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TECHNICAL NOTE—SYSTEMIC RISK AND CONTAGION ANALYSIS

September 2014

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FINANCIAL SECTOR ASSESSMENT PROGRAM

September 2014

TECHNICAL NOTE

SYSTEMIC RISK AND CONTAGION ANALYSIS

Prepared By

Monetary and Capital Markets Department

This Technical Note was prepared by IMF staff in the context of the Financial Sector Assessment Program in Switzerland. It contains technical analysis and detailed information underpinning the FSAP's findings and recommendations.

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Glossary

CDS	Credit Default Wwap
CIMDO	Consistent Information Multivariate Density Optimization
COMA	Contagion Matrix
EAD	Exposure at Default
ES	Expected Shortfall
FI	Financial Institution
FINMA	Swiss Financial Market Supervisory Authority
FSAP	Financial Sector Assessment Program
FSI	Financial stability Index
FSM	Financial Stability Measures
FSMD	Financial System's Portfolio Multivariate Density
GSIFI	Global Systemically Important Financial Institution
IGRA	Index of Global Risk Aversion
JPOD	Joint Probability of Default
MCSR	Marginal Contribution to Systemic Risk
OMT	Outright Monetary Transactions
POD	Probability of Default
SNB	Swiss National Bank
VAR	Value at Risk
VI	Vulnerability Index

EXECUTIVE SUMMARY[1]

This note summarizes the systemic risk and contagion analysis undertaken for the Swiss financial system as part of the Financial Sector Assessment Program (FSAP) Update. The analysis consists of four parts: (i) a domestic and international spillover analysis, (ii) a systematic risk analysis, (iii) a sovereign-financial contagion analysis, and (iv) an analysis of macro-financial linkages.

Contagion risks arising from interbank exposures in Switzerland appear to be contained. This analysis shows only moderate effects, consistent with restrictions imposed by the Swiss "large exposure rules" currently in place, and no material second round effects will materialize within the domestic interbank market. In terms of bank groups, domestic interbank exposure risks appear to be moderate for most banks, but a few small private banks and banks specialized in asset management appear to be somewhat vulnerable.[2]

The domestic contagion analysis finds that domestically-oriented financial institutions are gaining in importance in terms of systematic risk. While large Swiss financial institutions were the most vulnerable institutions during the financial crisis, over the past couple of years and more recently, domestically-orientated banks have become more vulnerable. The same pattern holds for their contribution to changes in the contagion vulnerability of other financial institutions.

The international contagion analysis suggests that global contagion risks among GSIFIs and the large Swiss financial institutions appear to be currently contained. At the height of the global financial crisis, large U.S. and Swiss financial institutions contributed the most to contagion among GSIFIs and were most vulnerable. However, during the European sovereign debt crisis and more recently, financial institutions of peripheral countries as well as French financial institutions appear to be the most vulnerable.

The systematic risk analysis shows that the relative contribution of domestically-oriented banks to systemic risk is increasing. Although still large, the share of large Swiss financial institutions has been declining in the years following the global financial crisis.

The bank-sovereign contagion analysis suggests that increases in banks capital buffers have contributed positively to limit contagion risks. In the midst of the financial crisis, contagion vulnerabilities of the Swiss sovereign to Swiss financial institutions increased substantially, owing to increased global risk aversion and a deterioration of banking fundamentals. Recently, contagion from banks to sovereign seems to be contained; the most

[1] This Technical Note was prepared by Carlos Caceres, Fabian Lipinsky,and Miguel Segoviano.

[2] These are small banks with a high exposure to one single counterpart. The aggregated balance sheet for the banks with a capital ratio falling below 8 percent represents around 2 percent of domestic banking sector assets.

significant factors, accompanying the strengthening of capital buffers, are the implementation of OMT and lower risk aversion. Nevertheless, the latter factors depend on international developments.

According to general equilibrium analysis, risk measures move closely with macroeconomic variables, owing to feedback channels between the financial sector and the real economy in Switzerland. Business investment reacts more strongly to credit conditions relative to residential investment. Indeed, residential investment and prices seem to be mainly driven by demand factors. This suggests that macro-prudential measures aimed at curtailing demand (e.g., tax incentives), could be more effective than credit-supply side measures at mitigating the potential build-up in real estate bubbles.

FINANCIAL STABILITY ASSESSMENT

1. **Contagion across financial institutions plays an important role in the realization of systemic risk.** The recent crisis underlined that proper estimation of contagion risks among financial institutions (FIs) in a financial system is essential for effective financial stability assessment. Clearly, the realization of simultaneous large losses in various FIs would affect a financial system's stability, and thus represents a major concern for authorities. Thus, the analysis of the financial system's stability should aim at understanding these contagion risks and their changes across the economic cycle.[3]

2. **A set of financial stability indicators and systemic loss measures were at the core of this analysis.** The financial stability indicators estimated under this approach incorporate: (i) measures of tail risk, (ii) contagion, and (iii) systemic loss measures. These measures will provide complementary perspectives to assess the financial stability of the Swiss financial system, including banks and nonbanks.

3. **Results from the contagion and systemic risk analysis are broadly in line with parallel stability assessments.** In order to complement the financial risk assessment performed in the Switzerland FSAP, based on individual bank and insurance companies' stress tests,[4] a series of financial stability indicators were estimated to take into account contagion and systemic risks among financial institutions. Based on a completely different data set and methodology, the results produced by this analysis are consistent with public's views, but also with complementary analysis performed by the FSAP team and the authorities.

4. **This framework offers the following advantages:**

- It is a comprehensive coverage: The methodology allows for the inclusion of banking and non-banking financial institutions (FIs)/sectors.
- It captures contagion effects: It takes into account inter-linkages (direct and indirect) amongst FIs.
- It captures changes of distress dependence across the economic cycle: Distress dependence can change significantly amongst FIs in periods of distress.
- It integrates complementary information: As mentioned above, these indicators were estimated exclusively with publicly available data.

[3] It is important to note that the analysis of financial stability presented in this section was performed exclusively with publicly available data, since the mission did not have access to bank-specific and confidential supervisory information. Nevertheless, the methodology presented below can easily be implemented with supervisory data if available.

[4] See accompanying technical notes "Stress Testing the Banking Sector" and "The Insurance Sector."

- It provides robust estimations: It benefits from robust estimation with restricted data (under the PIT criterion).

5. In addition, the framework enables the assessment of financial stability from the following perspectives:

- Financial stability at the local level. The FSAP team estimated the measures of financial stability described above, including the largest banks, domestically oriented banks and insurance companies.

- International spillovers. These effects are relevant due to the large and global nature of systemically important Swiss FIs. This section extended the analysis of interconnectedness between local institutions to take into account interlinkages with global SIFIs.

- Financial-sovereign contagion risk. Quantification of contagion risk between the Swiss financial system and its sovereign was also performed, aiming to identify the most significant risk factors and how these have changed across time.

- Analysis of macrofinancial linkages. Feedback loops between the financial sector and the real economy were analyzed. In order to analyze second round effects, a theoretical model was used to capture the lending behavior of financial institutions as a function of risk in the mortgage loan and corporate commercial loan portfolios.

6. The analysis covers a diverse sample of Swiss financial institutions, including both banks and non-banks. These include: the two large banks, two large insurance and re-insurance companies, five cantonal banks, and a medium-size bank specialized in asset management. In addition, the analysis of contagion risks among GSIFIs includes four large Swiss financial institutions together with other GSIFIs. These institutions are listed in Figure 1.

FRAMEWORK TO ASSESS FINANCIAL STABILITY

7. This analysis aims at estimating a set of financial stability indicators and the contribution to potential extreme systemic losses of each financial institution (FI) in the system. A key aspect of this estimation is that it accounts for direct and indirect linkages between FIs in the system. Direct linkages arise through inter-institution exposures (interbank deposits, lending, syndicated loans) and derivative transactions. However, indirect linkages can be due to exposures to common risk factors, which are not usually apparent during calm periods, but can take greater relevance in periods of economic and financial distress.

Figure 1. Switzerland: Coverage of Systematic Risk and Contagion Analysis

FSIs, Interconnectedness, and Sovereign-Financial analysis		Global Contagion	
Banks	**Non-banks**	**Banks**	**Non-banks**
UBS	Swiss Re	UBS	Swiss Re
Credit Suisse	Zurich Financial	Credit Suisse	Zurich Financial
Basel Cantonal Bank		Bank of America	
Bern Cantonal Bank		Citi	
Lucerne Cantonal Bank		Goldman Sachs	
Vaudoise Cantonal Bank		JP Morgan	
Julius Baer Bank		Morgan Stanley	
		Barclays	
		HSBC	
		Lloyds	
		RBS	
		Commerzbank	
		Deutsche Bank	
		BNP Paribas	
		Credit Agricole	
		Societe Generale	
		Unicredit	

Source: IMF staff.

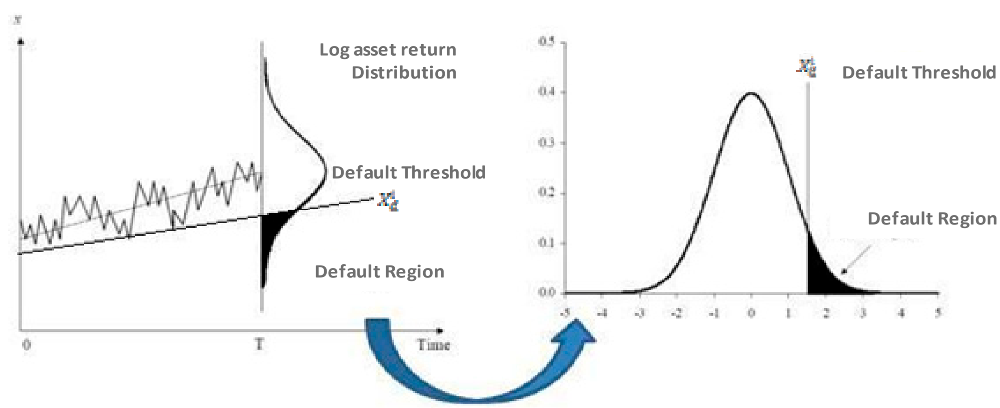
8. To achieve this objective, we conceptualize the banking system as a portfolio of banks comprising the banks operating in a country's banking system. We therefore apply the structural approach (SA) for modeling portfolio risk.[5] The SA is one of the most common approaches to modeling portfolio risk.[6] Under the SA, the change in the value of the assets of a borrower is related to the change in its credit risk quality. The basic premise of this approach is that a borrowing firm's underlying asset value evolves stochastically over time and default is triggered by a drop in the firm's asset value below a threshold value (default region), the latter being modeled as a function of the firm's financial structure. Thus, the likelihood of the firm's asset value falling below

[5] Note that the SA is normally used to measure credit risk in portfolios of loans. In contrast, in this exercise we apply the SA to measure risk in "portfolios of institutions," which characterize the banking system of a country.

