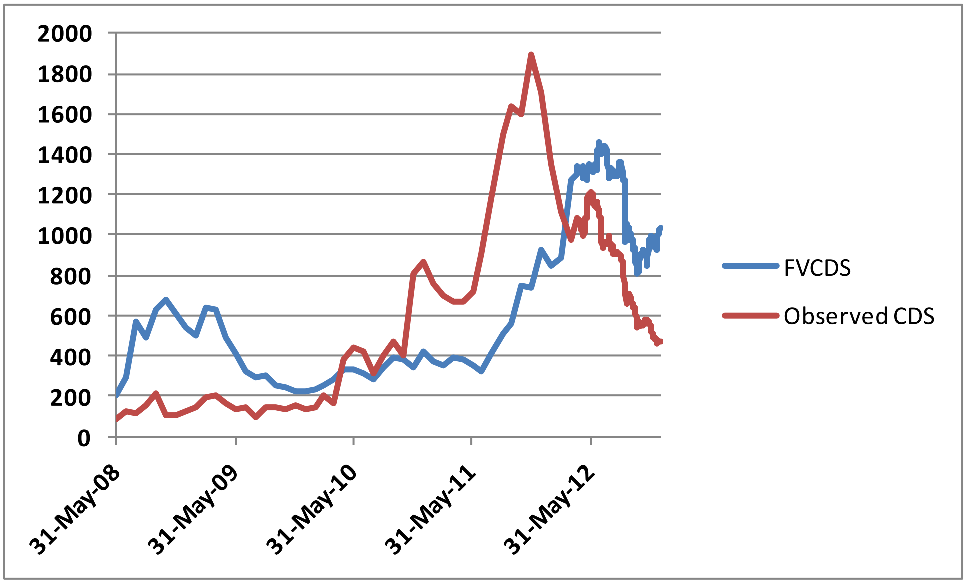


Source: Moody's CreditEdge

Since the sovereign crisis began in Europe in 2010, for countries such as Greece and Portugal the observed bank CDS spreads have surpassed FVCDS spreads. That may partly be due to a weakening of the sovereign guarantee. However, evidence from the Moody's CreditEdge data is that high sovereign spreads "spill over" into the bank spreads, raising them above the FVCDS. The value of the *LGD* that would be needed *to match the observed bank CDS spreads* is significantly over 100 percent for many banks in Greece and Portugal.[18]

The following example (a large Portuguese bank) in Figure 10 shows five year spreads in bps. The FVCDS is higher in than the observed CDS in 2008 and 2009. As pointed out many analysts and Moody's the difference is mostly due to the impact of the government guarantee (Moody's 2011, Gray and Jobst 2010, 2011). However, when the sovereign spread increases higher than the FVCDS, the observed CDS rise to be higher than or near the sovereign spreads as shown in the graph in 2010 and 2011.

Figure 10. Observed CDS Versus FVCDS Showing Spillover from Sovereign



Source: Moody's CreditEdge

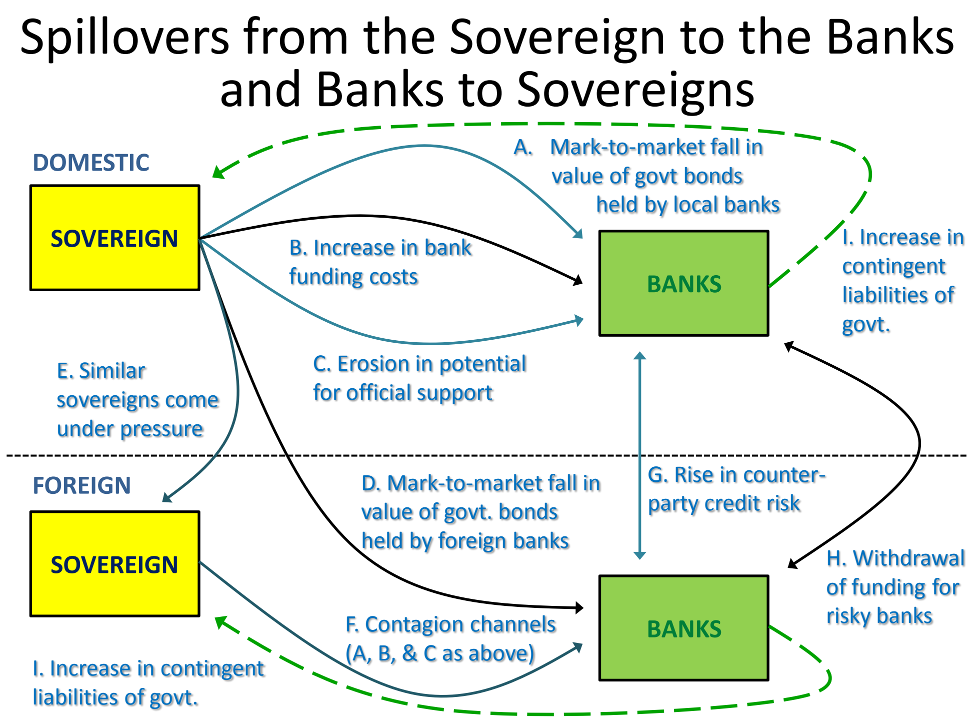
This is evidence of a weakened perceived guarantee, but its more than that, it appears to be a spillover from the sovereign spread to the bank from mid 2010 to early 2012. The fact that MKMV implied LGD needed to match the observed CDS needs to be about 1.3 to 1.6 is evidence of the spillover, an LGD of 0.7 may be plausible so the difference in spread caused by any LGD higher than 0.7 is evidence of spillover from the sovereign. For the above reasons, the FVCDS and its associated EL more closely reflects banks' risk. Bank CDS are affected significantly by implicit and explicit government guarantees and by sovereign spillover when sovereign spreads are high. The EL associated with the FVCDS is used in the CCA-GVAR for these reasons. Data for the 53 banks was from CreditEdge data base, 12 in United States, 5 in United Kingdom., 1 in Austria, 2 in Belgium, 1 in Denmark, 4 in France,

[18] LGDs would have to be as high as 160 percent (for example, for banks in Greece) to match observed CDS spreads. An *LGD* exceeding 100 percent does not make sense.

2 in Germany, 4 in Greece, 2 in Ireland, 3 in Italy, 4 in Netherlands, 1 in Norway, 3 in Portugal, 3 in Spain, 4 in Sweden and 2 in Switzerland (generally the largest banks with traded equity in the countries).

There are numerous channels of interaction between the sovereign and the banks. As shown in Figure 11 the mark-to-market fall in the value of sovereign bonds held by banks reduces bank assets. This can increase bank-funding costs, and if the sovereign is distressed enough, the value of official support (guarantees) will be eroded. These have knock-on effects, as shown. An adverse feedback loop ties sovereigns' stresses to banking-sector challenges.

Figure 11. Spillovers from the Sovereign to the Banks and Banks to Sovereign



Source: International Monetary Fund (2010).

Negative-feedback effects could arise in a situation where the financial system is outsized compared with the government. Thus, distress in the financial system triggers a large increase in government financial guarantees/contingent liabilities. Potential costs to the government, due to the guarantees, can lead to a rise in sovereign spreads. Bank's spreads depend on retained risk, which is lower given the application of government guarantees, and also on the creditworthiness of the sovereign (as a result of fiscal sustainability and debt service burden), as investors view the bank's and the sovereign's risks as intertwined. Concern that the government balance sheet will not be strong enough for it to make good on guarantees could lead to deposit withdrawals or a cutoff of credit to the financial sector, thereby triggering a destructive feedback loop where both bank and sovereign spreads increase. In some situations, this vicious cycle can spiral out of control, resulting in the inability of the government to provide sufficient guarantees to banks and leading to a systemic financial crisis and a sovereign debt crisis.

APPENDIX II. WEIGHT MATRICES

Weights for Real GDP

	AT	BE	CH	DE	DK	ES	FR	GR	IE	IT	NL	NO	PT	SE	UK	US
AT	0.0	5.5	5.3	9.5	3.6	2.5	3.9	4.6	4.4	3.4	4.8	2.8	4.9	0.0	1.4	3.9
BE	4.7	0.0	6.5	7.4	5.0	6.3	11.2	6.9	12.4	5.7	11.5	5.9	4.6	0.0	7.7	6.1
CH	7.9	5.2	0.0	8.3	4.3	2.2	5.6	2.9	4.2	7.0	4.8	1.2	1.1	18.3	4.9	7.4
DE	40.2	16.8	24.3	0.0	18.1	14.7	21.8	17.0	6.4	19.6	23.7	14.3	12.1	1.8	15.1	18.3
DK	3.9	1.0	2.4	3.0	0.0	0.8	4.4	3.4	6.7	2.7	3.2	4.1	4.5	0.0	1.8	1.7
ES	2.3	5.7	6.2	4.8	2.7	0.0	9.1	6.7	5.1	7.9	3.9	2.2	29.8	5.3	6.2	5.5
FR	7.5	13.3	8.6	14.4	7.0	17.8	0.0	7.5	4.8	13.6	9.5	6.7	9.0	0.0	8.1	9.7
GR	1.0	1.7	0.5	1.2	2.6	4.1	0.9	0.0	0.6	1.5	1.0	4.7	2.9	12.3	6.2	1.6
IE	1.0	5.2	5.5	1.2	4.6	1.8	1.6	2.1	0.0	0.8	1.2	1.0	3.6	4.3	8.2	4.7
IT	7.3	3.7	10.2	10.8	5.9	12.8	12.1	15.0	2.1	0.0	4.5	4.6	7.2	0.0	5.3	6.2
NL	7.8	15.0	5.3	11.9	8.0	6.1	10.0	6.7	6.6	7.7	0.0	12.2	5.7	0.0	9.4	7.6
NO	1.7	3.4	2.1	3.7	5.5	1.3	0.8	0.9	1.8	3.4	8.6	0.0	4.8	16.9	5.4	4.2
PT	4.7	3.4	1.1	3.1	4.1	8.5	3.5	5.1	2.9	5.2	5.0	4.5	0.0	0.0	1.6	0.8
SE	1.9	4.2	4.4	5.4	12.8	5.6	1.7	5.3	0.7	2.4	2.6	12.9	3.5	0.0	7.6	6.2
UK	5.2	10.5	7.3	9.1	8.5	10.0	7.3	8.6	20.8	9.5	7.8	17.5	4.0	0.0	0.0	16.1
US	2.8	5.2	10.3	6.1	7.4	5.6	6.3	7.1	20.4	9.4	8.1	5.4	2.5	41.1	11.3	0.0

Weights for Credit Growth

	AT	BE	CH	DE	DK	ES	FR	GR	IE	IT	NL	NO	PT	SE	UK	US
AT	0.0	0.0	6.8	6.9	23.9	26.4	0.0	0.0	0.3	31.4	0.0	1.5	0.0	2.4	0.0	8.9
BE	1.2	0.0	3.0	6.4	0.0	3.8	3.6	0.0	14.4	0.0	0.0	6.8	1.4	4.7	0.0	20.2
CH	0.2	42.9	0.0	7.3	0.0	0.0	7.3	1.4	4.8	0.0	39.8	4.0	0.8	5.9	0.0	7.7
DE	1.2	0.0	26.8	0.0	0.0	0.0	21.7	0.0	0.0	11.4	0.0	12.0	19.8	15.2	18.8	13.8
DK	38.0	0.0	5.0	1.8	0.0	8.8	11.6	16.4	24.0	11.2	0.0	5.6	17.2	11.6	0.0	6.4
ES	27.2	1.9	2.9	5.9	0.0	0.0	0.0	21.8	1.4	34.3	0.0	5.6	27.5	2.8	0.0	6.6
FR	0.0	31.5	9.4	14.6	0.0	4.8	0.0	2.1	0.0	0.0	25.1	7.2	10.7	8.6	8.0	8.4
GR	0.0	0.0	0.7	1.4	9.7	16.3	4.7	0.0	15.4	0.0	14.3	4.5	14.1	1.7	0.0	3.3
IE	0.0	11.4	4.5	2.1	5.0	2.7	0.0	9.0	0.0	0.0	9.6	2.2	0.0	1.7	14.8	8.3
IT	15.5	0.0	12.1	11.1	1.4	12.8	8.6	0.1	9.1	0.0	0.0	4.7	5.6	3.2	0.0	1.9
NL	0.0	1.3	3.5	14.3	0.0	3.1	12.9	8.6	11.5	0.0	0.0	9.6	0.0	6.0	0.0	0.0
NO	0.0	0.8	1.0	2.7	37.7	0.0	23.7	14.6	5.0	0.0	0.0	0.0	2.9	14.8	46.2	6.9
PT	0.0	0.0	5.3	2.2	18.2	19.8	0.0	20.2	0.0	5.8	0.0	1.6	0.0	0.9	0.0	0.0
SE	0.0	7.9	4.8	6.4	1.1	1.4	4.9	1.9	1.3	5.7	9.8	8.6	0.0	0.0	0.0	0.0
UK	3.1	0.0	5.4	9.8	0.0	0.0	0.9	1.7	10.3	0.3	1.4	18.8	0.0	11.5	0.0	7.7
US	13.7	2.4	8.6	7.1	2.9	0.0	0.0	2.4	2.6	0.0	0.0	7.3	0.0	8.8	12.2	0.0

Weights for Expected Loss Ratio Sovereigns

	AT	BE	CH	DE	DK	ES	FR	GR	IE	IT	NL	NO	PT	SE	UK	US
AT	0.0	0.0	0.0	7.0	0.0	0.0	23.4	11.9	0.0	5.4	7.8	7.4	0.0	7.6	0.0	0.0
BE	4.3	0.0	16.9	15.5	0.0	15.0	0.0	0.0	0.0	4.0	5.7	0.0	3.1	0.0	2.3	9.1
CH	0.0	7.8	0.0	0.0	0.0	6.4	3.3	6.3	7.3	0.1	10.2	0.0	0.0	0.6	10.8	8.7
DE	4.1	13.9	0.0	0.0	0.0	0.0	13.8	0.0	13.0	4.4	0.0	1.0	0.0	0.2	5.7	0.0
DK	1.9	0.0	0.0	0.0	0.0	0.0	3.3	0.0	0.0	8.3	10.5	0.0	0.0	3.3	2.7	0.3
ES	0.0	31.1	15.1	0.0	0.0	0.0	11.8	7.4	0.0	12.4	8.7	0.0	10.6	0.0	2.6	13.6
FR	36.8	0.0	0.0	42.6	2.8	15.3	0.0	0.0	0.0	0.0	11.8	0.0	4.4	0.0	12.2	11.5
GR	8.2	0.0	0.0	0.0	0.0	16.7	1.8	0.0	11.3	10.3	1.4	0.0	44.4	2.0	0.0	0.0
IE	0.0	0.0	9.7	15.2	0.0	0.0	0.0	0.4	0.0	1.8	0.0	9.6	3.0	1.8	9.1	4.0
IT	2.9	0.0	0.0	0.0	19.2	22.1	0.0	7.7	0.0	0.0	3.8	0.0	34.4	0.0	2.4	0.0
NL	14.0	26.2	19.3	0.0	53.4	0.0	12.8	0.0	0.0	7.2	0.0	33.6	0.0	21.3	14.4	0.0
NO	13.1	0.0	0.0	9.1	0.0	0.0	0.0	0.0	22.1	1.7	18.6	0.0	0.0	32.5	0.0	12.4
PT	0.0	6.8	0.0	0.0	0.0	19.4	14.9	60.2	22.7	40.5	0.0	0.0	0.0	0.0	0.5	1.1
SE	14.8	0.0	0.0	0.0	8.8	0.0	0.0	6.1	0.0	3.5	17.1	42.9	0.0	0.0	28.5	24.2
UK	0.0	3.9	28.9	10.5	15.8	0.0	8.7	0.0	18.5	0.5	4.3	0.0	0.0	22.6	0.0	15.1
US	0.0	10.3	10.2	0.0	0.0	5.1	6.3	0.0	5.1	0.0	0.0	5.6	0.0	8.2	8.7	0.0

Weights for Expected Loss Ratio Banking Systems

	AT	BE	CH	DE	DK	ES	FR	GR	IE	IT	NL	NO	PT	SE	UK	US
AT	0.0	36.0	0.0	6.5	0.0	0.0	4.0	15.5	0.0	0.0	0.0	0.0	17.7	8.0	6.6	0.0
BE	29.4	0.0	0.0	0.0	19.4	0.0	0.6	4.5	0.0	6.6	0.0	0.0	18.4	1.4	0.0	0.0
CH	0.0	0.0	0.0	11.3	0.0	8.7	17.2	14.2	10.1	3.7	0.0	13.9	0.0	19.7	7.3	0.0
DE	11.3	0.0	8.2	0.0	0.0	0.0	16.2	11.0	0.0	0.0	7.5	4.7	0.0	10.4	12.1	0.0
DK	0.4	23.8	0.0	0.0	0.0	0.0	12.2	0.0	20.3	0.6	0.0	30.7	0.0	18.5	0.0	0.0
ES	0.0	0.0	12.5	0.0	0.0	0.0	11.3	15.6	0.4	32.3	0.0	9.6	18.7	7.3	3.2	0.0
FR	3.5	0.0	35.3	30.2	23.4	22.4	0.0	0.0	0.0	0.0	28.0	10.3	20.4	0.0	8.2	8.8
GR	18.1	1.5	8.5	10.1	0.0	11.0	0.9	0.0	16.7	0.0	13.6	0.6	0.0	0.0	0.0	23.8
IE	0.0	0.0	4.7	0.0	9.1	0.9	0.0	3.7	0.0	11.5	0.0	0.1	0.0	0.0	0.0	12.9
IT	0.0	6.9	1.0	0.0	0.0	30.3	0.0	0.0	33.5	0.0	30.9	0.0	0.0	0.9	8.6	9.0
NL	0.0	0.0	0.0	13.7	0.0	0.0	15.4	15.3	0.0	26.4	0.0	0.0	0.0	9.2	11.0	0.0
NO	0.0	0.0	1.3	5.2	19.7	5.5	3.4	0.0	0.0	1.9	0.0	0.0	0.0	9.1	5.1	0.0
PT	18.2	23.8	0.0	0.0	0.0	10.5	7.9	0.0	0.0	0.0	0.0	0.0	0.0	3.2	0.0	20.7
SE	12.8	0.0	23.9	9.3	28.4	6.9	0.0	0.0	0.0	2.2	9.4	25.0	6.1	0.0	19.0	0.0
UK	6.3	0.0	4.7	13.7	0.0	2.5	1.9	0.0	0.0	9.2	10.5	5.0	0.0	12.3	0.0	24.7
US	0.0	8.0	0.0	0.0	0.0	1.3	9.0	20.2	19.0	5.6	0.0	0.0	18.7	0.0	18.8	0.0

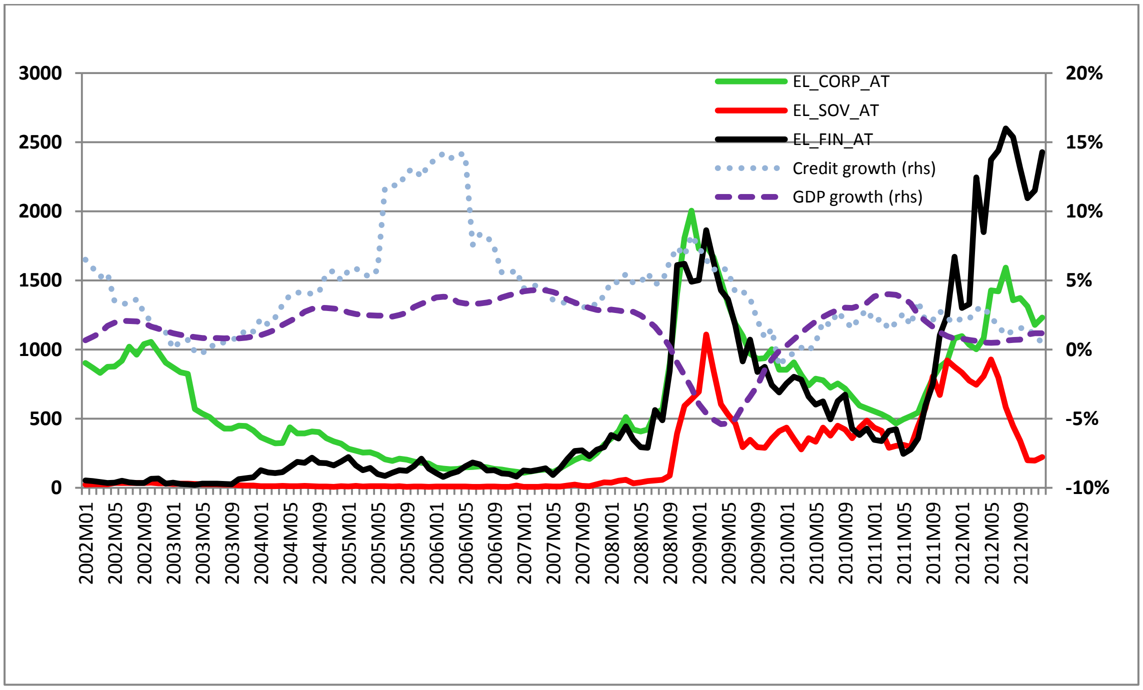
Weights for Expected Loss Ratio Corporate Sectors

	AT	BE	CH	DE	DK	ES	FR	GR	IE	IT	NL	NO	PT	SE	UK	US
AT	0.0	10.7	0.0	0.0	13.5	0.7	7.4	16.0	9.3	42.1	0.0	8.4	0.0	0.0	11.3	11.0
BE	4.9	0.0	21.2	0.0	3.6	0.0	4.0	0.0	0.0	0.0	21.4	0.0	6.1	1.2	0.0	0.0
CH	0.0	36.5	0.0	0.0	18.8	5.4	0.0	0.0	34.0	0.0	6.5	8.2	1.1	6.4	4.0	16.8
DE	0.0	0.0	0.0	0.0	6.4	0.0	16.1	13.9	25.7	7.6	10.2	0.0	0.0	15.9	0.0	15.3
DK	11.5	1.8	14.1	4.5	0.0	12.8	1.6	0.0	0.0	0.0	0.1	13.4	0.0	0.0	2.5	8.7
ES	2.6	0.0	4.7	0.0	16.4	0.0	13.0	9.3	0.0	1.8	0.0	0.4	26.3	0.0	18.9	2.6
FR	7.2	9.1	0.0	24.4	1.0	19.0	0.0	6.7	11.2	3.9	13.8	0.0	21.5	27.5	3.5	6.7
GR	12.9	0.0	0.0	8.1	0.0	6.6	5.2	0.0	0.0	11.8	9.1	12.6	18.1	0.0	3.6	0.0
IE	5.3	1.8	12.1	10.3	0.0	0.9	4.3	0.0	0.0	0.0	7.2	0.0	0.0	2.2	0.0	0.7
IT	14.5	0.9	0.0	1.3	0.0	2.8	2.7	7.5	0.0	0.0	2.8	0.0	1.2	0.7	2.5	0.0
NL	0.0	28.8	7.7	11.1	1.6	0.0	9.2	9.4	17.7	8.1	0.0	11.9	0.0	0.0	12.8	0.0
NO	8.8	0.0	7.3	0.0	13.9	0.0	0.3	8.7	0.0	0.0	11.2	0.0	1.2	12.6	5.8	1.6
PT	0.0	8.2	3.7	0.0	0.0	17.2	13.7	23.4	0.0	9.6	2.1	1.5	0.0	14.0	4.9	0.0
SE	0.0	2.2	2.9	16.5	0.0	0.0	15.6	0.2	2.1	0.0	0.0	19.7	18.1	0.0	5.8	8.6
UK	18.5	0.0	5.9	0.0	7.2	31.2	2.4	4.9	0.0	15.2	15.6	18.5	6.4	8.2	0.0	28.0
US	13.9	0.0	20.3	23.9	17.5	3.3	4.6	0.0	0.0	0.0	0.0	5.4	0.0	11.3	24.4	0.0

Note: The weight matrices presented here have been estimated jointly with the GVAR's other parameters. Weight error bounds are not reported here; they are available from the authors upon request. See text for further details.

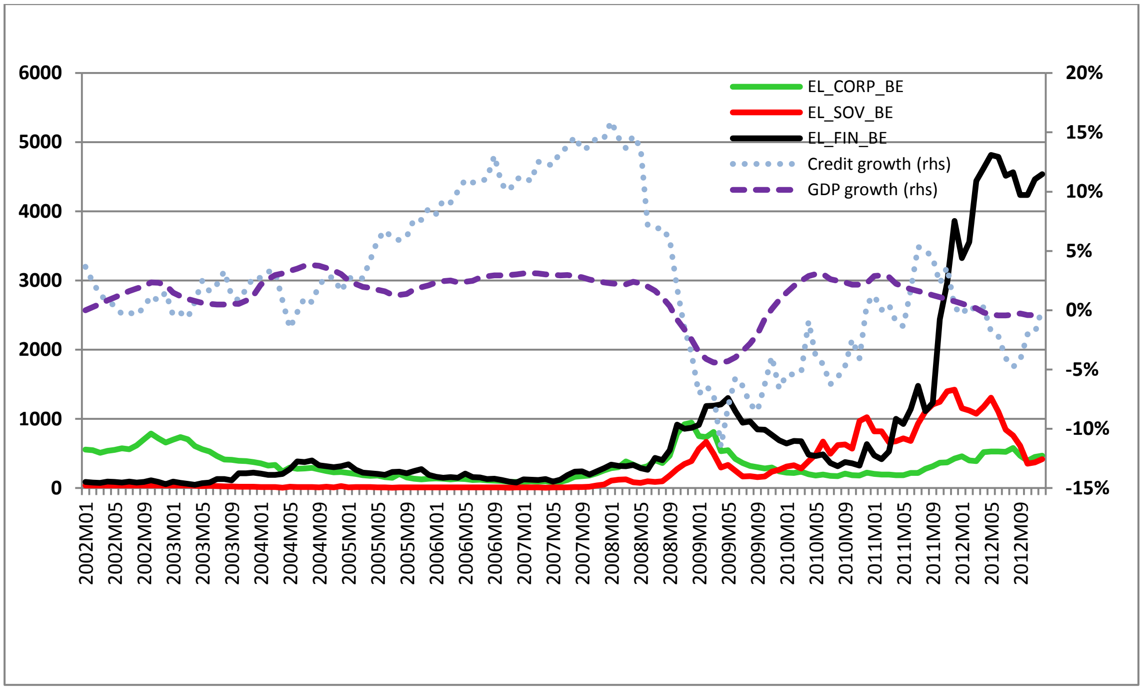
APPENDIX III. INPUT DATA FOR THE CCA-GVAR MODEL

Austria: Risk Indicators, GDP Growth and Credit Growth



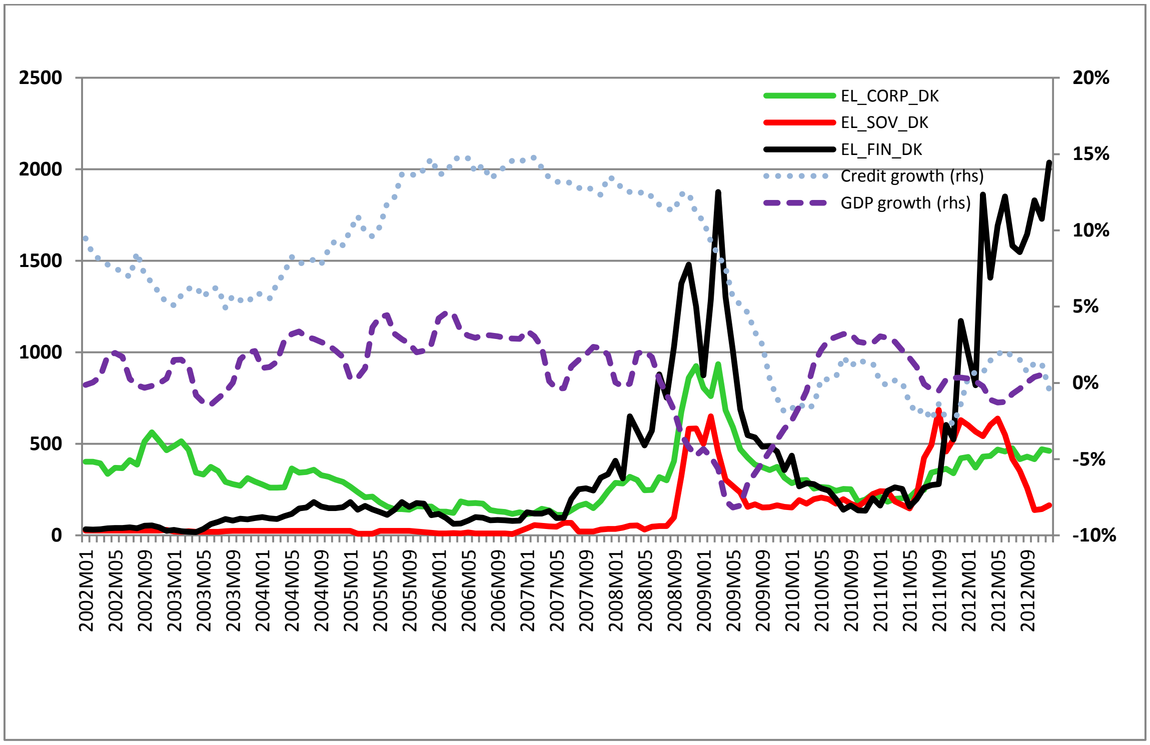
Source: Moody's CreditEdge, Eurostat, and author estimates.

Belgium: Risk Indicators, GDP Growth and Credit Growth



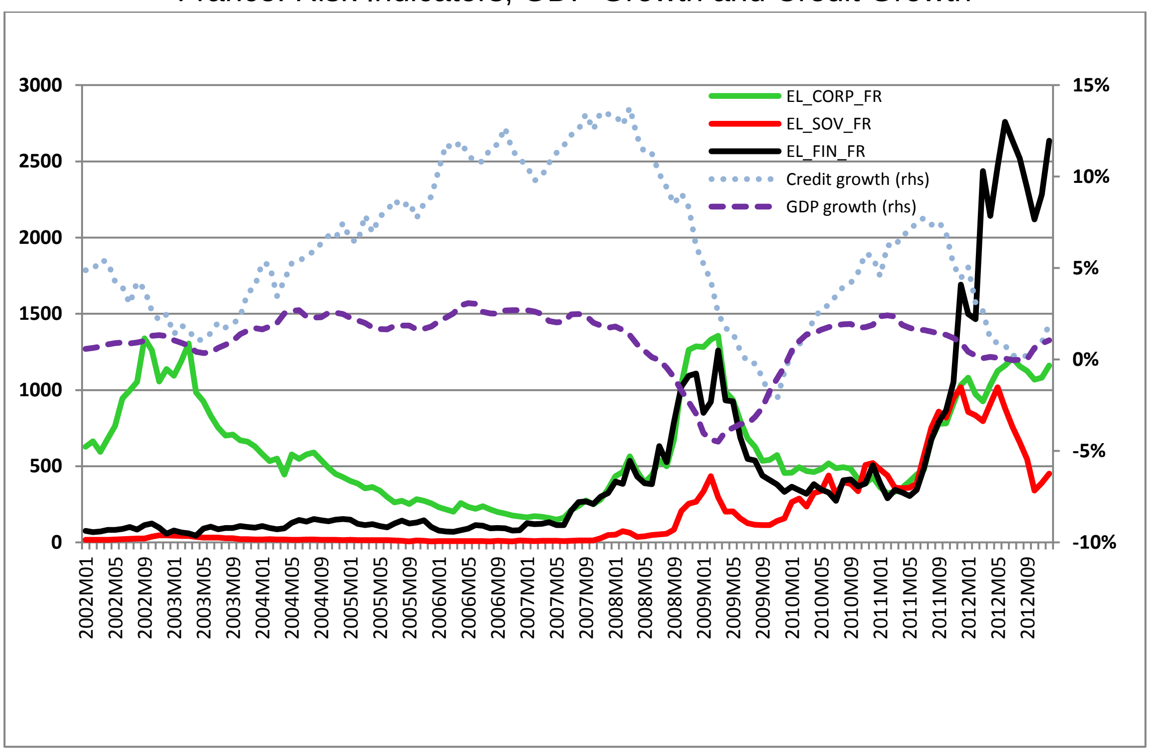
Source: Moody's CreditEdge, Eurostat, and author estimates.