[6] Widely known applications of the structural approach include the Credit Metrics framework (Gupton et al, 1997) and the KMV framework (Crosbie et al, 1998).

the default-threshold; therefore defaulting, is represented by the probability of default (PoD) of the firm (Figure 2).[7]

Figure 2. Switzerland: Basic Premise of the Structural Approach



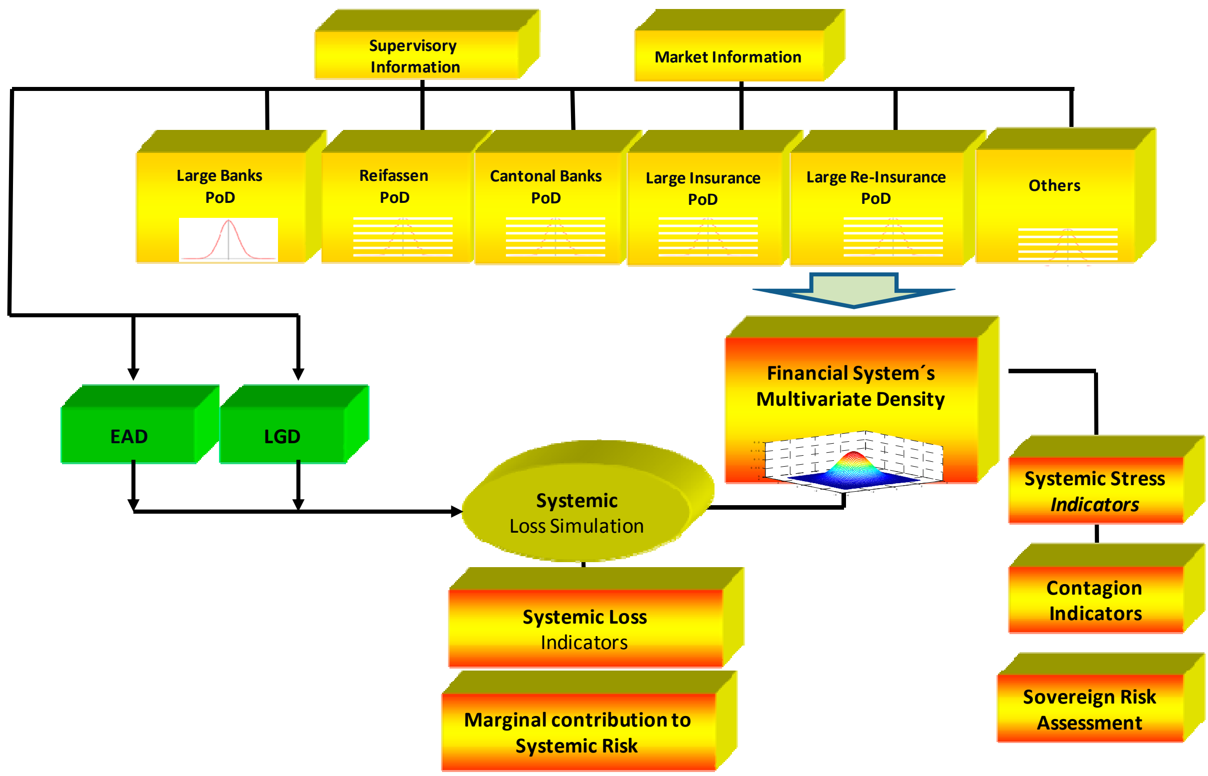
Source: IMF Staff.

9. Consistent with the structural approach's basic premise, the SA allows us to estimate the financial system's portfolio multivariate density (FSMD), which describes the joint likelihood of changes in the asset value of all the FIs that make up the portfolio that characterize the financial system. The FSMD allows us to estimate a set of systemic financial stability measures (FSMs) and loss measures that characterize systemic risk by taking into account distress dependence between FIs and its changes across the economic cycle. As presented in Segoviano and Goodhart (2009), the FSMs allow analyzing financial stability from three different, yet, complementary perspectives, by allowing the quantification of: (i) "common" distress in the system, (ii) distress between specific FIs, and (iii) distress in the system associated with a specific FI; i.e., "cascade effects." In addition to FSMs, this approach allows the estimation (via simulation) of losses at the systemic level, from which we quantify the marginal contribution to systemic risk (MCSR) for each FI in the system (Figure 3).

In order to implement this approach, we first model the FSMD, from which we estimate two sets of indicators, the (i) FSMs and (ii) systemic losses and the MCSR.

[7] The generalization of this approach includes, in addition to the default state, different credit risk quality states (ratings) and thus changes in credit risk quality are also triggered by changes in the firm's asset value with respect to threshold values.

Figure 3. Switzerland: Modeling Framework



Source: IMF staff.

MODELING THE SYSTEM'S PORTFOLIO MULTIVARIATE DENSITY

10. The proper estimation of loss distributions represents a key objective in financial risk management, since economic capital decisions and risk management strategies are heavily reliant on it. In order to estimate loss distributions that incorporate distress dependence across FIs, a procedure based on the implementation of the CIMDO methodology was developed. This methodology is easily implementable and robust to data constrained environments.[8] Segoviano (2006) presents the detailed developments of the CIMDO framework. We summarize these below.

[8] These features are of great importance, since the information available to model systemic risk is Switzerland was highly limited, due to the fact that the FSAP team did not have any access to supervisory information at the individual institution level.

The consistent information multivariate density optimization methodology

11. We recover the FSMD employing the CIMDO methodology and empirical measures of probabilities of distress (PoDs) of individual FIs. It is important to emphasize the fact that individual financial institutions' PoDs are exogenous variables in the CIMDO framework. Thus, it can be implemented with PoDs estimated with different approaches, including (i) Merton-type models, (ii) Credit Default Swaps (CDS), and (iii) Out of the Money Option Prices (OOM) or PoDs estimated based on supervisory information. Consequently, the CIMDO approach provides great flexibility in the estimation of the FSMD.

12. The CIMDO-methodology is based on the minimum cross-entropy approach (Kullback, 1959). Under this approach, a *posterior* multivariate distribution *p*—the CIMDO-density—is recovered using an optimization procedure by which a *prior* density *q* is updated with empirical information via a set of constraints. Thus, the *posterior* density satisfies the constraints imposed on the *prior* density. In this case, the banks' empirically estimated PoDs represent the information used to formulate the constraint set. Accordingly the CIMDO-density—the FSMD—is the *posterior* density that is closest to the *prior* distribution and that is *consistent* with the empirically estimated PoDs of the banks making up the system.

In order to formalize these ideas, Segoviano and Goodhart (2009) proceed by defining a banking system—portfolio of banks—comprising two banks;[9] i.e., bank X and bank Y, whose logarithmic returns are characterized by the random variables x and y. Hence we define the CIMDO-objective

function as: $C[p,q]=\int\int p(x,y)\ln\left[\frac{p(x,y)}{q(x,y)}\right]dxdy$, where $q(x,y)$ and $p(x,y) \in \mathbf{R}^2$.

It is important to point out that the *prior* distribution follows a parametric form q that is consistent with economic intuition (e.g., default is triggered by a drop in the firm's asset value below a threshold value) and with theoretical models (i.e., the structural approach to model risk). However, the parametric density *q* is usually inconsistent with the empirically observed measures of distress. Hence, the information provided by the empirical measures of distress of each bank in the system is of prime importance for the recovery of the *posterior* distribution. In order to incorporate this information into the *posterior* density, we formulate consistency-constraint equations that have to be fulfilled when optimizing the CIMDO-objective function. These constraints are imposed on the marginal densities of the multivariate *posterior* density, and are of the form:

$$\int\int p(x,y)\,\chi_{\left(x_d^x,\infty\right)}dxdy=PoD_t^x,\ \int\int p(x,y)\,\chi_{\left(x_d^y,\infty\right)}dydx=PoD_t^y \qquad (1)$$

[9] These stylized facts apply equally to bank and non-bank financial institutions.

where $p(x,y)$ is the *posterior* multivariate distribution that represents the unknown to be solved. PoD_t^x and PoD_t^y are the empirically estimated probabilities of distress (PoDs) of each of the banks in the system, and $\chi_{\left[x_d^x,\infty\right)}$, $\chi_{\left[x_d^y,\infty\right)}$ are indicating functions defined with the distress thresholds x_d^x, x_d^y, estimated for each bank in the portfolio. In order to ensure that the solution for $p(x,y)$ represents a valid density, the conditions that $p(x,y) \geq 0$ and the probability additivity constraint $\int\int p(x,y)dxdy = 1,$ also need to be satisfied. Once the set of constraints is defined, the CIMDO-density is recovered by minimizing the functional:

$$L[p,q] = \int\int p(x,y)\ln p(x,y)dxdy - \int\int p(x,y)\ln q(x,y)\,dxdy + \tag{2}$$

$$\lambda_1\left[\int\int p(x,y)\,\chi_{[x_d^x,\infty)}dxdy - PoD_t^x\right] + \lambda_2\left[\int\int p(x,y)\,\chi_{[x_d^y,\infty)}dydx - PoD_t^y\right] + \mu\left[\int\int p(x,y)\,dxdy - 1\right]$$

where λ_1, λ_2 represent the Lagrange multipliers of the consistency constraints and μ represents the Lagrange multiplier of the probability additivity constraint. By using the calculus of variations, the optimization procedure can be performed. Hence, the optimal solution is represented by a *posterior* multivariate density that takes the form

$$\hat{p}(x,y) = q(x,y)\exp\left\{-\left[1+\hat{\mu}+(\hat{\lambda}_1\chi_{\left[x_d^x,\infty\right)})+(\hat{\lambda}_2\,\chi_{\left[x_d^y,\infty\right)})\right]\right\} \tag{3}$$

From the functional defined in equation (2), it is clear that the CIMDO recovers the distribution that minimizes the probabilistic divergence; i.e., "entropy distance," from the prior distribution and that is consistent with the information embedded in the moment-consistency constraints. Thus, out of all the distributions satisfying the moment-consistency constraints, the proposed procedure provides a rationale by which we select the posterior that is closest to the prior (Kullback, 1959), thereby, solving the under-identified problem that was faced when trying to determine the unknown multivariate distribution from the partial information provided by the PoDs. Intuitively, although a prior distribution is based on economic intuition and chosen in consistency with the SA, it is usually inconsistent with empirical observations. Thus, using the cross-entropy solution, one solves this inconsistency, reconciling in the best possible way the distribution that is closest to the prior but consistent with empirical observations.