Denmark: Risk Indicators, GDP Growth and Credit Growth



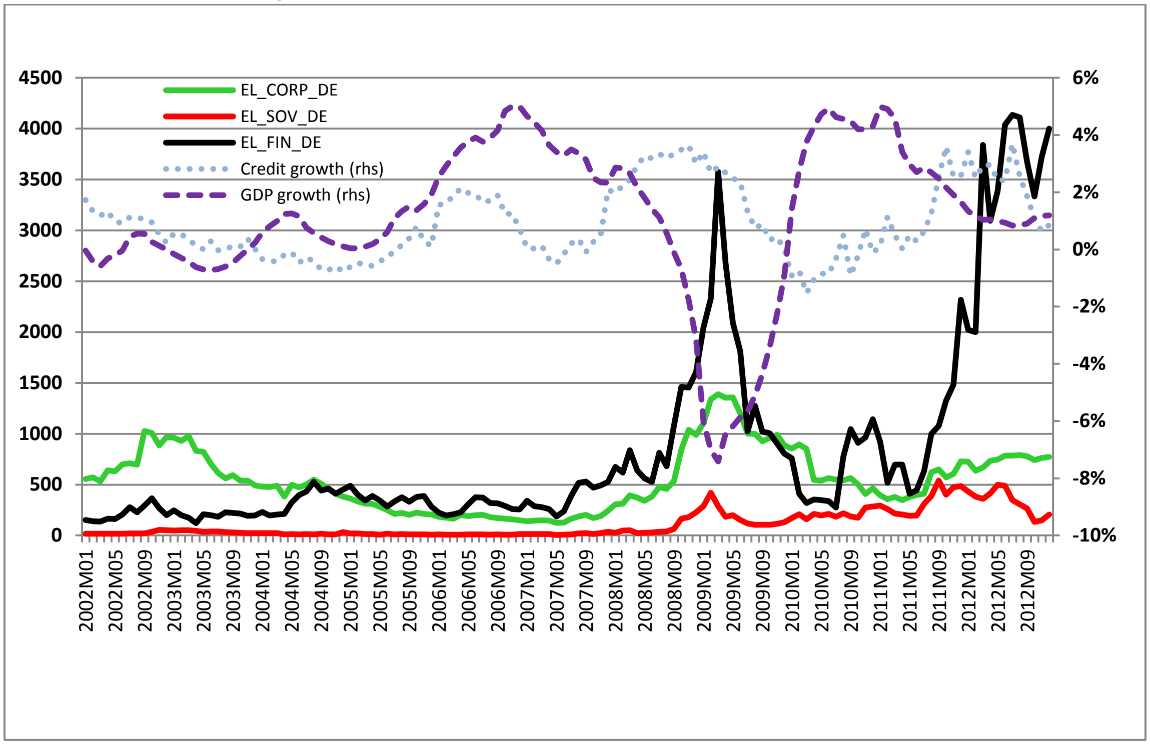
Source: Moody's CreditEdge, Eurostat, and author estimates.

France: Risk Indicators, GDP Growth and Credit Growth



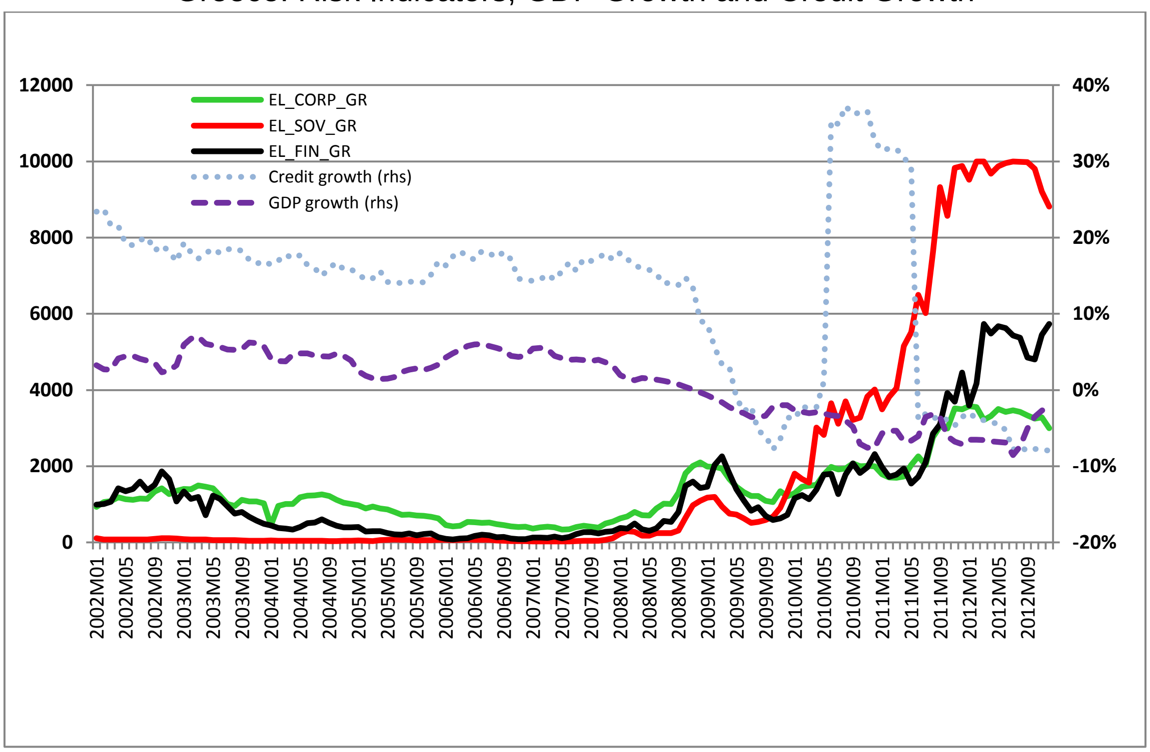
Source: Moody's CreditEdge, Eurostat, and author estimates.

Germany: Risk Indicators, GDP Growth and Credit Growth



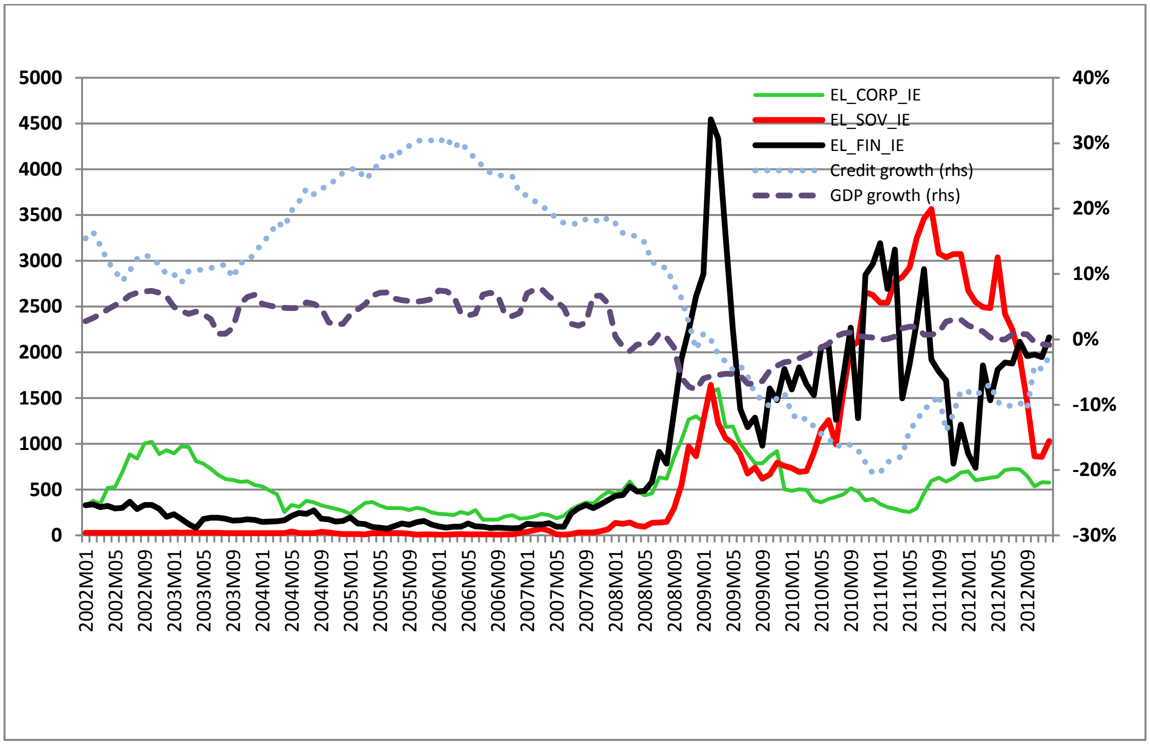
Source: Moody's CreditEdge, Eurostat, and author estimates.

Greece: Risk Indicators, GDP Growth and Credit Growth



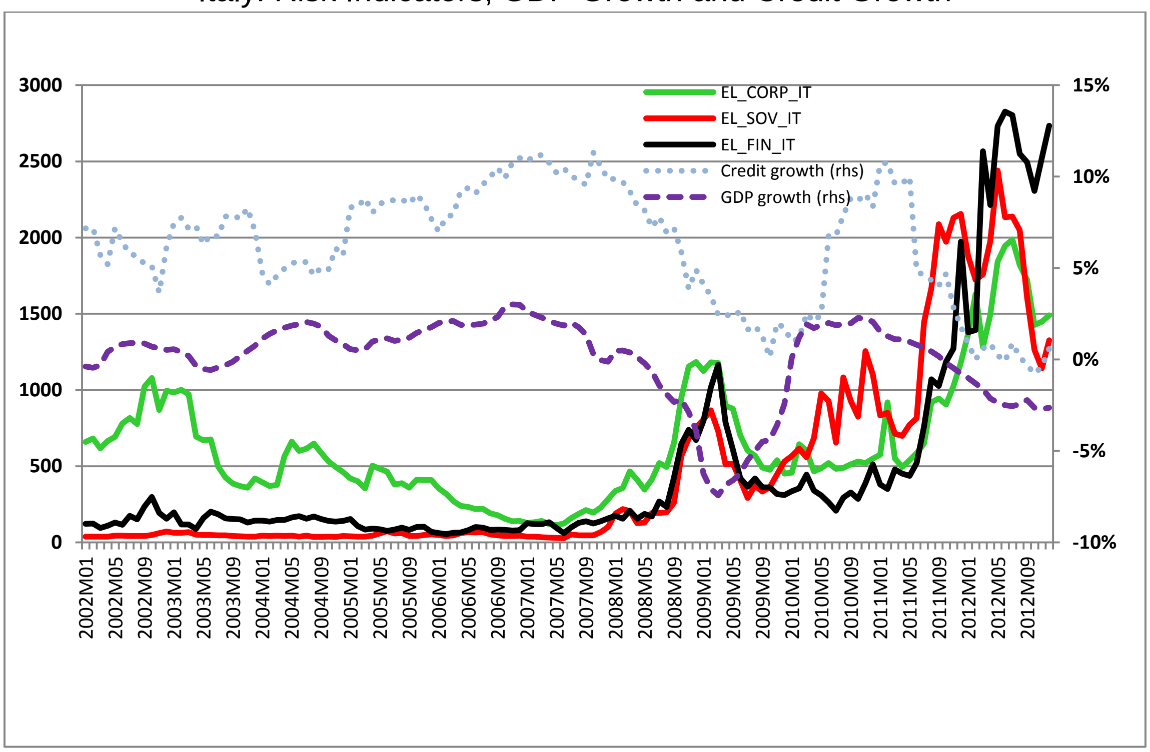
Source: Moody's CreditEdge, Eurostat, and author estimates.

Ireland: Risk Indicators, GDP Growth and Credit Growth



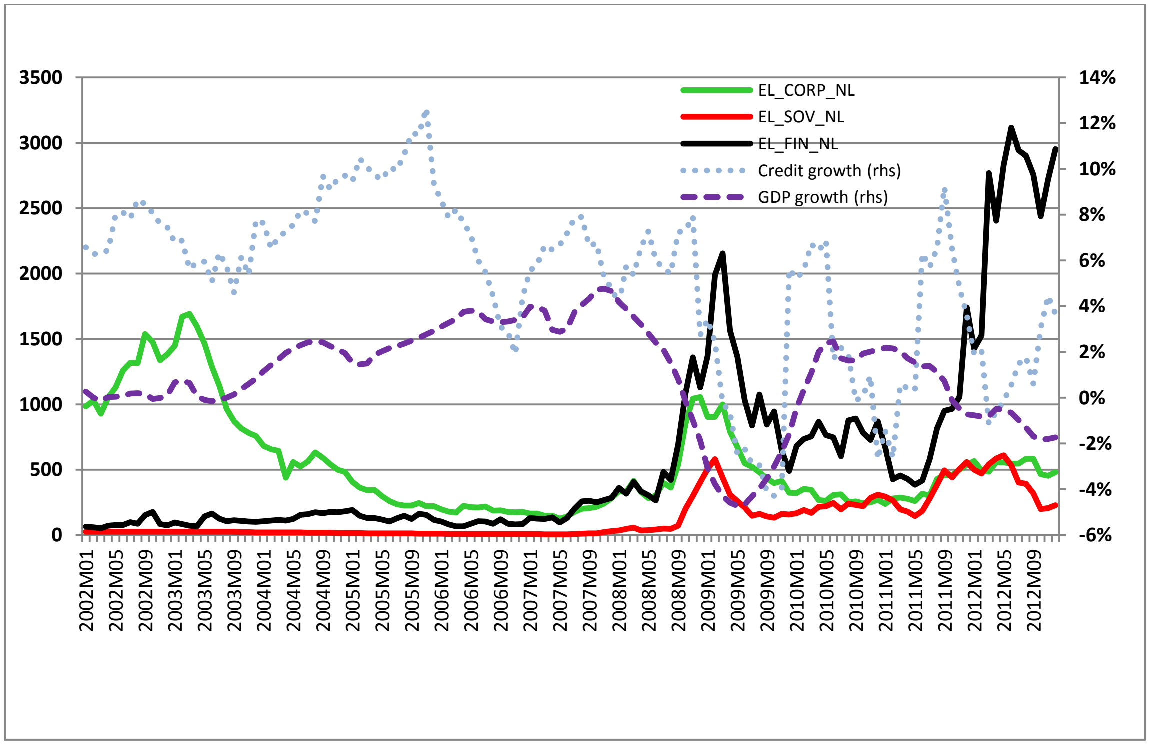
Source: Moody's CreditEdge, Eurostat, and author estimates.

Italy: Risk Indicators, GDP Growth and Credit Growth



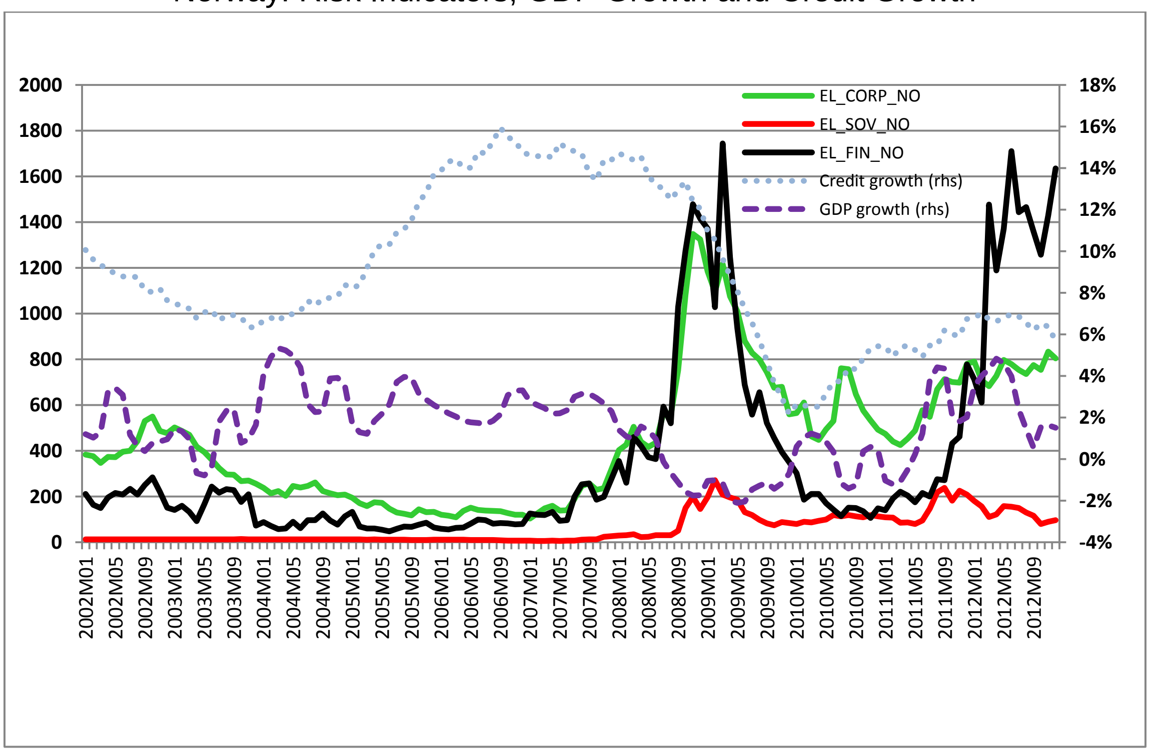
Source: Moody's CreditEdge, Eurostat, and author estimates.

Netherlands: Risk Indicators, GDP Growth and Credit Growth



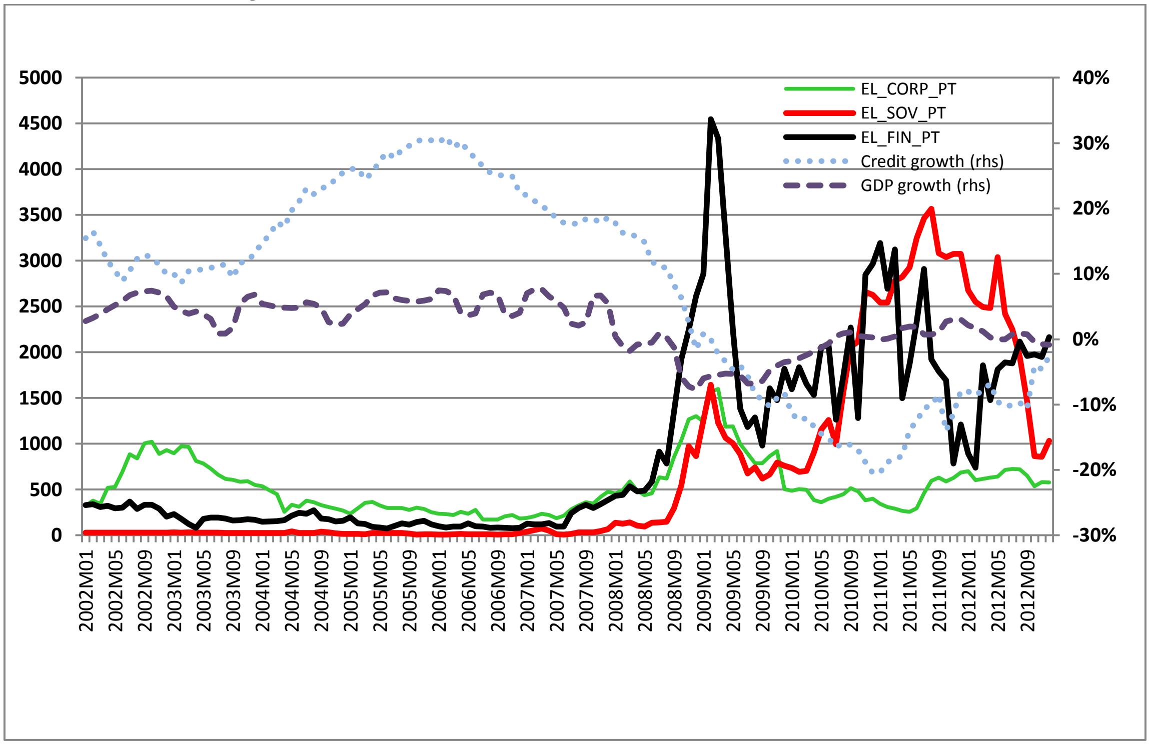
Source: Moody's CreditEdge, Eurostat, and author estimates.

Norway: Risk Indicators, GDP Growth and Credit Growth



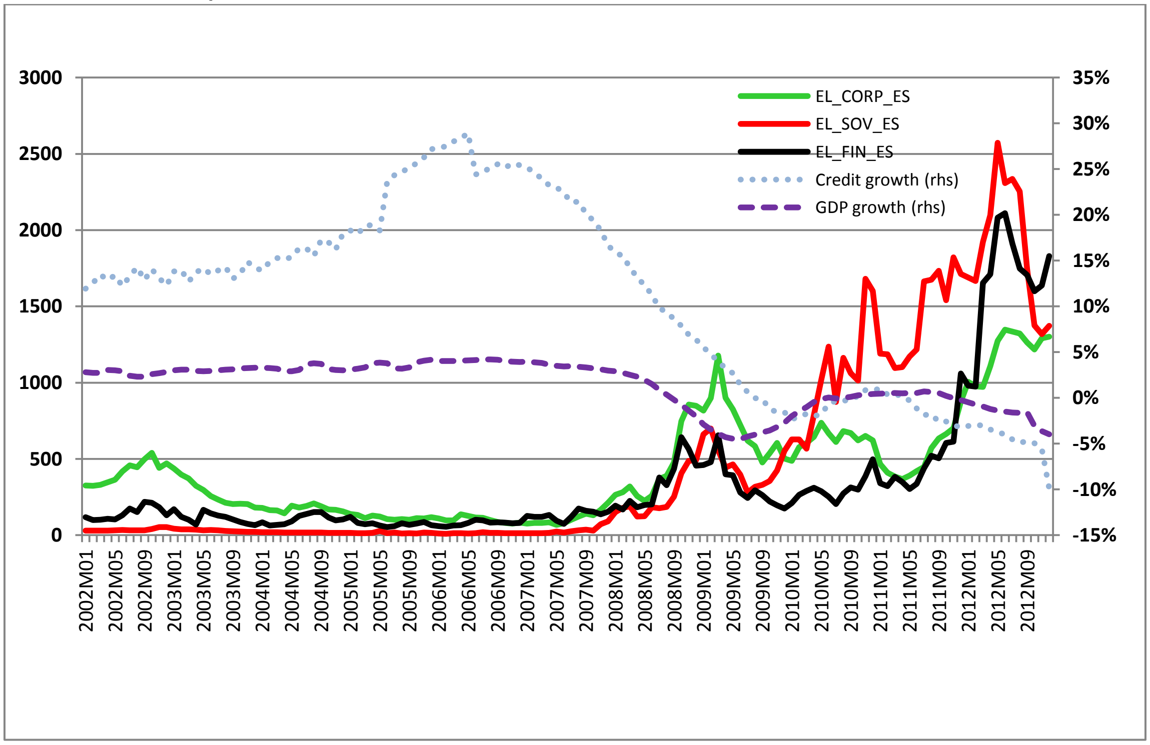
Source: Moody's CreditEdge, Eurostat, and author estimates.

Portugal: Risk Indicators, GDP Growth and Credit Growth



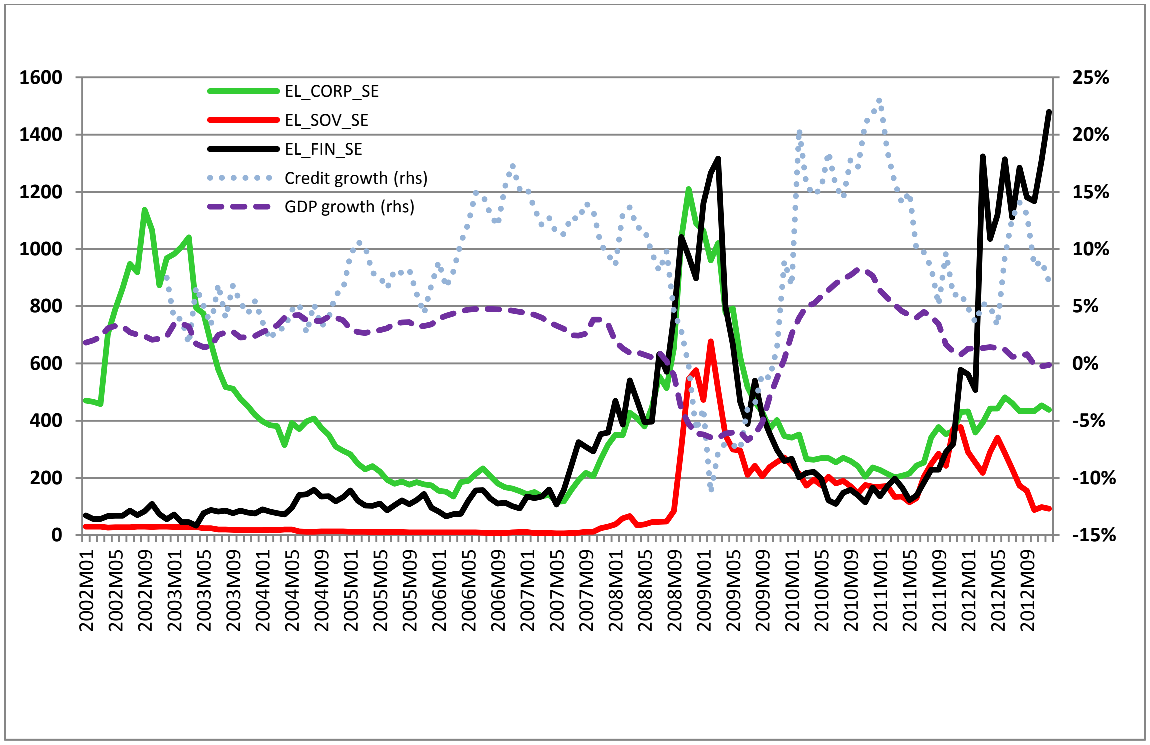
Source: Moody's CreditEdge, Eurostat, and author estimates.

Spain: Risk Indicators, GDP Growth and Credit Growth



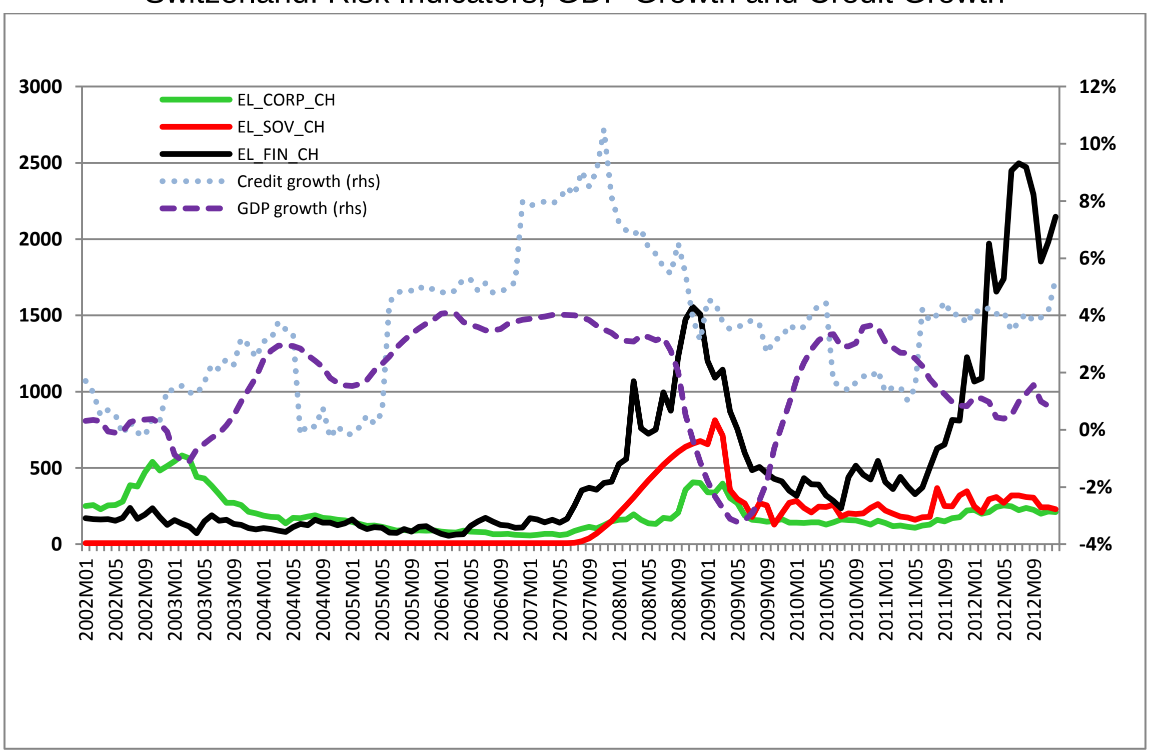
Source: Moody's CreditEdge, Eurostat, and author estimates.

Sweden: Risk Indicators, GDP Growth and Credit Growth



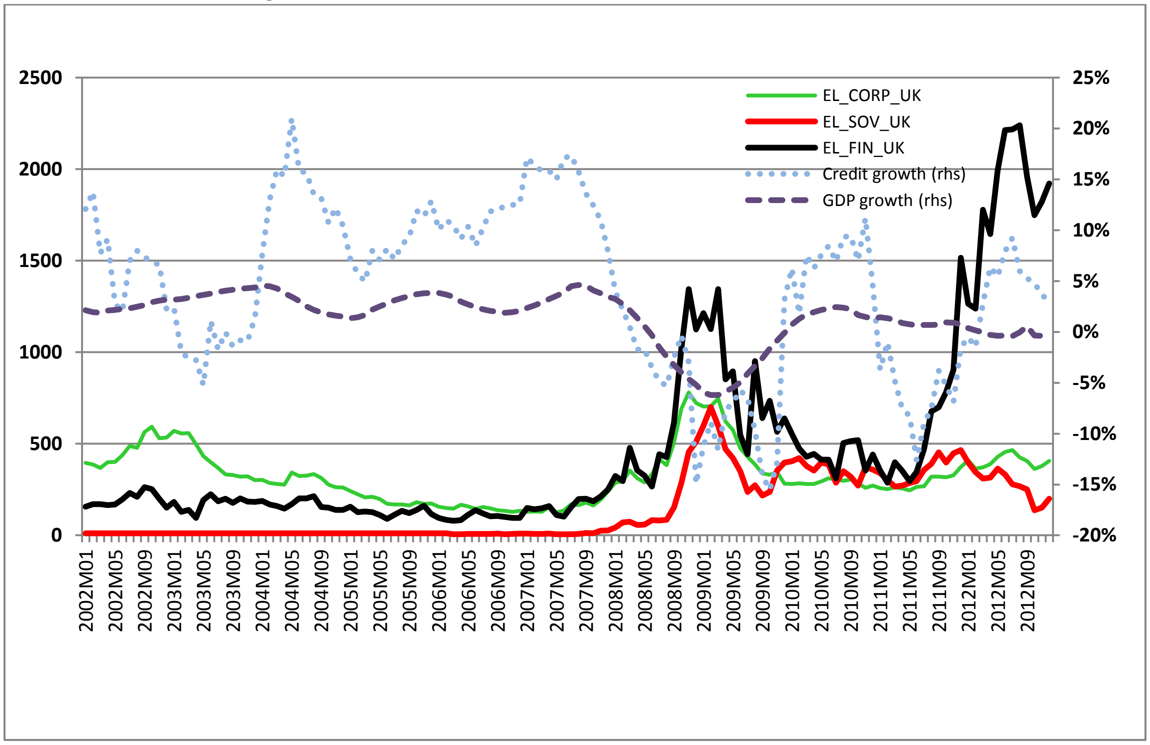
Source: Moody's CreditEdge, Eurostat, and author estimates.