13. When we use CIMDO to solve for the CIMDO-density, the problem is converted from one of deductive mathematics to one of inference involving an optimization procedure. This is because instead of assuming parametric probabilities to characterize information contained in the data, this approach uses the data information to infer values for the unknown probability density. Thus the recovered probability values can be interpreted as inverse probabilities. Using this procedure, we look to make the best possible predictions from the scarce information that we have. This feature of the methodology not only makes implementation simple and straightforward, it also seems to reduce model and parameter risks of the recovered distribution, as indicated by the PIT criterion (Segoviano, 2006). This is because in order to recover the posterior density, only variables that are directly observable for the type of institutions that are the subject of our interest (PoDs and stock prices) are needed. Moreover, by construction, the recovered posterior density is consistent with the empirically observed probabilities of distress. Thus, the proposed methodology represents a more flexible approach to modeling multivariate densities, making use of the limited available information in a more efficient manner.

14. An important contribution of the CIMDO approach is the copula function. This function describes the dependence structure embedded in the multivariate CIMDO-density (i.e., dependence structure of the log asset returns characterized by the CIMDO-density) is recovered simultaneously when inferring the CIMDO-density. When modeling parametric copula functions, a key challenge is to calibrate adequately such functions. Due to the information constraints that modelers face when modeling the risk, dependence modeling becomes a daunting task. The CIMDO approach recovers the CIMDO-copula simultaneously when inferring the CIMDO-density. Thus, no additional modeling is required for the CIMDO-copula.

15. The CIMDO-copula adjusts automatically to different stages of the economic cycle. Therefore, when the economic situation worsens, distress dependence structure between log asset return increases. This is consistent with empirical facts. This is a key feature of the CIMDO approach, since dependence structure dynamically adjusts to changes in PoDs. Therefore, when PoDs increase, dependence increases.

QUANTIFICATION OF SYSTEMATIC LOSSES AND THE MARGINAL CONTRIBUTION TO SYSTEMATIC RISK

16. The marginal contribution to systemic (MCSR) risk indicates the losses that a given FI can cause in the system. This indicator incorporates two important factors that should be taken into account in systemic risk measurement; i.e., size of the institution and interconnectedness of the institution with the system.

17. The MCSR is based in the Shapley Value, which requires the estimation of losses at the systemic level. Therefore, in what follows we explain how such losses are simulated and how the Shapely value is estimated from these losses.

Simulation of systematic losses

Once the FSMD is estimated using the CIMDO approach, a Monte-Carlo simulation is performed to generate $\boldsymbol{X}$ random numbers. For every simulation i two cases have to be considered:

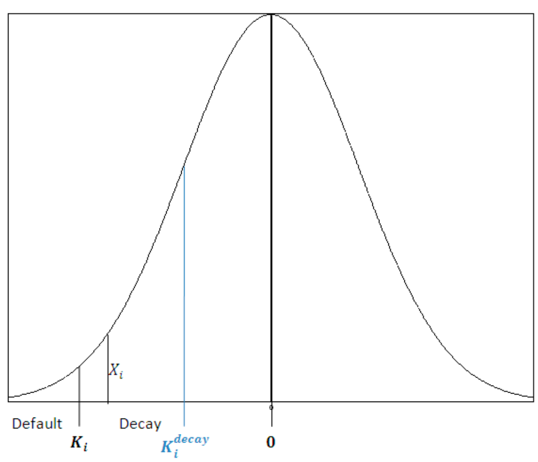
a. If $X_i \leq K_i$ then the FI i has defaulted and $\mathcal{X}_{(-\infty,x_d^i]} = 1$.
b. If $X_i > K_i$ then the FI i has survived and $\mathcal{X}_{(-\infty,x_d^i]} = 0$.

Nevertheless, in addition to the binary case (default or not default) described above, a financial institution can also experience losses if its risk quality gets deteriorated with respect to its current state. In order to capture this effect, we map losses to the returns if they fall into a decay zone (lower risk quality zone). Hence, if a return falls in the decay zone, then a loss will be assigned to this return, which is proportional to the severity of the return. If we define the decay threshold for a given FI as K_i^{decay} then we will now define the random variable Y_i as follows:

$$Y_i = \begin{cases} 0 \; if \; X_i > K_i^{decay} \\ \dfrac{\phi_i\left(K_i^{decay}\right) - \phi(X_i)}{\phi_i\left(K_i^{decay}\right) - \phi(K_i)} \; if \; K_i < X_i < K_i^{decay} \\ 1 \; if \; X_i < K_i \end{cases}$$

where ϕ_i is the cumulative distribution function of the returns of FI B_i. (See Figure 4)

Figure 4. Switzerland: Loss Thresholds



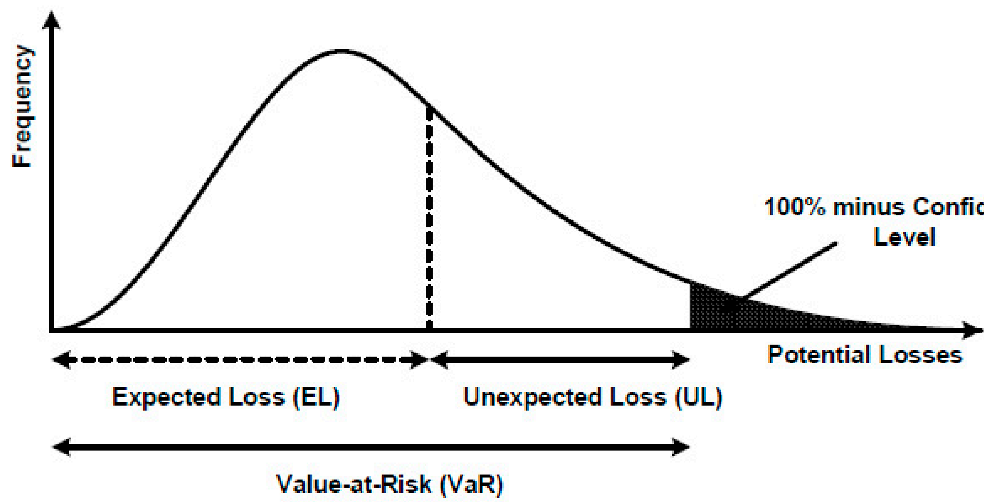
Then, for each company i, the loss is defined as:

$$LGD_i \cdot EAD_i \cdot Y_i \quad ,$$

where LGD_i is the is the loss given default, and EAD_i represents the exposure of the system to a given FI. Therefore, EAD_i is quantified by the total assets of each FI at a given time t.

18. The quantification of unexpected losses at the systemic level relies on the estimation of the distribution of systemic losses. These losses represent the extreme losses at a given confidence level, which are characterized by a Value at Risk or an Expected Shortfall amount (See Figure 5).

Figure 5. Switzerland: Distribution of Systemic Losses



Source: Basel Committee on Banking Supervision, July 2005.

Quantification of the marginal contribution to systematic risk

19. The methodology that we use in order to assess the systemic importance of an institution and the level of the systemic risk follows two steps:

- The inference of the distribution of systemic losses (under the CIMDO approach).
- The use of mathematical tools that taking as input the simulated losses of the financial system give the measures of systemic importance and level of the systemic risk in the system.

First we present two concepts that are used for measure the level of systemic risk in the financial system: Value at Risk (VaR) and Expected Shortfall (ES). Second we present the Shapley Value of a financial institution, a tool that measures the importance of a financial institution on a financial system.

Measures of level of systemic risk

Value at risk

The α-VaR of a loss distribution is given by the smallest number ξ such that the probability that the loss L exceeds ξ is not larger than $(1-\alpha)$. Mathematically:

$$\alpha - VaR(L) = inf\{\xi \in L\colon \mathbb{P}(L > \xi) \leq 1 - \alpha\}.$$

Expected shortfall

The α-ES of a loss distribution is the expected value of the α-tail distribution. We can compute it using the next proposition:

Proposition: Suppose that the probability measure $\mathbb{P}$ is concentrated in a finite number of points y_k in Y. For each $x \in X$ the loss distribution L is a staircase function with jumps in the points $z_1 < z_2 < \cdots < z_N$ and with p_k the probability ok z_k. Let k_α the unique index such that:

$$\sum_{k=1}^{k_\alpha} p_k \geq \alpha > \sum_{k=1}^{k_\alpha - 1} p_k.$$

The α-ES of the loss distribution is given by:

$$\alpha - \mathrm{ES}(x) = \frac{1}{1-\alpha}\left[\left(\sum_{k=1}^{k_\alpha} p_k - \alpha\right) z_{k_\alpha} + \sum_{k=k_\alpha+1}^{N} p_k z_k\right].$$

Measure of systemic importance

Shapley value

The Shapley value was originally developed in the context of cooperative game theory. Given a total payoff which is the generated by the collective effort of all the players, the Shapley value decompose it with the purpose of dividing it to each player according to their corresponding contribution.

Suppose that we have a measure of systemic risk (VaR or Expected Shortfall) applicable to any sub-group of a financial system S. When we want to create a model of macro prudential supervision one naturally wonders about the contribution of each institution to the level of systemic risk of the whole financial system; that is to say on the systemic importance of each institution. In this case, the value to divide is the Value at Risk (VaR) or the Expected Shortfall for a given confidence level.

20. With the Shapley value method we could measure the systemic importance of an institution in a financial system. Supposing that the financial system consists of N institutions, the Shapley value method divides the systemic risk of the whole financial system in N parts corresponding to each institution according to their contribution.

Letting $\boldsymbol{ShB_j}$ denote the systemic importance of the institution B_j we will proceed to give an intuitive interpretation of the concept of the Shapley value.

Suppose that the N institutions are ordered randomly in a line and consider the subgroup S_j that consists of all the institutions up to and including B_j. We define the contribution of the institution B_j as the level of systemic risk of the subgroup S_j minus the level of systemic risk of the subgroup $(S_j - \{B_j\})$. With the definition described above the systemic importance of the financial institution B_j is then the average contribution over all the possible $N!$ orderings of the N financial institutions.

We will now proceed to formalize the intuition presented above.