Switzerland: Risk Indicators, GDP Growth and Credit Growth



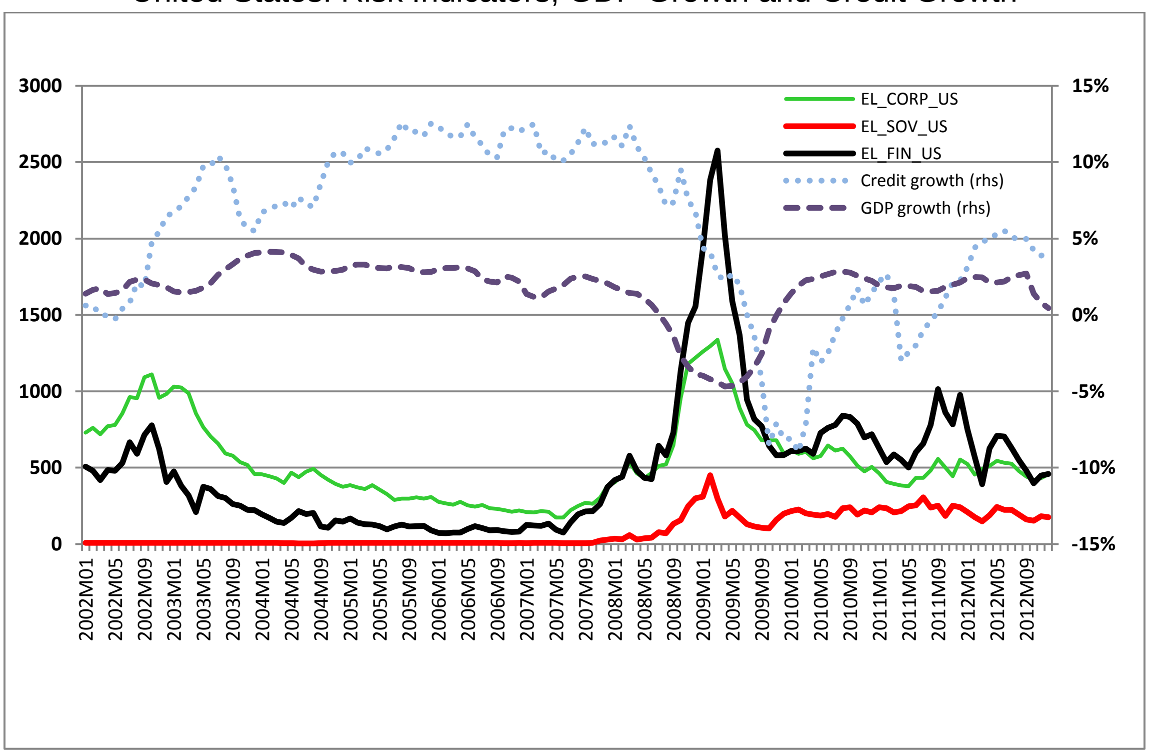
Source: Moody's CreditEdge, Eurostat, and author estimates.

United Kingdom: Risk Indicators, GDP Growth and Credit Growth



Source: Moody's CreditEdge, Eurostat, and author estimates.

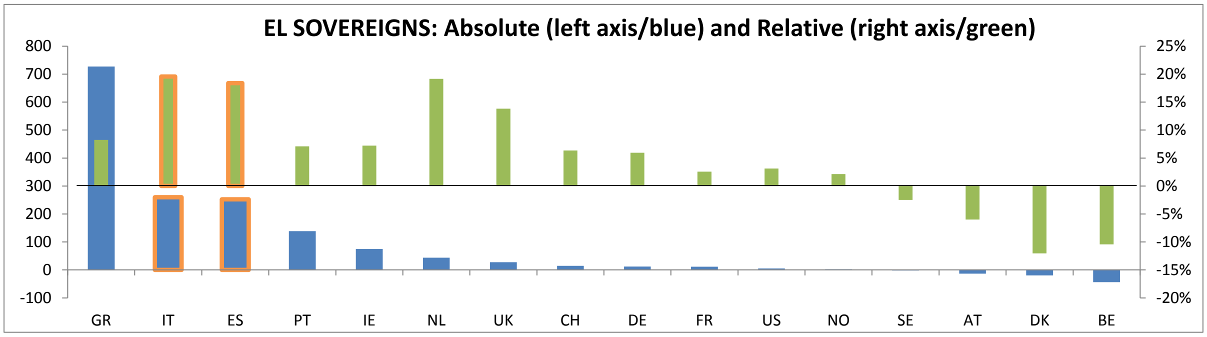
United States: Risk Indicators, GDP Growth and Credit Growth

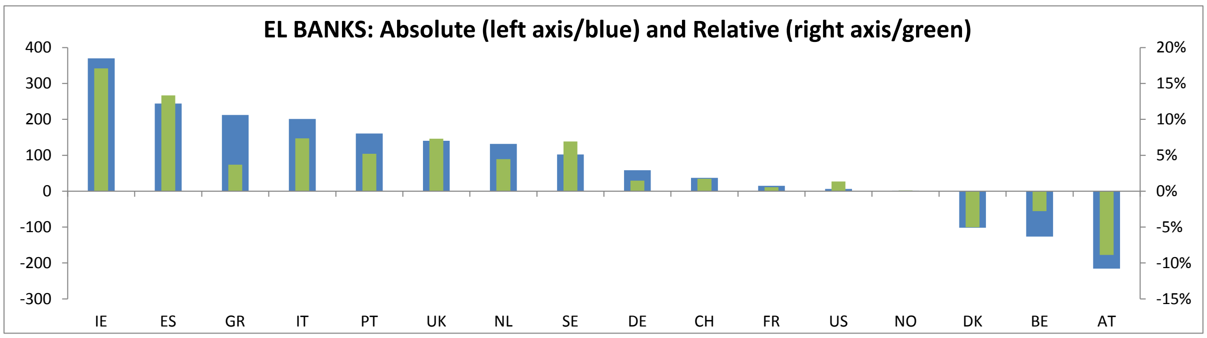


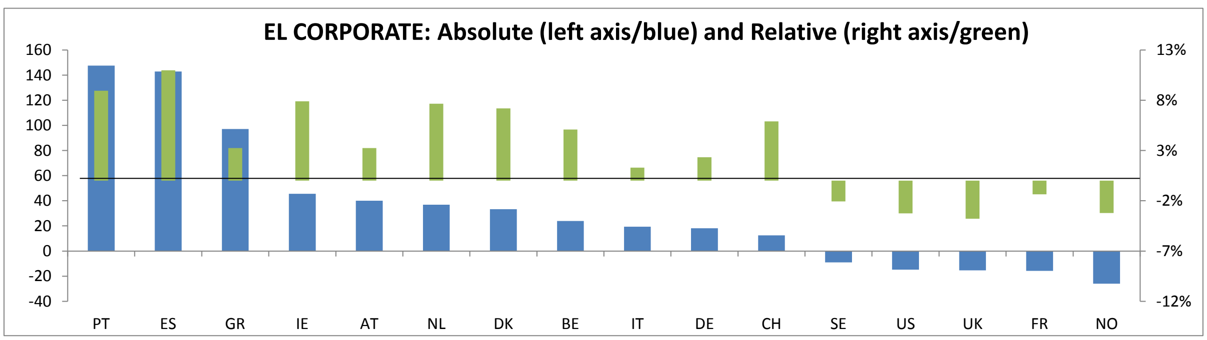
Source: Moody's CreditEdge, Eurostat, and author estimates.

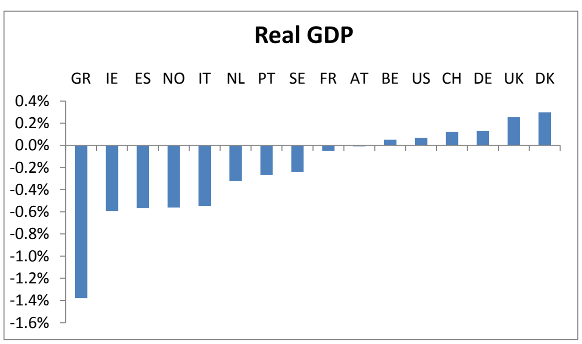
Appendix IV. Scenario Profiles on Impact at T=1

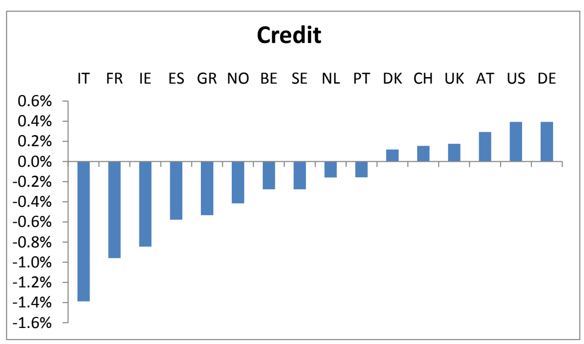
Scenario One—Adverse Shocks to EL Sovereigns in Italy and Spain





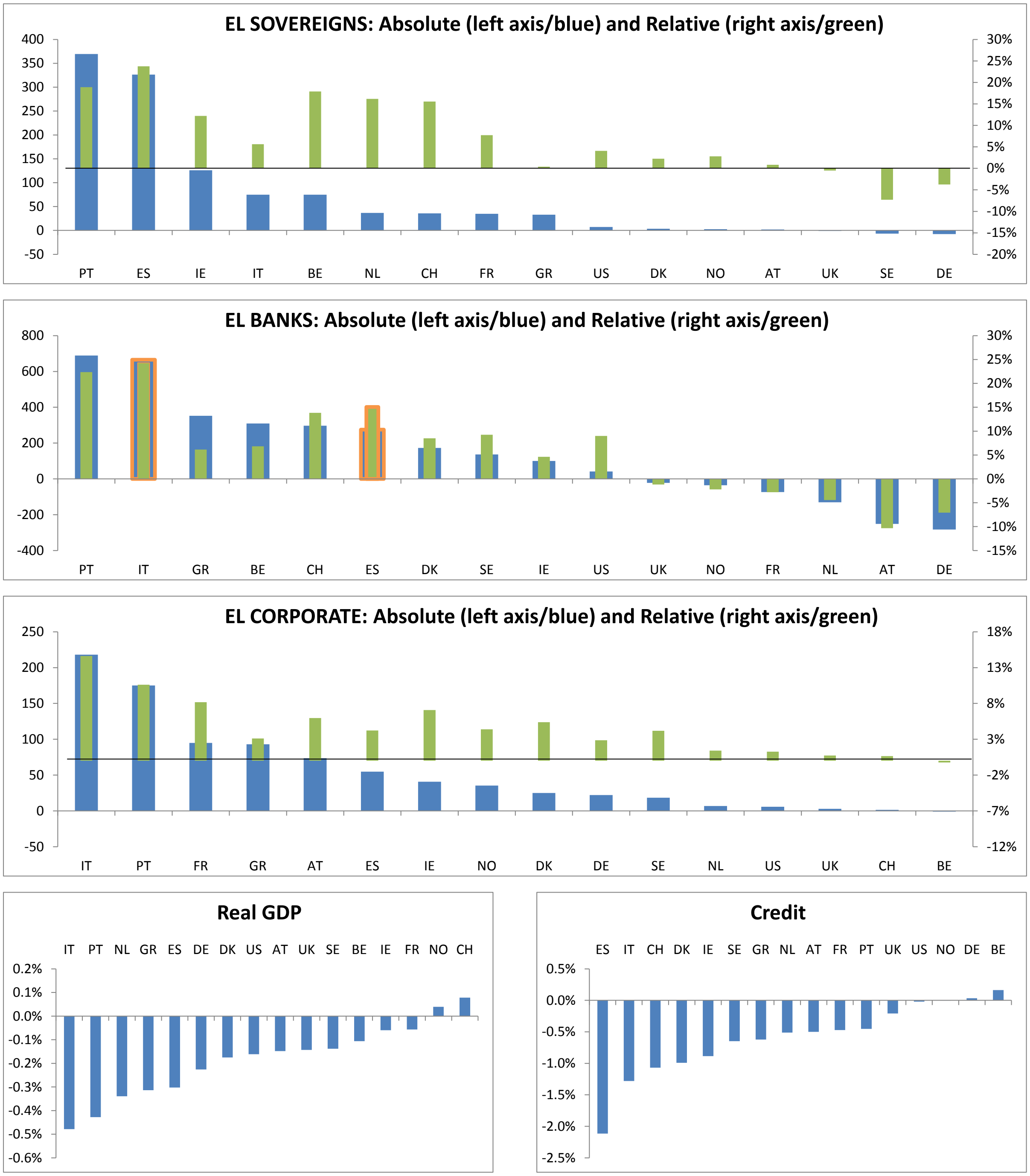






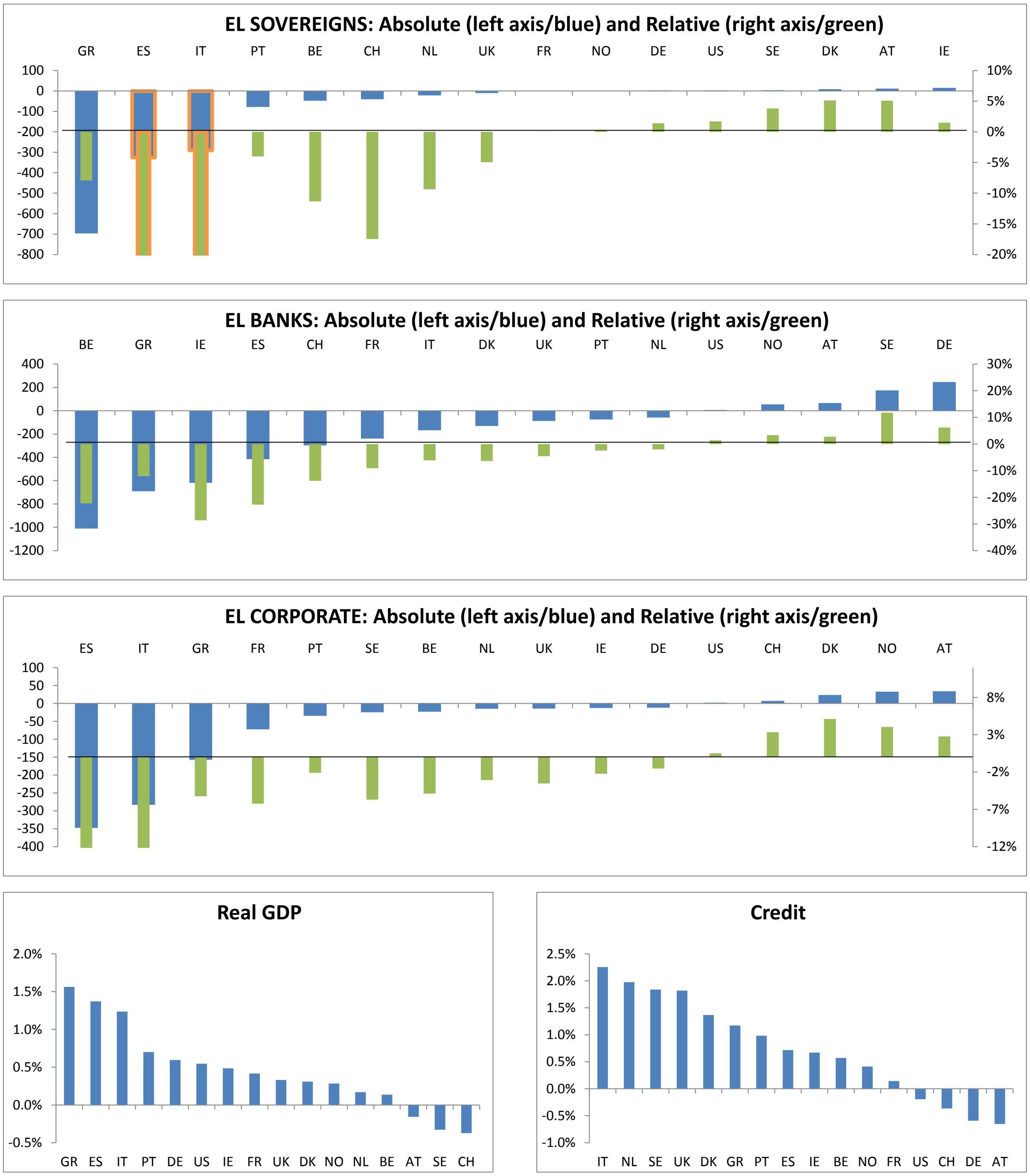
Source: Author estimates.

Scenario Two—Adverse Shocks to EL Banking Systems in Italy and Spain



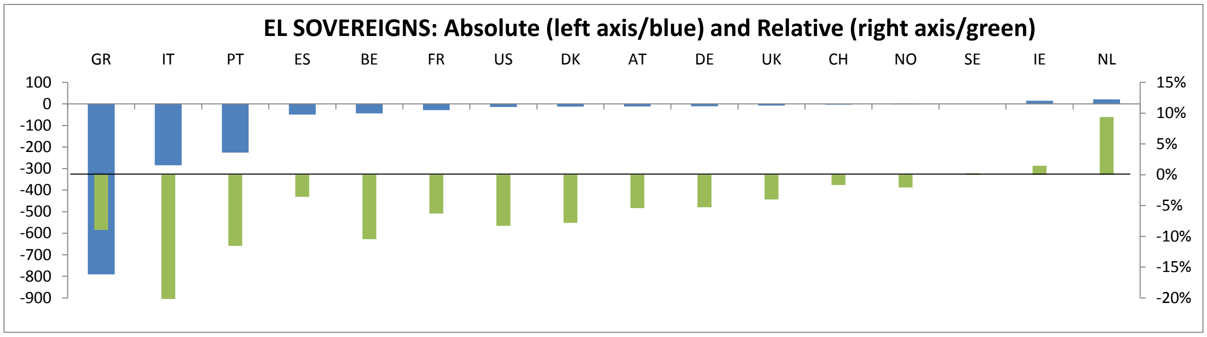
Source: Author estimates.

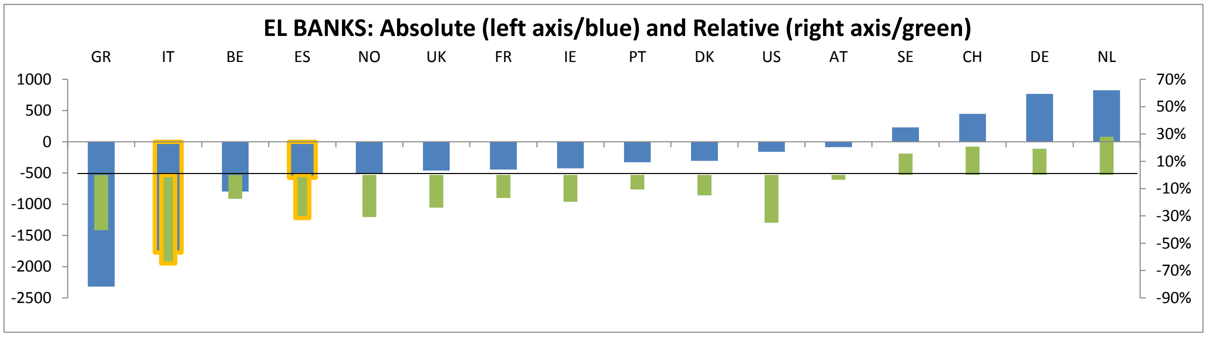
Scenario Three—Positive Shocks to EL Sovereigns in Italy and Spain

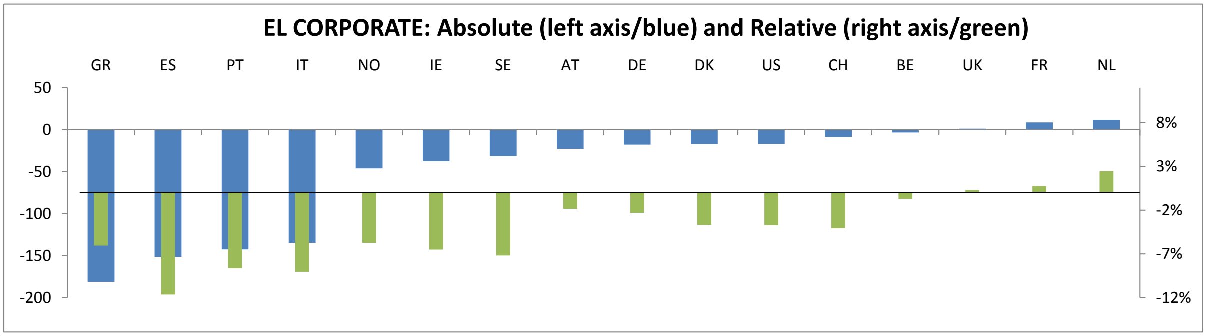


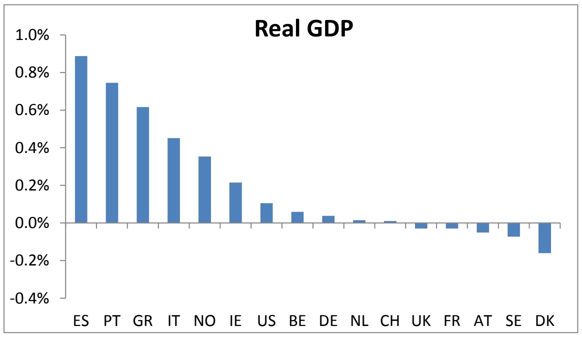
Source: Author estimates.

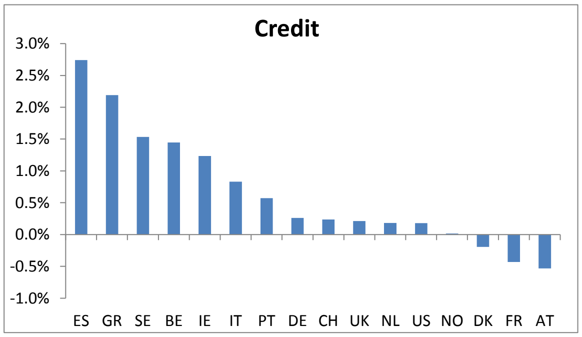
Scenario Four—Positive shocks to EL banking systems in Italy and Spain







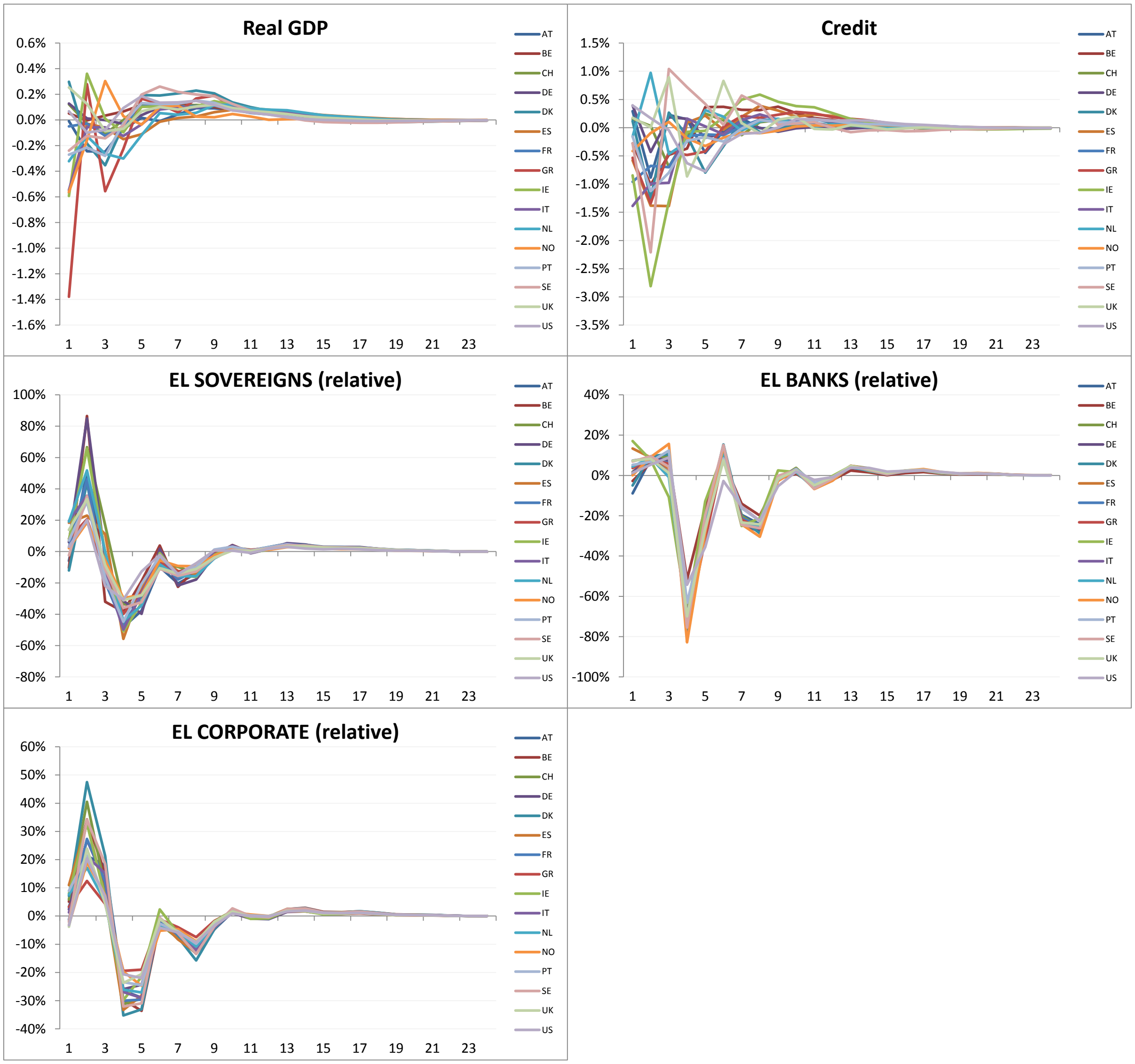




Source: Author estimates.

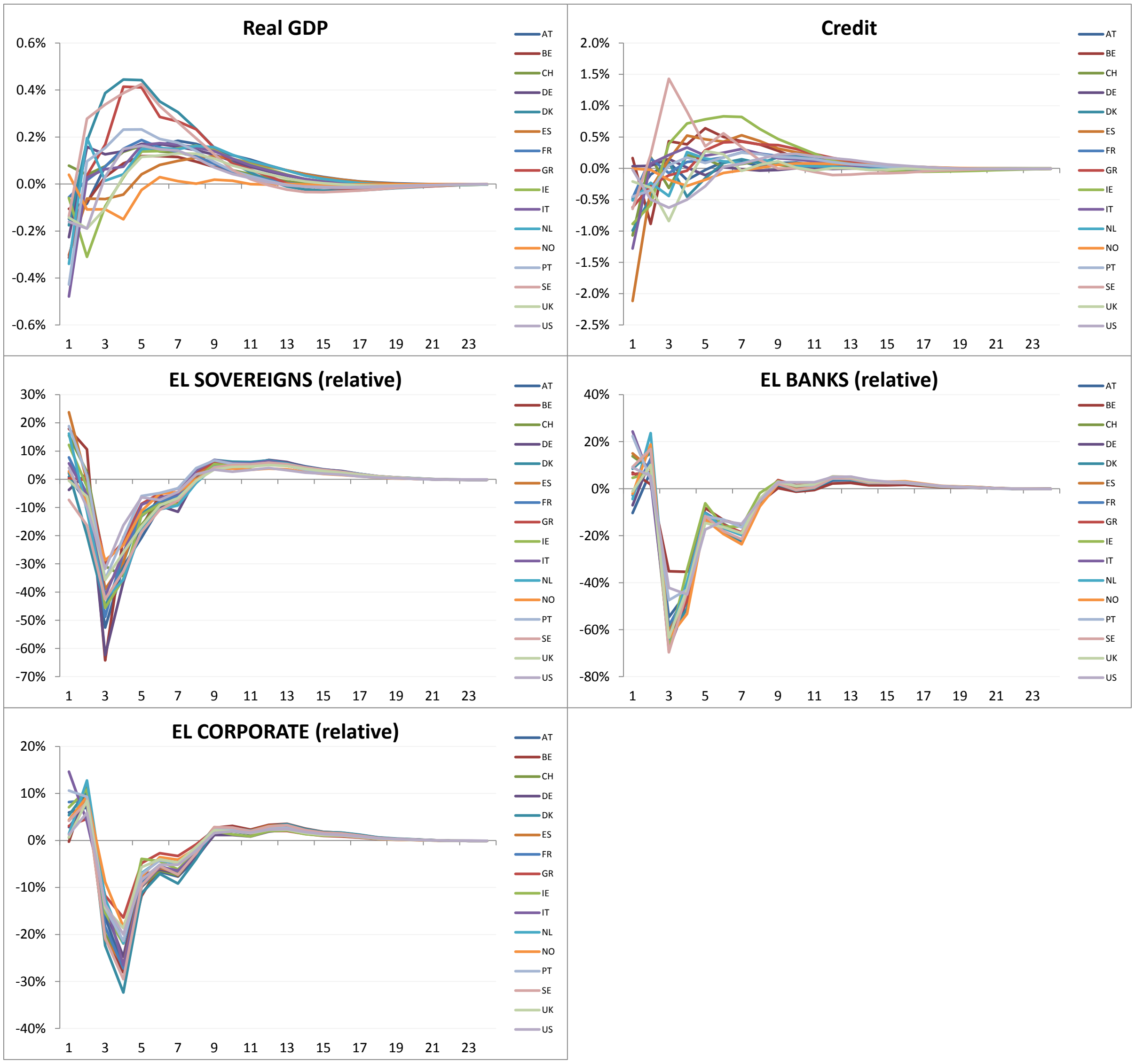
APPENDIX V. DYNAMIC SCENARIO RESPONSES

Scenario One—Adverse Shocks to EL Sovereigns in Italy and Spain



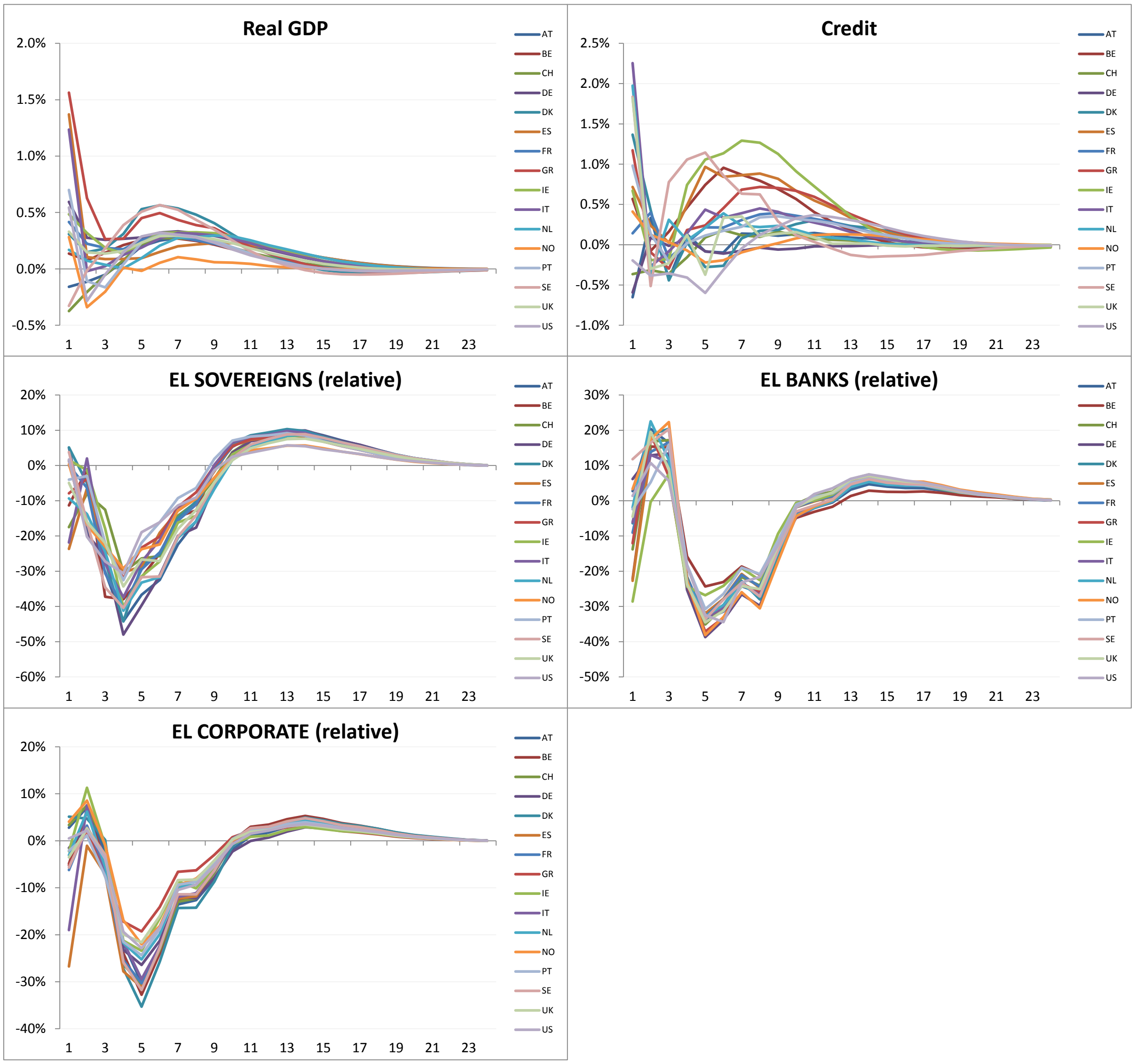
Source: Author estimates.