Consider the following measurable space $(A, \mathcal{A}, \mathbb{P})$ where:

A is the set of all permutations of the N financial institutions.

$\mathcal{A}$ is the sigma-algebra generated by A.

$\mathbb{P}$ is the uniform measure over A.

V is our measure of systemic risk which is a function that goes from $\mathcal{A}$ to the real numbers.

Define the following random variable $\mathrm{X}_j: \mathcal{A} \rightarrow \mathbb{R}$ as:

$$\mathrm{X}_j(\mathrm{a}) = \mathrm{V}(\mathrm{S}_j) - \mathrm{V}(\mathrm{S}_j - \{B_j\}).$$

Where a is an element of A (therefore a is a permutation) and S_j is as defined above.
We will define the systemic importance of the financial institution B_j as:
$\boldsymbol{ShB_j} = \mathbb{E}_{\mathbb{P}}[\mathrm{X}_j]$.

It is important to note that the method distributes all the systemic in the financial system. This is expressed by:

$$\sum_{j=1}^{N} \boldsymbol{ShB_j} = V(S)$$

21. The Shapley value method divides the systemic risk of the whole financial system in N parts corresponding to each institution. The share allocated to each institution is based on their contribution to the level of systemic risk of the financial system. This distribution also captures the systemic importance of each institution of the financial system.

Next, we provide an example: Let us suppose the financial system consists of three banks: $S = \{B_1, B_2, B_3\}$ with the following characteristic function V:

Sub-Group	V
$\emptyset$	0
B_1	1
B_2	3
B_3	5
B_1B_2	3.5
B_1B_3	5.5
B_2B_3	7
$B_1B_2B_3$	8.5

Now, in order to clarify the concept let's just calculate the Shapley value for the institution B_1. First, we need to obtain the value of X_1 for all permutations$(3! = 6)$:

Permutation	Sub-Group (including B_1)	$\boldsymbol{X_1}$
$B_1B_2B_3$	B_1	$V(B_1) - V(\emptyset) = 1$
$B_1B_3B_2$	B_1	$V(B_1) - V(\emptyset) = 1$
$B_2B_1B_3$	B_2B_1	$V(B_2, B_1) - V(B_2) = 3.5 - 3 = 0.5$
$B_3B_1B_2$	B_3B_1	$V(B_3, B_1) - V(B_3) = 5.5 - 5 = 0.5$
$B_3B_2B_1$	$B_3B_2B_1$	$V(B_3, B_2, B_1) - V(B_3, B_2) = 8.5 - 7 = 1.5$
$B_2B_3B_1$	$B_2B_3B_1$	$V(B_2, B_3, B_1) - V(B_2, B_3) = 8.5 - 7 = 1.5$
		$\boldsymbol{ShB_1} = \mathbb{E}_{\mathbb{P}}[X_1] = 1$

Note that the Shapley value for the institution B_1 is just the arithmetic mean (because $\mathbb{P}$ is the uniform measure) of the values of X_1 over all permutations of the financial system $S = \{B_1, B_2, B_3\}$.

Another way to express the Shapley value for this example is:

$$\boldsymbol{ShB_1} = \frac{1}{6}\{2[V(B_2, B_1) - V(B_2)] + [V(B_2, B_1) - V(B_2)] + [V(B_3, B_1) - V(B_3)] + 2[V(B_3, B_2, B_1) - V(B_3, B_2)]\}.$$

In general, for a system of N institutions, the expression for the Shapley value of any institution j is given by:

$$\boldsymbol{ShB_j} = \frac{1}{N!}\sum_{\substack{m=1\\ |S_j|=m}}^{N} (m-1)!\,(N-m)!\left[V\left(S_j\right) - V\left(S_j - \{B_j\}\right)\right].$$

FINANCIAL STABILITY ASSESSMENT

22. **The FSMD characterizes the probability of distress of the individual FI included in the portfolio, their distress dependence, and changes across the economic cycle.** This is a rich set of information that allows us to analyze (define) financial stability from three different, yet complementary, perspectives. For this purpose, we define a set of FSMs as a set of conditional probabilities estimated from the FSMD to quantify:

- Tail risk; i.e., common distress in the system.
- Contagion between FIs.
- Cascade effects; i.e., distress in the system associated with a specific FI.

23. **The complementary perspectives of financial stability brought by the proposed FSMs and MCSR represent a useful tool for financial supervisors.** These measures allow the identification of how risks are evolving and where contagion might most easily develop. For illustration purposes, and to make it easier to present definitions below, we proceed by defining a financial system—portfolio of FIs—comprising three FIs, whose asset values are characterized by the random variables x and y and r. Hence, following the procedure described previously, we infer the FSMD, which takes the form:

$$\hat{p}(x,y,r) = q(x,y,r)\exp\left\{-\left[1+\hat{\mu}+(\hat{\lambda}_1\chi_{[x_d^x,\infty)})+(\hat{\lambda}_2\,\chi_{[x_d^y,\infty)})+(\hat{\lambda}_3\,\chi_{[x_d^r,\infty)})\right]\right\}. \quad (4)$$

where $q(x,y,r)$ and $p(x,y,r) \in \mathbf{R}^3$.

A. Common Distress in the System

In order to analyze common distress in the FI comprising the system, we propose the *Joint Probability of Distress* (JPoD) and the *Financial Stability Index* (FSI).

The joint probability of distress

24. The Joint Probability of Distress (JPoD) represents the probability of all the FIs in the system (portfolio) becoming distressed, i.e., *the tail risk* of the system. The JPoD embeds not only changes in the individual FIs' PoDs, it also captures changes in the distress dependence among the FIs, which increases in times of financial distress; therefore, in such periods, the banking system's JPoD may experience larger and nonlinear increases than those experienced by the (average) PoDs of individual banks. For the hypothetical system defined in equation (4) the JPoD is defined as $P\left(X \cap Y \cap R\right)$ and it is estimated by integrating the density (FSMD) as follows:

$$\int_{x_d^r}^{\infty}\int_{x_d^y}^{\infty}\int_{x_d^x}^{\infty} p(x,y,r)\,dxdydr = JPoD \qquad (5)$$

The financial stability index

25. The *Financial Stability Index* (FSI) is based on the conditional expectation of default probability measure developed by Huang (1992).[10] The BSI reflects the *expected number of FIs becoming distressed* given that *at least one* FI has become distressed. A higher number signifies increased instability.

For example, for a system of two FIs, the FSI is defined as follows:

$$\text{BSI} = \frac{P\left(X \geq x_d^x\right) + P\left(Y \geq x_d^y\right)}{1 - P\left(X < x_d^x, Y < x_d^y\right)}.$$

The BSI represents a probability measure that conditions on *any bank* becoming distressed, without indicating the specific bank.[11]

[10] This function is presented in Huang (1992). For empirical applications see Hartmann et al (2001).

[11] Huang (1992) shows that this measure can also be interpreted as a relative measure of *banking linkage*. When the BSI=1 in the limit, banking linkage is weak (asymptotic independence). As the value of the BSI increases, banking linkage increases (asymptotic dependence).

B. Contagion Measures[12]

Contagion matrix

26. **For each period under analysis, for each pair of banks in the portfolio, we estimate the set of pair-wise conditional probabilities of distress, which are presented in the *Contagion Matrix* (CoMa).** This matrix contains the probability of *distress* of *the bank specified in the row*, given that *the bank specified in the column* becomes distressed. Although conditional probabilities do not imply causation, this set of pairwise conditional probabilities can provide important insights into interlinkages and the likelihood of contagion between the banks in the system. For the hypothetical banking system defined in equation (4), at a given date, the CoMa is represented in Table 1.

Table 1. Switzerland: Contagion Matrix

	Bank X	Bank Y	Bank R
Bank X	1	P(X/Y)	P(X/R)
Bank Y	P(Y/X)	1	P(Y/R)
Bank R	P(R/X)	P(R/Y)	1

Source: Authors' calculations.

Where for example, the probability of distress of bank X conditional on bank Y becoming distressed is estimated by $P\left(X \geq x_d^x \middle| Y \geq x_d^y\right) = \dfrac{P\left(X \geq x_d^x, Y \geq x_d^y\right)}{P\left(Y \geq x_d^y\right)}$.

Distress in specific banks/*groups* of banks associated with distress in other banks/*groups* of banks

27. **The BSMD allows us to estimate any conditional probability of distress, including conditional probabilities of *groups* or specific banks.** This feature provides great flexibility to analyze linkages among diverse groups of banks. For example, we can estimate conditional probabilities between groups or individual banks in different business lines or geographical zones.

[12] The term "contagion" used throughout this report does not embed the idea of "Granger causality" (or causality at large). Instead, it is used here to denote the idea of interrelation and co-movement, reflecting both direct and indirect linkages.

C. The Index of Global Risk Aversion (IGRA)

28. The credit crisis raised the importance of assessing the underlying dynamics of default probabilities. These probabilities can be estimated by using models of the value of the firm (e.g., the Black-Scholes-Merton model) or by relying on measures of market assessment, such as CDS spreads.

29. CDS spreads are widely used to generate risk-neutral probabilities of default.[13] Yet, these spreads, just as any other market risk indicator, are in fact asset prices that depend on global risk aversion as well as idiosyncratic news on the actual probability of default of a specific firm or sovereign. Therefore, it is necessary to strip out the price effect of risk aversion in order to be able to use CDS spreads to compute probabilities of default.

Espinoza and Segoviano (2010) propose an original method to estimate the market price of risk under stress (Box 1). The market price of risk under stress, in other words the expectation of the market price of risk exceeding a certain threshold, is computed from its two moments: the variance of the market price of risk and its discount factor, which is simply the inverse of the expected market price of risk. The price of risk can be estimated through different methods. For instance, it can be derived from the VIX[14] or from the factors in a Fama-MacBeth regression.[15]

30. On average, the actual probability of a CDS pay-off is around 40 percent of the risk-neutral probability of distress. The rest is explained by macroeconomic and financial factors. These factors matter because creditworthiness depends on fundamentals and on the liquidity environment. This percentage has likely declined during the Lehman crisis to around 30 percent, as global risk increased and therefore a larger share of CDS was being driven by the market price of risk.

For this analysis, the IGRA was constructed using the formula:

$$IGRA_t = -(1-PoR_t)$$

where PoR_t is the share of the market price of risk in the actual probability of the stress event (as estimated in Espinoza and Segoviano, 2010). This index reflects the market perception of risk[16] at

[13] These probabilities of default are estimated by dividing the level of the Credit Default Swap (CDS) by its Recovery Rate (RR). See Luo (2005).