Scenario Two—Adverse Shocks to EL Banking Systems in Italy and Spain



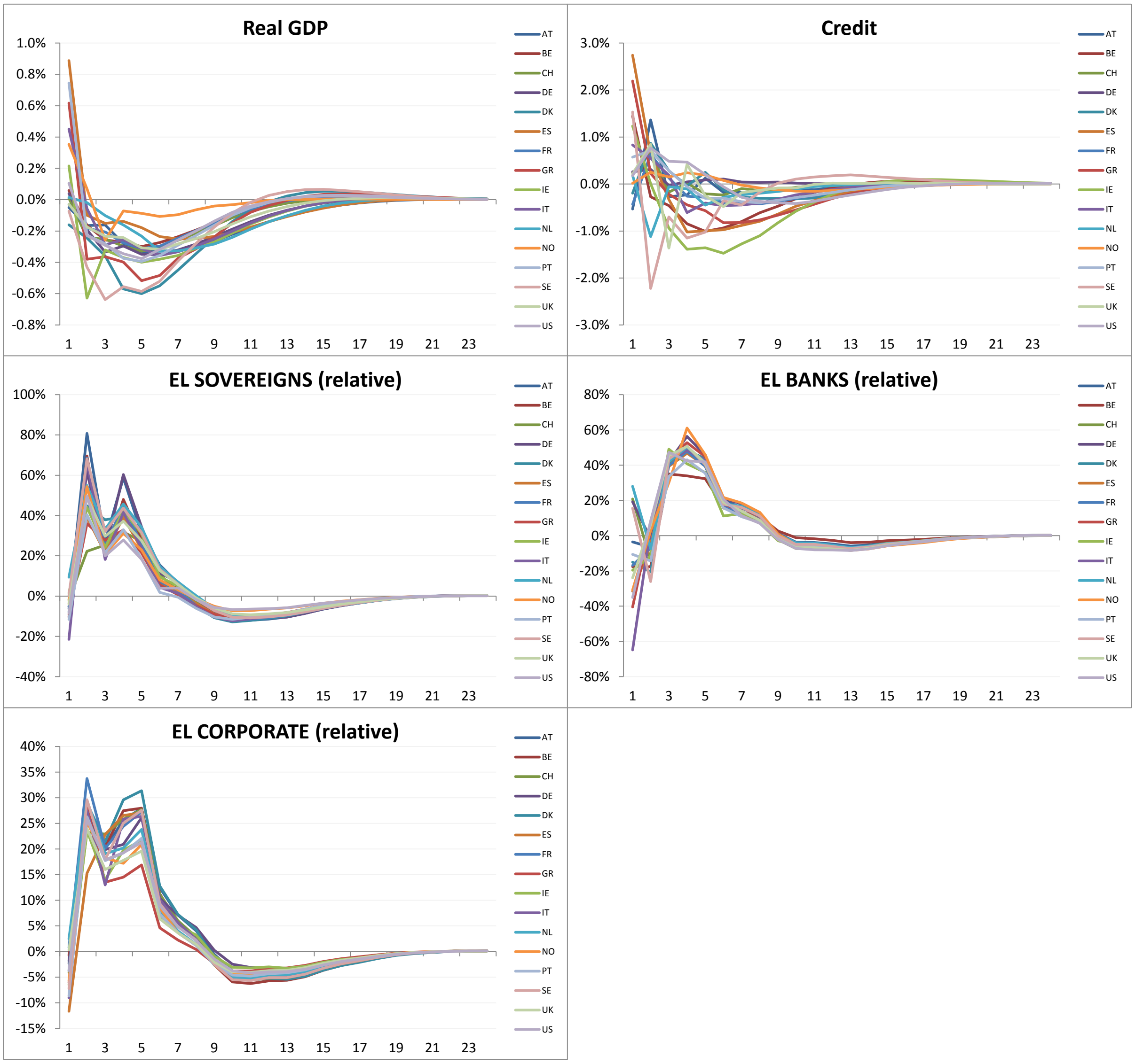
Source: Author estimates.

Scenario Three—Positive Shocks to EL Sovereigns in Italy and Spain



Source: Author estimates.

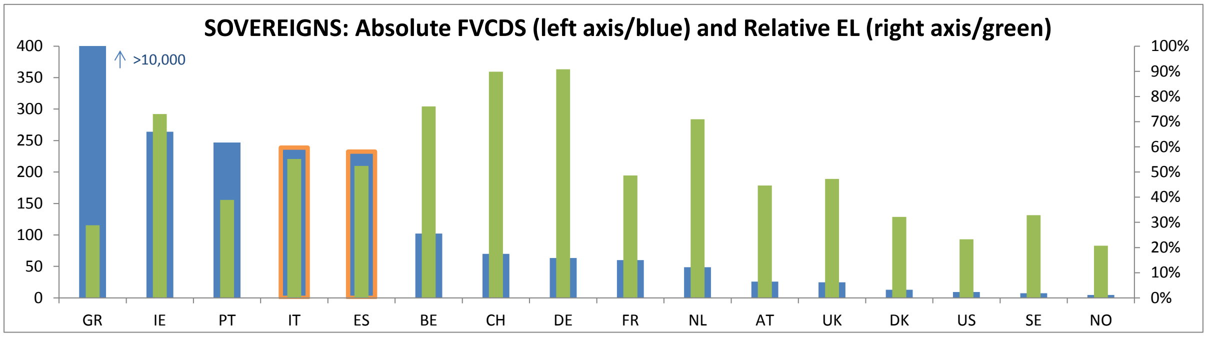
Scenario Four—Positive Shocks to EL Banking Systems in Italy and Spain

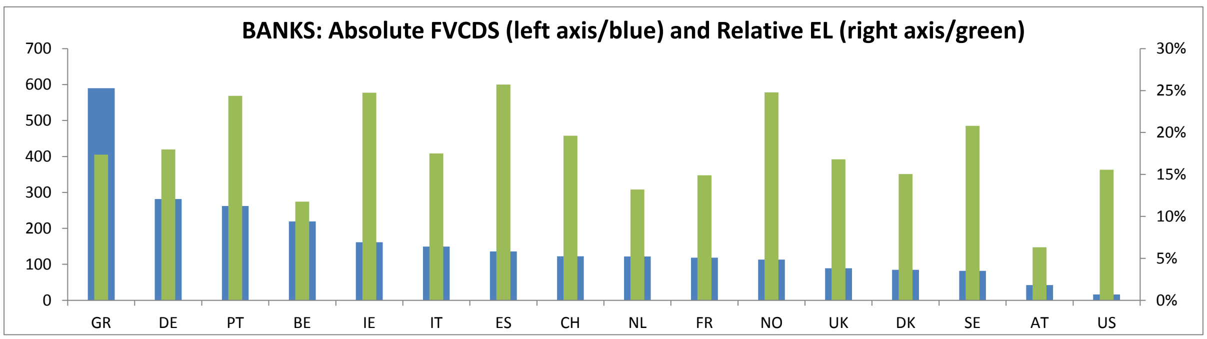


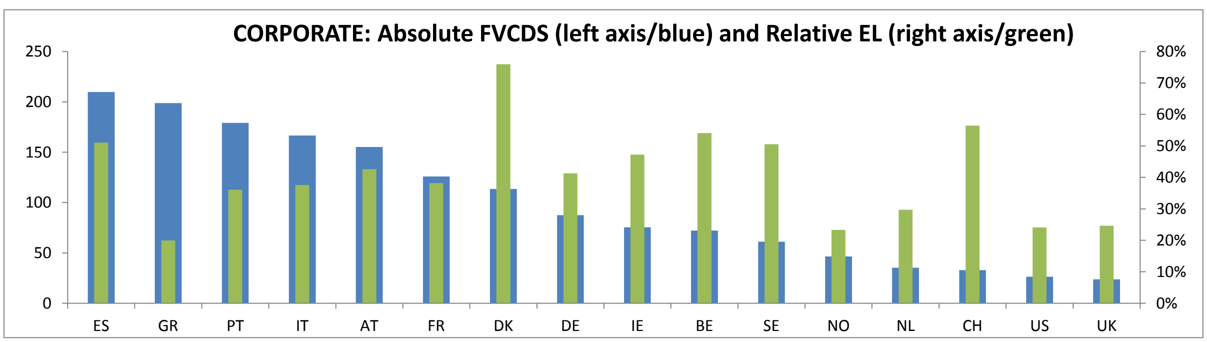
Source: Author estimates.

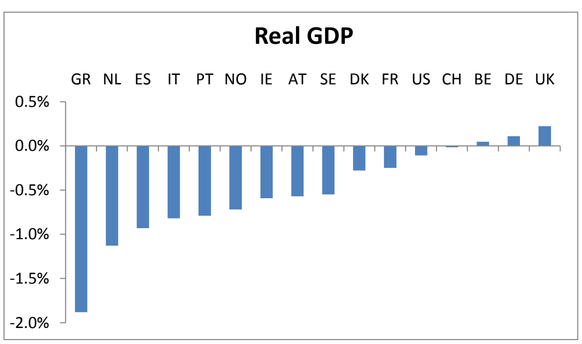
APPENDIX VI. MAXIMUM CUMULATIVE IMPULSE RESPONSES ALONG TWO-YEAR HORIZON

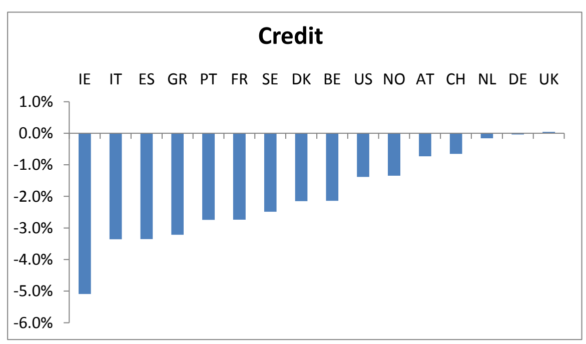
Scenario One—Negative Shocks to EL Sovereigns in Italy and Spain









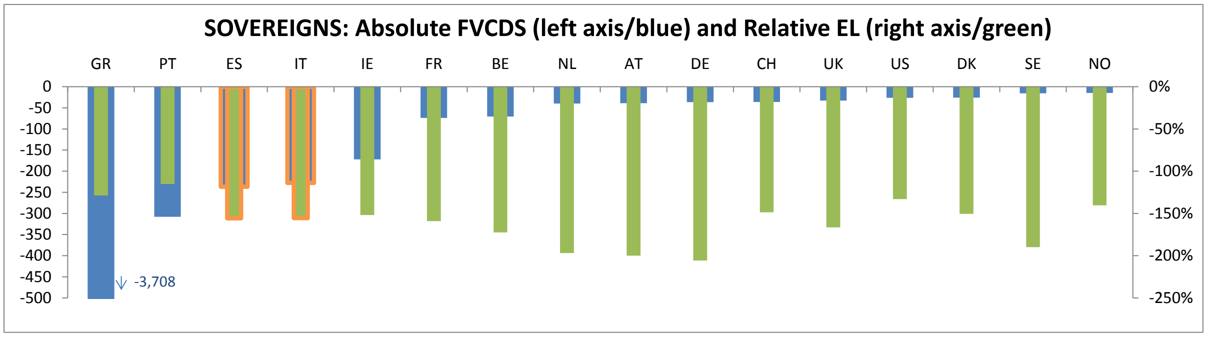


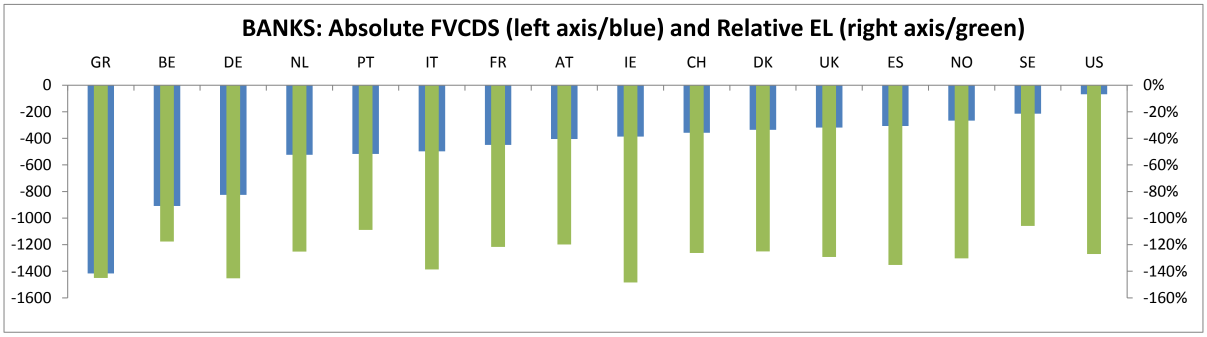
Source: Author estimates.

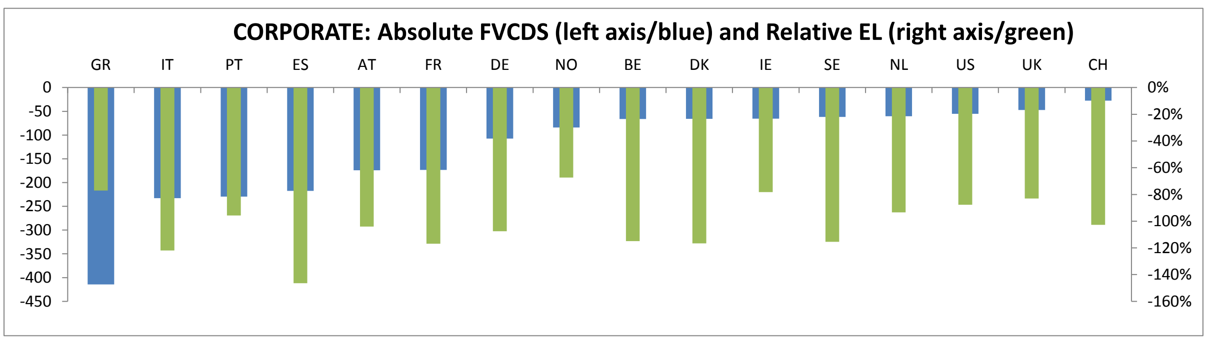
Scenario Two—Negative Shocks to EL Banking Systems in Italy and Spain

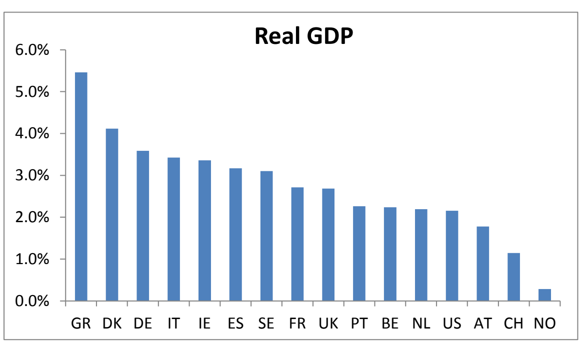
Source: Author estimates.