[14] VIX is the Chicago Board Options Exchange Volatility Index, a popular measure of implied volatility of S&P 500 index options.

[15] The Fama-MacBeth regression is a method used to estimate parameters for asset pricing models such as the Capital Asset Pricing Model (CAPM).

[16] This is a single, exogenously given, measure of global risk aversion, for all the countries included in the sample. Note that Espinoza and Segoviano (2010) estimate this market price of risk using the US Libor OIS rate and the VIX, thus not relying on any country-specific information from the euro area economies (see Box 1 for details).

every point in time, and—as highlighted in Figure 6—it captures the sharp increase in global risk aversion observed after September 2008, followed by a gradual reduction throughout most of 2009.

Box 1. The Market Price of Risk and Global Risk Aversion

CDS spreads are asset prices that depend on global risk aversion as well as idiosyncratic news on the **actual** probability of default of a specific firm. It is therefore necessary to strip out the price effect of risk aversion in order to be able to use CDS spreads to compute probabilities of default. The linear pricing and the risk-neutral pricing formulae (see Cochrane, 2001) state that, if $m_{t+1}(s)$ is the price of a security paying $1 in state *s*, then the price of an asset paying off an uncertain stream x_{t+1} next period is:

$$P_t = \sum_s \pi_{t+1}(s) m_{t+1}(s) x_{t+1}(s) = \frac{1}{1+r_t^f} \sum \hat{\pi}_{t+1}(s) x_{t+1}(s) = \frac{\hat{E}_t[x_{t+1}]}{1+r_t^f}$$

$\pi_{t+1}(s)$ is the *actual* probability of nature that state *s* occurs and r_t^f is the risk-free rate. Note that:

$$\sum_s m_{t+1}(s) = 1/(1+r_t^f) \text{ and } \hat{\pi}_{t+1}(s) = (1+r_t^f)\pi_{t+1}(s) m_{t+1}(s) \tag{6}$$

is called the *risk-neutral* probability because it is the probability measure that a risk-neutral investor would need to use, when forming her expectations and computing an NPV consistent with the market price of the asset P_t.

Estimating the *actual* probability of default from a CDS spread-implied *risk-neutral* probability is equivalent to estimating the market price of risk in the state where the CDS pays off (the *distress* test). Espinoza and Segoviano (2010) use the conditional expectation formula for normal distributions to estimate

$$E_t[m_{t+1} \mid distress] = E_t[m_{t+1} \mid m_{t+1} > threshold] = E_t[m_{t+1}] + \sqrt{\text{var}_t[m_{t+1}]}\frac{\varphi(\alpha_t)}{1-\Phi^{-1}[\alpha_t]} \tag{7}$$

where $\alpha_t = (threshold - E_t[m_{t+1}]) / \sqrt{\text{var}_t[m_{t+1}]}$, φ is the normal distribution density function, and Φ^{-1} is the inverse cumulative distribution function of the normal distribution. $\sqrt{\text{var}_t[m_{t+1}]}$ is deduced from the *price* of risk $\lambda_m = (1+r_t^f)\,\text{var}(m_{t+1})$, which is an important variable in the CAPM literature. In a CAPM, excess returns are equal to the *price* of risk multiplied by the *quantity* of risk—the beta of an asset—since $E_t[r_{t+1}^i] - r_t^f = \beta_{i,m}\lambda_m$. The *price* of risk can be estimated via the Fama-MacBeth regressions. Espinoza and Segoviano (2010) suggest a calibration based on the VIX.

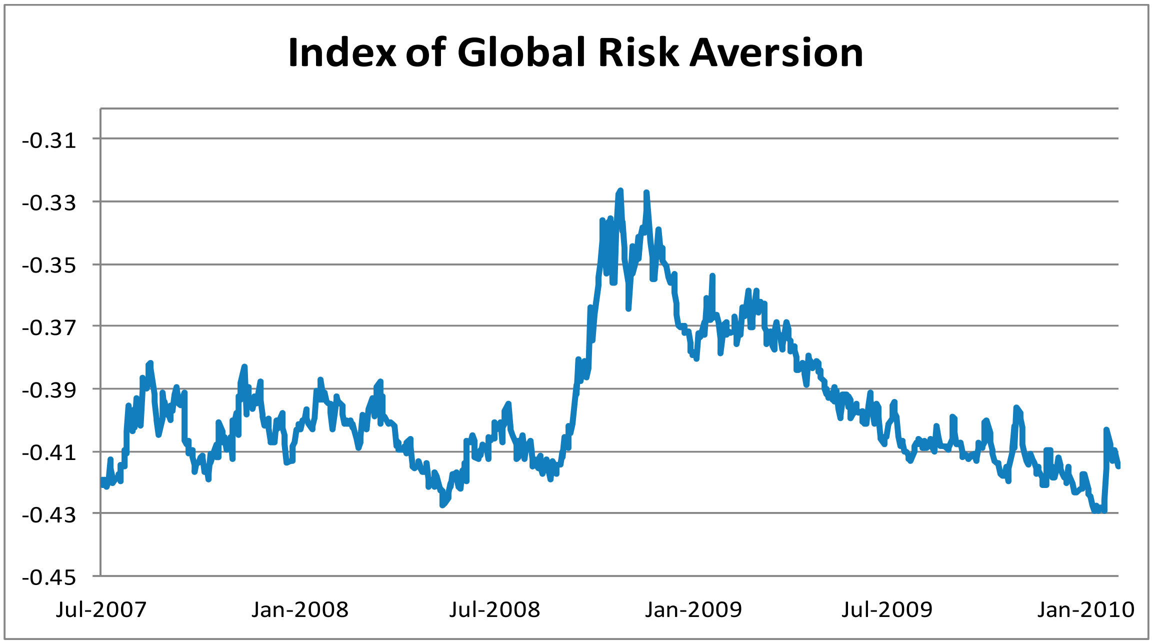
At any single point in time, the market price of risk under stress (the conditional expectation) is re-calculated since the risk-free rate (the mean) and the price of risk (the variance) are changing. This results in a single measure of the market price of risk under stress, which is the same across all financial institutions.[17] The threshold defines the scenario under which the asset is under distress. It can be defined exogenously or it can be chosen, in a more consistent way, such that the probability that the market-price of risk exceeds the threshold is equal to the actual probability of nature:

$$threshold = E[m] + \Phi^{-1}[1-\pi_t] * \sqrt{\text{var}(m)} \tag{8}$$

In that case, the nonlinear equations [6], [7] and [8] have to be solved jointly. Espinoza and Segoviano (2010) show that there is a unique solution.

[17] In theory, this is based on the assumption of market completeness, which should hold for all financial institutions. From a practical viewpoint, however, one could price several financial institutions' assets using a one factor model (for instance, by performing Fama-MacBeth regressions on the sample of stocks under consideration).

Figure 6. Switzerland: Index of Global Risk Aversion (IGRA)



Source: IMF Staff calculations.

D. The Vulnerability Index

31. **We constructed a measure of distress dependence, the Vulnerability Index (VI)—in order to quantify the role that contagion plays in the underlying risk of default of a given financial institution.** Essentially, the VI characterizes the probability of distress of a financial institution conditional on other financial institutions becoming distressed. The VI was developed by Caceres, Guzzo, and Segoviano (2010) to assess the vulnerability of an institution to contagion from all other institutions in the sample.[18]

For each financial institution A_i, the VI is computed using the formula:

$$VI(A_i) = \sum P(A_i/A_j) \cdot P(A_j) \qquad \text{for all} \quad j \neq I$$

which is essentially the weighted sum of the probability of distress of financial institution A_i given a default in each of the other financial institutions in the sample. This measure of distress dependence is appropriately weighed by the probability of each of these events to occur.

[18] In fact, Caceres, Guzzo and Segoviano (2010) apply this technique to a sample comprising ten euro area sovereigns.

The probability of distress of a financial institution A_i given a default by financial institution A_j, referred here as the probability of A_i given A_j, denoted by $P(A_i/A_j)$, is obtained in three steps:

- The marginal probabilities of default for financial institutions A_i and A_j, $P(A_i)$ and $P(A_j)$ respectively, are extracted from individual CDS spreads of these financial institutions and, when the latter are not available, from their stock price returns and volatilities (see Appendix [II] for details).[19]

- Then, the joint probability of default of A_i and A_j, $P(A_i, A_j)$, is obtained using the CIMDO methodology developed by Segoviano (2006). This methodology is used to estimate the multivariate empirical distribution (CIMDO-distribution) that characterizes the probabilities of distress of each of the financial institutions under analysis, their distress dependence, and how such dependence changes along the economic cycle. The CIMDO methodology is a nonparametric methodology, based on the Kullback (1959) cross-entropy approach, which does not impose parametric pre-determined distributional forms; whilst being constrained to characterize the empirical probabilities of distress observed for each institution under analysis (extracted from the CDS spreads). The joint probability of distress of the entire group of sovereigns under analysis and all the pair wise combinations of financial institutions within this group, i.e., $P(A_i, A_j)$, are estimated from the CIMDO-distribution.

- Finally, the conditional probability of default $P(A_i/A_j)$ is obtained by using the Bayes' law: $P(A_i/A_j) = P(A_i,A_j) / P(A_j)$.

E. Distress in the System Associated with a Specific Bank

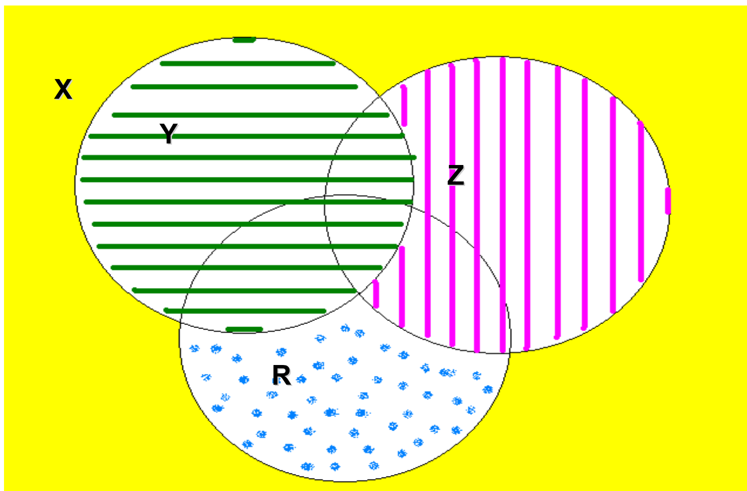
32. The *Probability of Cascade Effects* (PCE), given that a *specific* bank becomes distressed, characterizes the likelihood that one (or more) institutions in the system become distressed. Therefore, this measure quantifies the potential "cascade" effects in the system given distress in a *specific* bank. Consequently, we propose this measure as an indicator to quantify the systemic importance of a *specific* bank if it becomes distressed. Again, it is worth noting that conditional probabilities do not imply causation; however, we consider that the PCE can provide important insights into *systemic* interlinkages among the banks comprising a system.

For example, in a banking system with four banks, X, Y, Z, and R, the PCE given that bank X becomes distressed, corresponds to the probability set marked in the Venn diagram (Figure 7). In this example, the PCE can be defined as follows:

[19] We assume a recovery rate of 40 percent for financial institutions, as commonly used in the literature.

$$
\begin{aligned}
&PCE = P(Y/X) + P(Z/X) + P(R/X) \\
&-\left[P(Y \cap R/X) + P(Y \cap Z/X) + P(Z \cap R/X)\right] \\
&+P(Y \cap R \cap Z/X)
\end{aligned}
$$

Figure 7. Switzerland: Probability of Cascade Effects



Source: Authors' estimations.

SOVEREIGN-FINANCIAL CONTAGION

33. This section focus on analyzing contagion risks between the Swiss financial system and its sovereign. In recent years, conventional wisdom and perceptions about the inter-relationship between financial stability and sovereign risk have been challenged. The experience of the recent years has highlighted the need for better readiness on the part of policymakers and financial stability authorities in anticipating and managing stress conditions in the financial system that could amplify vulnerabilities of the sovereigns. Hence, this analysis focus on quantifying global and local factors that have an effect on the probability of distress of the Swiss sovereign conditional on distress of Swiss FIs. In addition, the analysis of bank-sovereign contagion complements the analysis of contagion and systemic risk described above.

34. Specifically, the sovereign-financial contagion analysis aims at addressing the following issues:

- Definition of an adequate measure for quantifying contagion risk between the sovereign and the financial system (SFCO).

- Identification of how specific risk factors of the financial system interact to have an impact on the level of systemic risk; i.e., what are the factors that increase sovereign-financial contagion risk?

- Assessment of changes across time of contagion risk, and the factors that explain it.

35. The probability of default of the Swiss Government, conditional on default of one of the domestic banks was computed for this analysis. It is derived according to the CIMDO methodology developed by Segoviano (2006). The analysis of Espinoza and Segoviano (2013, forthcoming) then uses a panel model on quarterly data between 2005–Q1 and 2012–Q4 to assess the relevance of underlying structural characteristics in explaining the possibility of contagion (a positive bar contributing positively to the probability of default, while a negative bar causes a reduction; in addition 14 other advanced economies were analyzed).

36. Overall, contagion from bank to sovereigns has decreased significantly in recent years (Box 2). Moreover, factors that explain such contagion have changed significantly in the aftermath of the global financial crisis. Contagion reached its peak towards the beginning of 2009, explained by the simultaneous deterioration of banking and economic fundamentals and increased risk aversion. Recently, contagion from banks to sovereign seems to be contained; the most significant factors of these positive developments appear to be the strengthening of capital buffers, the implementation of OMT and lower risk aversion. Nevertheless, the latter factors depend on international developments.

MACRO-FINANCIAL LINKAGES

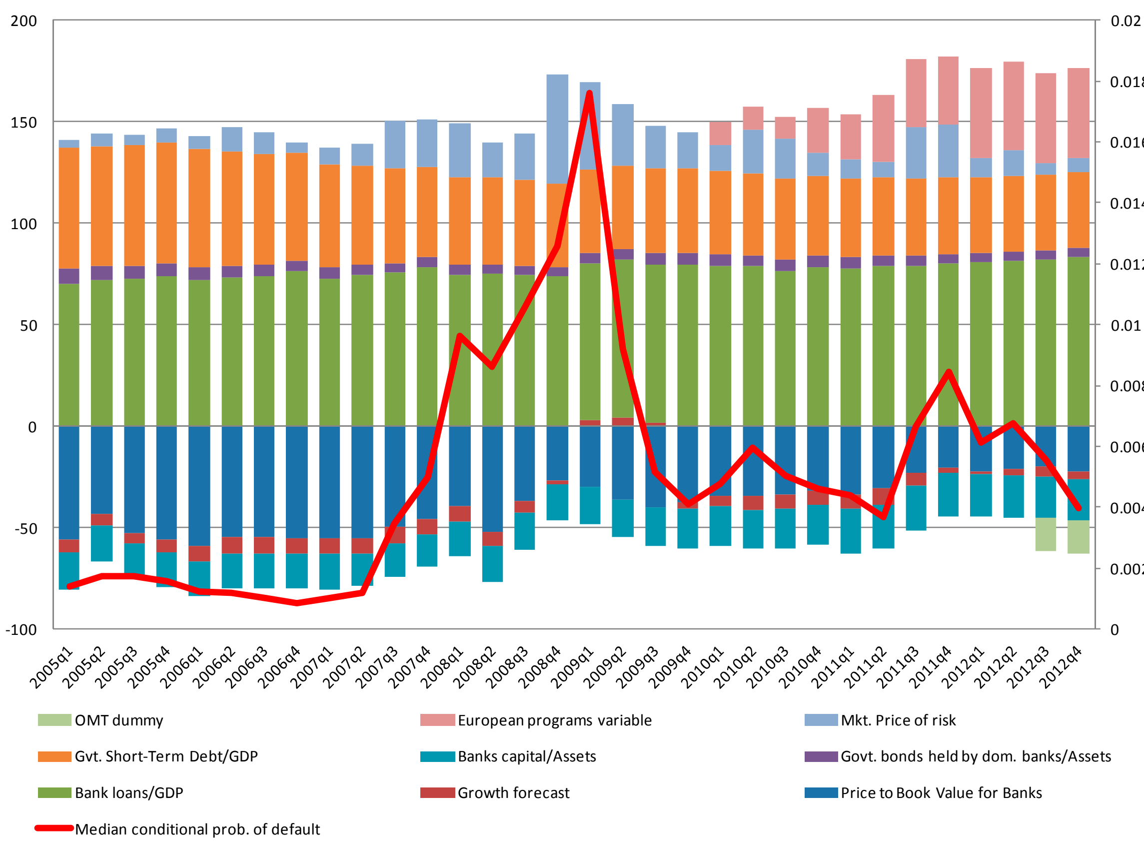
37. In order to complement our analysis of financial stability, an assessment of macro-financial linkages and second round effects was implemented. While the systemic macro-financial stress test concentrates on the PoDs of FIs, the analysis of macro-financial linkages concentrates on the interaction between macroeconomic variables and the probabilities of default of the different asset classes (PDs) on FIs' balance sheet (see Box 3).

38. A theoretical general equilibrium model was developed to analyze how the Swiss economy reacts to adverse shocks to the financial sector. Stress testing frameworks analyze the impact of an adverse change in macroeconomic variables such as GDP on the banking sector. This poses the question of how such shocks to the banking sector then affect the real economy. More generally, a model was needed that captures the dynamics of the multi-period feedback loops between the financial sector and the real economy.

Box 2. Swiss Financial-Sovereign Contagion

The analysis shows that during the financial crisis the increase in the conditional probability of distress was mainly due to increased market price of risk, a deterioration of the price to book value of Swiss banks and deterioration of growth forecast. Exposure to credit risk seems to be a significant factor, indicating that banks' exposure relative to the government's tax base is a significant driver for sovereign spreads; while the contribution of Bank Loans/GDP is large in absolute terms, the level has not varied significantly. More recently, in the aftermath of the European sovereign debt crisis, the conditional probability of distress of the Swiss sovereign has decreased significantly. Moreover, the factors that explain it have changed, being the most important, on the negative side the crises in some of the periphery countries (European program variable), lower growth forecasts. On the positive side, Banks' capital seems to have a significant impact (consistent with the results of the Swiss banking system), while low government short term debt/GDP has contributed. Declines in the market price of risk together with the introduction of OMT have been important downward drivers during the second half of 2012.

Switzerland: Contribution to Changes in the Sovereign Distress Dependence Index



Source: IMF staff calculations.

Box 3. Macro-Financial Linkages

In stress testing, the change in the probability of default of an asset class depends usually on a predetermined correlation coefficient of the asset with GDP or another macro-financial factor.

$$\Delta Y \rightarrow \Delta PD$$

Macro-financial analysis includes second round effects in the analysis. Following an actual change in PDs, financial institutions will respond to changes in risk and constraint future lending. Consequently, a change in PDs effects macro-economic variables.

$$\Delta Y \rightarrow \Delta PD \rightarrow \Delta Y \rightarrow \Delta PD \rightarrow \Delta Y$$

The impact of changes in macro-economic variables on PDs depends on leverage of the different agents in the economy. For example, household leverage (mortgage portfolio), firm leverage (commercial loan portfolio), sovereign leverage (sovereign bonds) determine to which extend PDs vary. Through spillovers, leverage levels of all sectors of the economy determine the response to changes in GDP.

$$\Delta PD_i = Function\left(\Delta Y, Leverage_i, Leverage_j, \dots\right)$$

The impact of changes in PDs on macro-economic variables depends on capital in the financial sector as well as on the capital levels of the different agents in the economy. In order to determine how PDs will respond to shocks and will feed back to the real economy, current leverage and capital levels are taken as a starting point of the analysis. As a counterfactual, optimal leverage and capital levels can be determined, resulting in the model from a trade-off between the benefits of debt and the cost of default.

$$\Delta \mathrm{Y} = \mathrm{Function}\left(\Delta \mathrm{TFP}, \Delta \mathrm{PD_i}, \Delta \mathrm{PD_j}, \mathrm{Equity_i}, \mathrm{Equity_j}, \dots\right)$$

Methodology

Theoretical Approach: In order to model feed-back loops, a dynamic stochastic general equilibrium framework is chosen, which links balance sheets of households and firms with balance sheets of financial institutions. Agents maximize lifetime consumption and investment and consumption as well as borrowing and lending results from agent’s rational behavior and market clearing of goods and credit markets in general equilibrium. The model is described in detail in Lipinsky (2014, forthcoming).

Empirical Approach: The model parameters can either be calibrated or estimated. In the case of Switzerland, the parameters were estimated with Bayesian estimation techniques. For a more detailed description of the method see Christiano, Motto and Rostagno (2010).