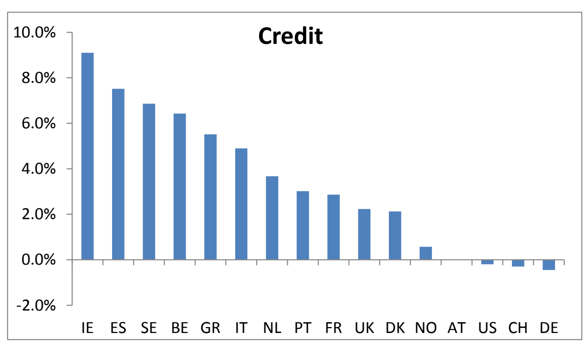
Scenario Three—Positive Shocks to EL Sovereigns in Italy and Spain





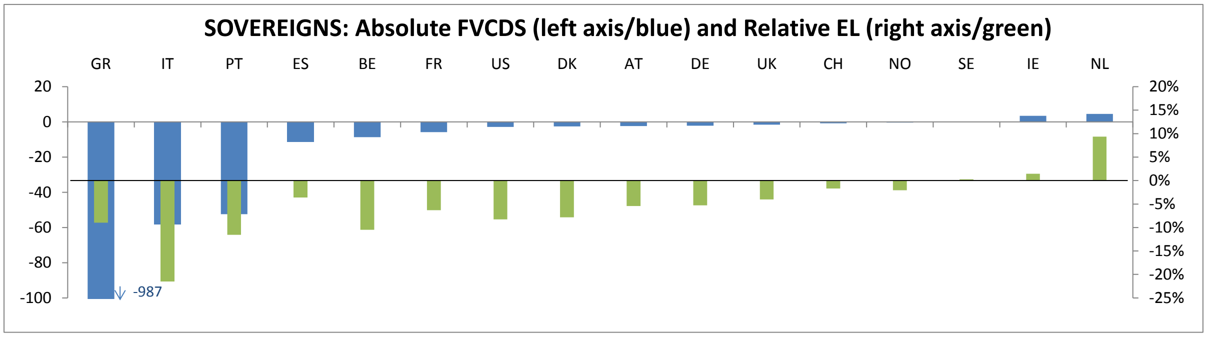


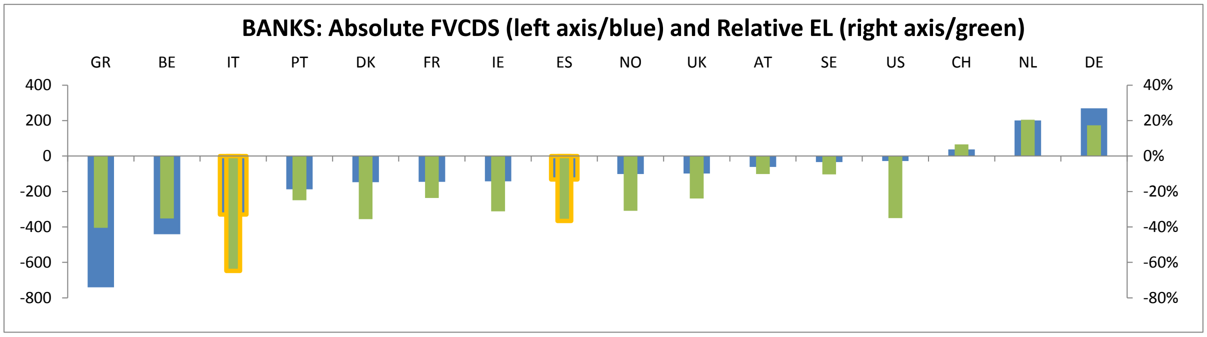


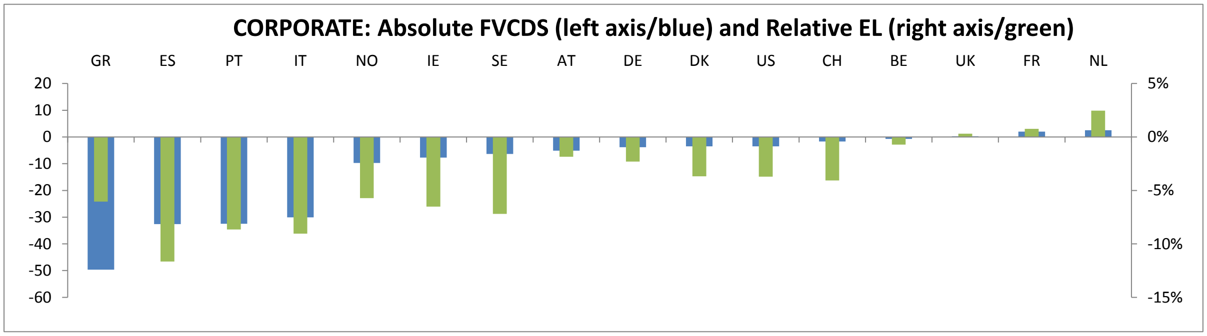


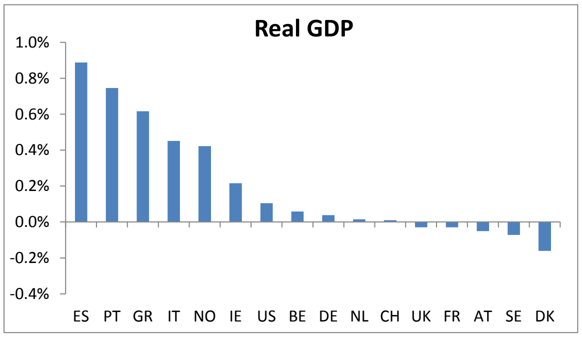
Source: Author estimates.

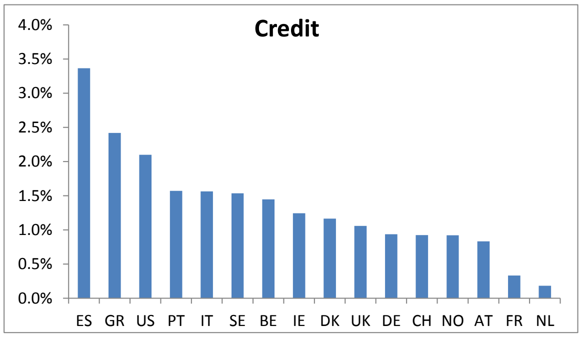
Scenario Four—Positive Shocks to EL Banking Systems in Italy and Spain











Source: Author estimates.

APPENDIX VII. SIGNIFICANCE OF SCENARIO RESPONSES

EL SOV	AT	BE	CH	DE	DK	ES	FR	GR	IE	IT	NL	NO	PT	SE	UK	US
Scenario 1		10	5	10		10		10	10	5						
Scenario 2			10			5			10				10			
Scenario 3						5		10		10			5			
Scenario 4	10	10					10			10		10		10	10	10
EL FIN	AT	BE	CH	DE	DK	ES	FR	GR	IE	IT	NL	NO	PT	SE	UK	US
Scenario 1			5	5		5		5	5	5	5	5	5	5	5	
Scenario 2				5		5				10	10		10			
Scenario 3		10					10						5			
Scenario 4								10					5			
EL CORP	AT	BE	CH	DE	DK	ES	FR	GR	IE	IT	NL	NO	PT	SE	UK	US
Scenario 1	10	10		10	5	10	10		10	10			10			
Scenario 2							10		10	5		10	10			
Scenario 3								10		5			5			
Scenario 4								10		10						
GDP	AT	BE	CH	DE	DK	ES	FR	GR	IE	IT	NL	NO	PT	SE	UK	US
Scenario 1	5					10		5			5		10			
Scenario 2						5			10	10					10	
Scenario 3					10			5				5				
Scenario 4			10	10			10		10	5			10	10	10	
CREDIT	AT	BE	CH	DE	DK	ES	FR	GR	IE	IT	NL	NO	PT	SE	UK	US
Scenario 1	5	1				5	1	5	1	5	10	10	1	5		
Scenario 2						5			10						10	
Scenario 3		5				10			1							
Scenario 4						10		5						5		

Source: Author estimates.

Note: The table indicates whether maximum/minimum responses (maximum/minimum depending on the variables' stress orientation and the type of the scenario) were significant at a 1 percent, 5 percent, or 10 percent level. See text for details.

REFERENCES

Acharya, V., I. Drechsler, P. Schnabl, 2011, "A Pyrrhic Victory? – Bank Bailouts and Sovereign Credit Risk", NBER Working Paper 17136, NBER Cambridge MA.

Backus, David, Foresi, Silvereio and Liuren Wu, 2004, "Accounting for Biases in Black-Scholes," Working Paper, New York University, Goldman Sachs Group, and Baruch College.

Billio, M., M. Getmansky, D. Gray, A. Lo, R. Merton, 2013, "Sovereign, Bank and Insurance Credit Spreads: Connectedness and System Networks," forthcoming.

Binder, M. and M. Gross, 2013, "Regime Switching Global Vector Autoregressive Models", ECB Working Paper 1569, August.

Bohn, J., 2000, "An Empirical Assessment of a Simple Contingent Claims Model for the Valuation of Risky Debt," *Journal of Risk Finance*, 1, pp. 55–77.

Chen, Q., D. Gray, P. N'Diaye, and H. Oura, 2010, "International Transmission of Bank and Corporate Distress", IMF Working Paper No. 10/124 (Washington: International Monetary Fund).

Crouhy, M., Galai, D. and Mark, R., 2000, *Risk Management*, McGraw Hill, New York.

Chudik, A. and M. Fratzscher, 2011, "Identifying the global transmission of the 2007–2009 financial crisis in a GVAR model", *European Economic Review*, 55(3), pp. 325–339.

Davidson, R. and J.G. MacKinnon, 2005, "Bootstrap methods in econometrics", Chapter 23 in *Palgrave Handbook of Econometrics: Volume 1 Theoretical Econometrics*, ed. K. Patterson and T.C. Mills, Basingstoke, Palgrave Macmillan.

Dees, S., F. Di Mauro, M.H. Pesaran, and L.V. Smith, 2007, "Exploring the international linkages of the euro area: A global VAR analysis", *Journal of Applied Econometrics*, 22, pp. 1-38.

Dwyer, D. and I. Korablev, 2007, "Power and Level Validation of Moody's KMV EDF™ Credit Measures in North America, Europe, and Asia," Moody's Analytics White Paper.

Draghi, M., F. Giavazzi, R. C. Merton, 2003, "Transparency, Risk Management and International Financial Fragility" NBER Working Paper 9806, June. (Earlier version presented at the Fourth Geneva Conference on the World Economy: Financial Markets: Shock Absorbers or Shock Creators? May 2002.)

Dwyer, D., Z. Li, S. Qu, H. Russell and J. Zhang, 2010, "CDS-implied EDF™ Credit Measures and Fair-value Spreads," Moody's Analytics White Paper.

ECB, 2013, Financial Stability Review, Box 8 pages 87 to 90, May.

Eickmeier, S. and T. Ng, 2011, "How do credit supply shocks propagate internationally? A GVAR approach", Bundesbank Discussion Paper No. 27/2011.

Ejsing, J. and W. Lemke, 2009, "The Janus-Headed Salvation: Sovereign and Bank Credit Risk Premia During 2008-09", ECB Working Paper No. 1127, December.

Gabaix. X., 2008, “Variable Rare Disasters: An Exactly Solved Framework for Ten Puzzles in Macro-Finance”, NBER Working Paper 13724, NBER Cambridge, MA.

Gapen M. T., Gray, D. F., Lim C. H., Xiao Y., 2005, “Measuring and Analyzing Sovereign Risk with Contingent Claims,” IMF Staff Papers Volume 55.

Gapen M. T., 2009, “Evaluating the implicit guarantee to Fannie Mae and Freddie Mac using contingent claims” in Credit, Capital, Currency, and Derivatives: Instruments of Global FinancialStability or Crisis? (International Finance Review), ed. JJ Choi, MG Papaioannou, 10:329–52. Bingley, UK: Emerald Group

Garcia, C., D. Gray, L. Luna, J. Restrepo, 2011, “Incorporating Financial Sector into Monetary Policy Models: Application to Chile”, IMF WP/11/228.

Gray, D. and S. Malone, 2008, *Macrofinancial Risk Analysis*, (Wiley Finance Book).

Gray, D. F., Merton R. C. and Z. Bodie, 2008, “A New Framework for Measuring and Managing Macrofinancial Risk and Financial Stability”, Harvard Business School Working Paper No. 09–015.

Gray, D. F., Merton R. C. and Z. Bodie, 2007, “Contingent Claims Approach to Measuring and Managing Sovereign Credit Risk, Journal of Investment Management, 5(4), pp. 5–28.

Gray, Dale, Robert C. Merton, Zvi Bodie, 2002, “A New Framework for Analyzing and Managing Macrofinancial Risks,” C.V. Starr Conference on Finance and Macroeconomics**.** October 2, 2002**,** New York University.

Gray, D., A. Jobst, 2011, “Modeling Systemic Financial Sector and Sovereign Risk,” Sveriges Riksbank Economic Review, September.

Gray, D. F., Jobst, A. A., and S. Malone, 2010, “Quantifying Systemic Risk and Reconceptualizing the Role of Finance for Economic Growth,” *Journal of Investment Management*, 8(2), pp. 90-110.

Gray, D., A. Jobst, S. Malone, 2011, “Sovereign Debt, Banking Sector Vunerability, and Dynamic Risk Spillovers in Europe,” EC conference on Debt and Growth, December 2010.

Gray, D. and S. Malone, 2012, “Sovereign and Financial Sector Risk: Measurement and Interactions”, *Annual Review of Financial Economics*, 4(9).

Gray, D. and J. Walsh, 2008, “Factor Model for Stress-testing with a Contingent Claims Model of the Chilean Banking System.” IMF Working Paper 08/89. (Washington: International Monetary Fund).

Gross, M. 2013, “Estimating GVAR weight matrices”, ECB Working Paper No. 1523.

International Monetary Fund (IMF), 2010, “Global Financial Stability Report: Sovereigns, Funding, and Systemic Liquidity” (October).

International Monetary Fund (IMF), 2013, “Old Risks, New Challenges,” Chapter 2 on Sovereign CDS Market (April).

Jobst, A. and D. Gray, 2013, "Systemic Contingent Claims Analysis –Estimating Market-Implied Systemic Risk", IMF Working Paper 13/54 (Washington: International Monetary Fund).

Korablev, Irina and S. Qu, 2009, "Validating the Public EDF Model Performance During the Credit Crisis", Moody's Analytics White Paper.

Merton, R.C., 1973, "Theory of Rational Option Pricing," *Bell Journal of Economics* and Management Science, 4 (Spring), pp. 141-83 (Chapter 8 in Continuous-Time Finance).

Merton, R.C., 1974, "On the Pricing of Corporate Debt: The Risk Structure of Interest Rates," *Journal of Finance,* 29 (May), pp. 449-70. (Chapter 12 in *Continuous-Time Finance*).

Merton, R.C., 1977, "An Analytic Derivation of the Cost of Loan Guarantees and Deposit Insurance: An Application of Modern Option Pricing Theory." *Journal of Banking and Finance,* 1 (June), pp. 3-11 (Chapter 19 in *Continuous-Time Finance*).

Merton, R. C., 1992, *Continuous-Time Finance*. Oxford, U.K.: Basil Blackwell, (Rev. ed.)

Merton, R.C., Billio, M., Getmansky, M., Gray, D., Lo, A.W. and L. Pelizzon, 2013, "On a New Approach for Analyzing and Managing Macrofinancial Risks," *Financial Analysts Journal,* 69(2).

Moody's Analytics, 2011, "Quantifying the Value of Implicit Government Guarantees for Large Financial Institutions," Moody's Analytics Quantitative Research Group, January.

Pesaran, M.H., Schuermann, T. and S.M. Weiner, 2004, "Modeling Regional Interdependencies Using a Global Error-Correcting Macroeconometric Model", *Journal of Business & Economic Statistics,* 22(2).

Pesaran, M.H., Schuermann, T., Treutler, B.-J. and S.M. Weiner, 2006, "Macroeconomic Dynamics and Credit Risk: A Global Perspective", *Journal of Money, Credit, and Banking,* 38(5), pp. 1211-1261.

Pesaran, M.H., Schuermann, T. and L.V. Smith, 2009, "Forecasting economic and financial variables with global VARs", *International Journal of Forecasting*, 25(4), pp. 642–675.

Pesaran, M.H., Smith, L.V. and R.P. Smith, 2007, "What if the UK or Sweden had joined the euro in 1999? An empirical evaluation using a Global VAR", *International Journal of Finance & Economics*, 12(1), pp. 55–87.

Schweikhard, F.A., and Z. Tsesmelidakis. 2012. "The Impact of Government Interventions on CDS and Equity Markets", Paper presented at Preliminary Program of the Allied Social Science Associations, Chicago (January).