39. The model was then used to detangle to which extent credit demand or supply shocks have driven investment in Switzerland over the last decade. Figure 10 shows residential and business investment of Switzerland between 1994Q1 and 2013Q1. The bars show to which extent and in which direction various types of exogenous shocks have driven investment (the sum of the bars adds up to the observation). The shock decomposition results from Bayesian estimation techniques. Five time series—consumption, business investment, residential investment, corporate credit spreads and mortgage credit spreads—were used to estimate the risk on mortgages (higher risk results in tightening of mortgage credit conditions), the risk on corporate lending (higher risk results in tightening of corporate credit conditions), the willingness for households to buy real estate (similar to a cost shock or shock to future prospects), the willingness for firms to invest, and total factor productivity (TFP).

40. The model shows that lending and consequently business investment and residential investment would be negatively affected by a worsening in risk parameters. Following an increase in risk, banks need to increase provisions and might be forced to raise additional capital as a buffer in case risks do materialize. As a consequence, banks will tighten lending conditions (e.g., increase lending spreads to maintain profitability), which adversely affects investment.

41. The estimated model can then be used for the scenario building and forecasting of macroeconomic variables for stress testing. Similar to the approach chosen in the balance sheet stress, the impulse functions of equilibrium model indicate that risk measures such as default probabilities, loss given default and regulatory risk-weights commove with macroeconomic variables such as investment and output.

RESULTS AND CONCLUSIONS

Contagion within the Swiss financial system

42. Contagion risks arising from direct interbank exposures in Switzerland appear to be contained. Analysis covering the entire Swiss banking sector and assessing the impact of a hypothetical default of any one domestic bank on the other banks shows only moderate effects, consistent with the prudential restrictions imposed by the "large exposure rules" currently in place, and no material second round effects materialize within the domestic interbank market. In terms of groups, interbank exposure risks appear to be moderate for most domestically-oriented banks, but some small private banks and banks specializing in securities dealing appear to be somewhat vulnerable.[20]

[20] These are small banks with a high exposure to one single counterpart. The aggregated balance sheet for the banks with a capital ratio falling below 8 percent in the stress tests represents around 2 percent of domestic banking sector assets. The large exposure limit is relaxed for small banks. (For details see DAR CP 19.)

43. The relative contribution to contagion risks of domestically oriented banks has increased in recent years (Figure 8). During the GFC, market-based financial stability indicators suggested a heightened increase in risks and vulnerabilities for the large Swiss financial institutions. The increase in market-implied risks during the peak of euro area periphery stress was somewhat lower than that observed around the Lehman Brothers collapse, likely reflecting the limited direct exposure to sovereign debt instruments issued by these countries. More recently, risks seem to be increasing at the smaller, domestically-oriented banks. Various concerns, including U.S. investigations regarding tax evasion, have triggered noticeable falls and increased volatility in the stock prices of some of these banks.

44. Domestically oriented banks are gaining importance in terms of systemic risks. Quantitative results suggest that the potential systemic risks losses have been rising for cantonal banks in the aftermath of the GFC (Figure 8). Although still significant for large banks, systemic risk losses have been in decline. Market-based measures indicating higher risks in these banks are also consistent with other FSAP findings that these banks are exposed to highly concentrated portfolios, heterogeneity in terms of corporate governance and risk management, and possibly political interference. Therefore, it is important to mitigate potential contagion by minimizing reputational risks.[21]

Contagion among Swiss and G-SIFIs

45. Global contagion risks among G-SIFIs and the large Swiss financial institutions appear to be currently contained (Figure 9). Contagion vulnerabilities, measured by the "vulnerability index," were relatively high for the Swiss and a few of the U.S. G-SIFIs at the outset of the GFC. Uncertainty related to these institutions' holdings' of "toxic assets" (e.g., mortgage-backed securities) and, in some cases, high dependence on wholesale funding, led to the increase of their CDS spreads and other market-implied credit risk measures. However, during the heights of the euro periphery stress, systemic Swiss financial institutions exhibited lower spillover risks, compared to other countries' G-SIFIs with larger holding of euro area periphery sovereign debt (e.g., Italy, France).

Sovereign-financial interlinkages

46. Contagion from bank to sovereigns has decreased significantly in recent years (Box 2 and Appendix I). Moreover, factors that explain such contagion have changed significantly in the aftermath of the global financial crisis. Contagion reached its peak towards the beginning of 2009, explained by the simultaneous deterioration of banking and economic fundamentals and increased risk aversion. Recently, contagion from banks to sovereign seems to be contained; the most

[21] Recent reputational risk episodes, involving possible litigation cases, had an impact on several cantonal banks simultaneously. In some cases, although only a few institutions were directly involved, given that the news concerned the reputation of the sector as a whole, the stock prices of several banks were significantly affected. Another channel are funding costs, e.g., news about a single bank affected the entire sector as a whole, as investors and depositors re-asses their positions based on the reputation of the sector.

significant factors of these positive developments appear to be the strengthening of capital buffers, the implementation of OMT and lower risk aversion. Nevertheless, the latter factors depend on international developments.

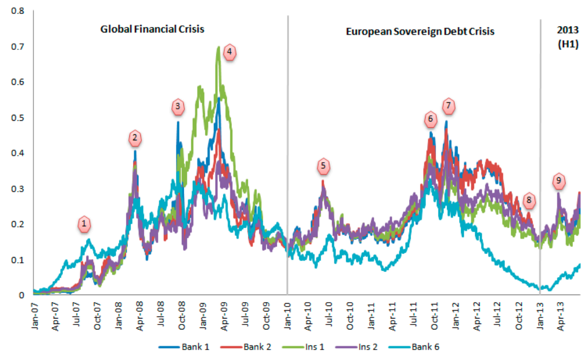
Macro-financial interlinkages

47. Demand has been driving the increase in real estate lending and residential house prices in the aftermath of the financial crisis. While adverse credit conditions (negative red bars are equal to an increase in risk) were negatively affecting residential investment during the financial crisis, residential investment recovered relatively quickly due to higher demand. This is also reflected in increasing in house prices during that period and suggests that demand-based measures could be more effective at addressing risks of overheating in the real estate market than credit supply measures.

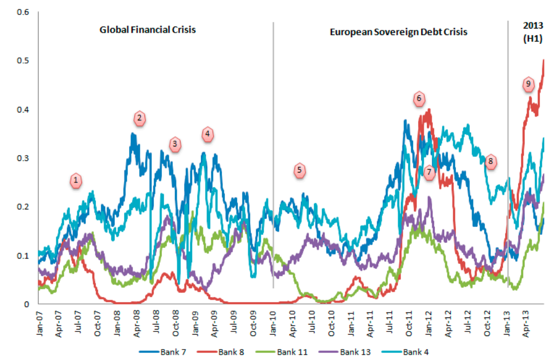
48. Conversely, credit conditions seem to have a larger effect on business investment. Whilst more recently corporate credit conditions are not tight, firms are deferring their investment plans owing to increased uncertainty about the economic outlook. During the financial crisis, tighter credit conditions (negative light blue bars) had a strong negative impact on business investment. This also negatively affected households and residential investment, as lower investment lead to a decline in output and lower incomes. The negative feedback effect is visible in the negative contribution of corporate credit supply shocks to residential investment (the negative light blue bars).

Figure 8. Switzerland: Contagion and Systemic Risk Analysis of Swiss Financial Institutions

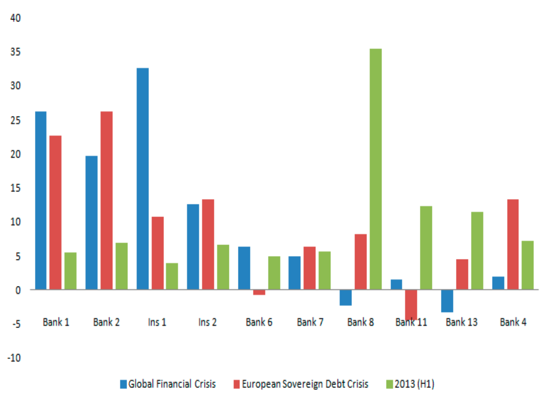
Contagion: Vulnerability Index
Large Banks and Insurance Companies,
and a Private Bank



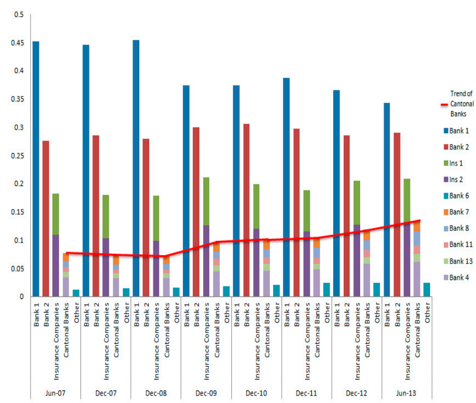
Contagion: Vulnerability Index
Cantonal Banks



Contagion: Contribution to Vulnerability
Swiss Financial Institutions



Share of potential systemic risk losses:
Swiss Financial Institutions



Source: IMF staff calculations

Notes:

(1) IKB, July 30, 2007.

(2) Surprising Trading Loss of a Cantonal Bank, April 18, 2008; Bear Stearns, March 15, 2008.

(3) Lehmann, September 15, 2008.

(4) GSIFI Stocks Bottomed, Swiss Re Management Resignation, March 9, 2009.

(5) Greece, Portugal and Spain Downgraded, April–May 2010.

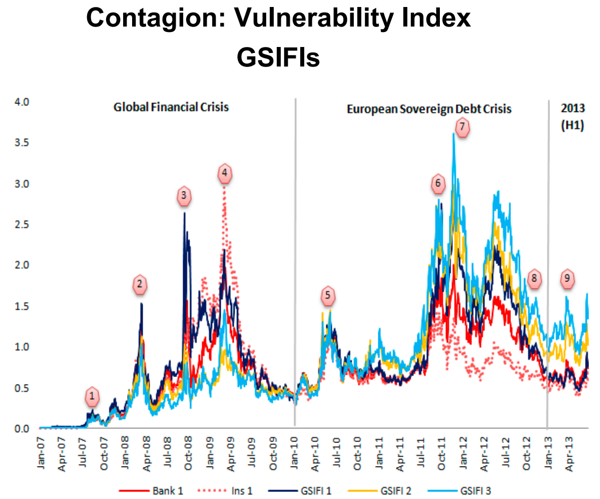
(6) A large Cantonal Bank Involved in Tax Evasion Scandal, December 2010–October 2011; Italian Banks Downgraded, September 21, 2011; Heavy Losses on Greek Debt for French Banks.

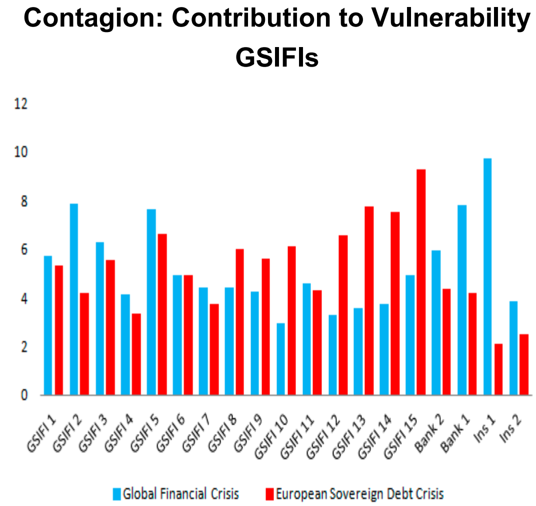
(7) Belgium Downgraded, November 25, 2011.

(8) OMT, September 6, 2012.

(9) Reputational Risk due to U.S. Tax Charges.

Figure 9. Switzerland: Contagion Risk Analysis of Swiss and Global G-SIFIs





Source: IMF staff calculations.

Notes:

(1) IKB, July 30, 2007.

(2) Bear Stearns, March 15, 2008.

(3) Lehmann, September 15, 2008.

(4) Stocks bottomed, Swiss Re management resignation, March 9, 2008.

(5) Greece, Portugal, and Spain downgraded, April–May 2010.

(6) Italian banks downgraded, September 21, 2011; Heavy Losses on Greek debt for French Banks.

(7) Belgium downgraded, November 25, 2011.

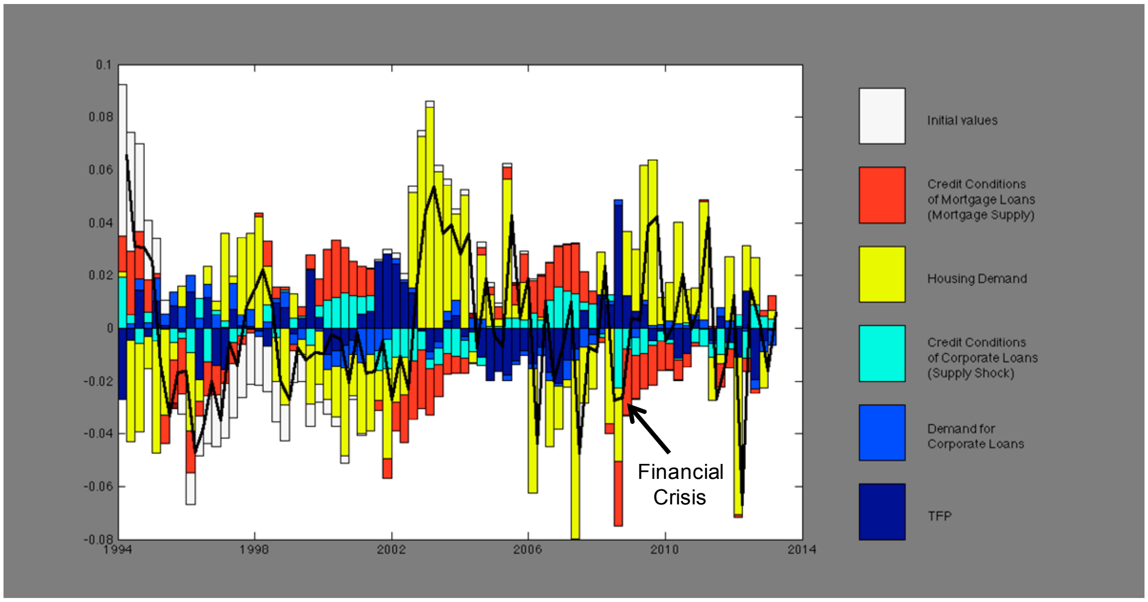
(8) OMT, September 6, 2012.

(9) Continuing spillovers to GSIFIs.

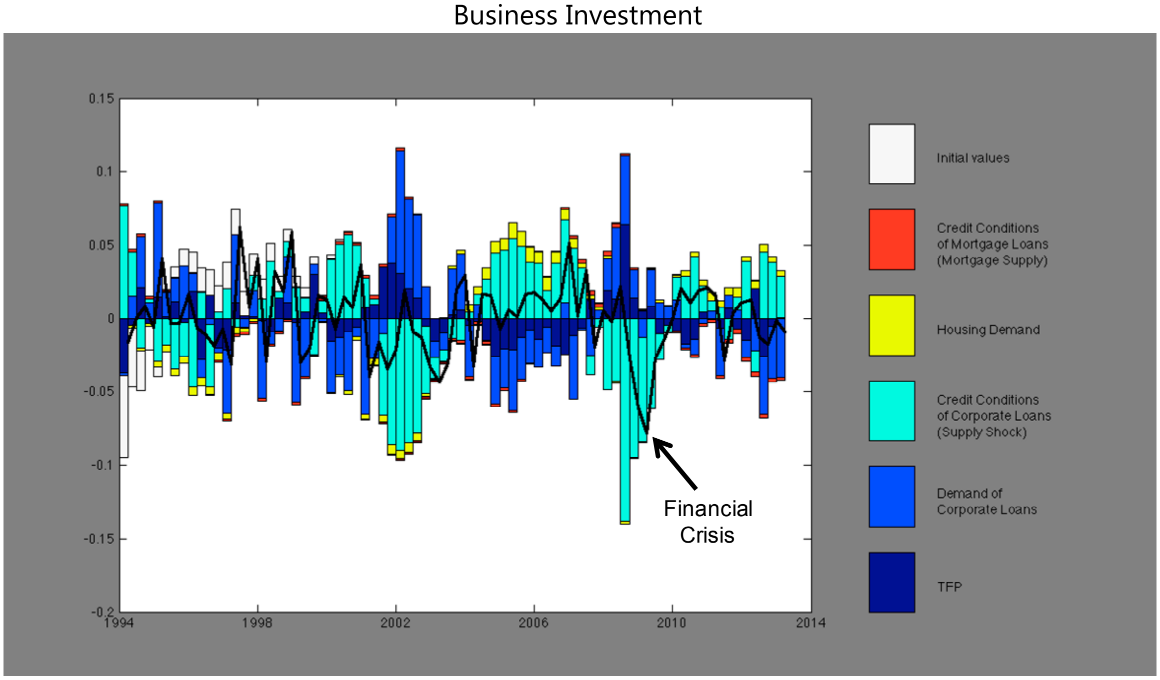
Figure 10. Switzerland: Macro-Financial Feedback Loops

Shock Decomposition of Credit Supply and Demand Shocks

Residential Investment



Business Investment



Source: IMF staff calculations.

Notes: The two figures above show residential and business investment (the black line, demeaned quarterly percentage changes) of Switzerland between 1994Q1 to 2013Q1. The bars show to which extent and in which direction various types of exogenous shocks have driven investment (the sum of the bars adds up to the observation). Demand shocks (the yellow bars) are dominating residential investment. Corporate credit supply shocks (the light blue bars) are dominating business investment.

Appendix I. Swiss Financial-Sovereign Contagion

49. Following the box on Swiss financial-sovereign contagion (Box 2), **lower growth forecasts led to an increase in the vulnerability of the Swiss sovereign to financial institutions during the financial crisis**. This was also the case more recently. This can be seen in Appendix Figure 9, which shows various factors influencing the Sovereign's vulnerability to contagion from the finance system.

50. A relative high share of bank loans to GDP in Switzerland further supports the finding the banking sector as a whole, by virtue of its relative size, contributes noticeably to the sovereign's vulnerability. This is possibly due to the fact that a banking sector guarantee from the government is priced in the sovereign spreads. On the other hand, the ratio of bank capital to assets has been continuously improving, which has been reducing the Sovereign's vulnerability.

Figure 11. Switzerland: Macroeconomic and Financial Factors Influencing the Conditional Probability of Default of Switzerland

Switzerland in Comparison to Other Countries

Source: IMF staff calculations.

Note: Core Euro-zone countries include Austria, Belgium, France, Germany and Netherlands. Euro-zone countries under stress include Greece, Ireland, Italy, Spain and Portugal. Countries outside the Euro-zone include Sweden, Japan, the UK, and the US.

Appendix II. Computation of Default Probabilities of Financial Institutions

51. The analysis of systemic risk uses probabilities of default (PDs) of financial institutions to determine measures of systematic risk and risk dependencies. The PDs are therefore an important input for the analysis of financial stability.

52. We use historical data on stock returns to compute a distress threshold. When data about default (whether outright or technical default) is scarce, and data on CDS spreads are not available, the question arises how such information can be extracted from other publicly available data. The main idea resides on the concept that a very drastic fall in the share price of an institution indicates distress. In a second step, we use time-varying information on the distribution of returns—such as their time-varying mean and variance—to compute a time-varying probability that returns fall below the threshold, which is the probability of distress.

53. Following this intuition, the concrete steps taken to compute the stock return-implied PDs were the following:

Step one: default threshold:

- Based on series of stock prices, compute a time series of returns.
- Normalize the series, subtracting the mean and dividing by the standard deviation.
- A general critique of normal distributions is that tails are not big enough. We adjust for big tails by multiplying each observation with a factor of e^(-alpha*|return|), where the size of the coefficient "alpha" determines the magnitude of the adjustment.
- Based on the entire normalized adjusted sample, we compute the mean and the variance, apply a normal distribution and compute a default threshold, such that only with a probability of 7.5 percent returns fall below the threshold.
- The level of 7.5 percent was determined so that when both CDS spreads and stock prices were available, the PDs computed from both series would exhibit similar time-varying properties (in terms of levels and variability).
- Step one produces a time-invariant return threshold.

Step two: time-varying probability of distress:

- For each point in time, we take a window of six months centered around that data—i.e., ranging from three months prior to the date to three months after the date - and compute the mean and variance of returns within this window period.

- The choice of six months was again the result of intensive simulations to match PDs implied by CDS spreads, where CDS spreads were available, with those derived from stock price returns using this methodology (similar as in step one).
- Using again the properties of the normal distribution and the return threshold computed in step one, we can compute the probability of distress at every point in time.

Step two produces a time series of time-varying probabilities of default, which are taking as the input for the systemic risk and contagion analysis.

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