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# UNITED KINGDOM

## FINANCIAL SECTOR ASSESSMENT PROGRAM

June 2016

## SYSTEMIC RISK AND INTERCONNECTEDNESS ANALYSIS—TECHNICAL NOTE

This Technical Note on Systemic Risk and Interconnectedness Analysis on the United Kingdom was prepared by a staff team of the International Monetary Fund. It is based on the information available at the time it was completed in March 2016.

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# TECHNICAL NOTE

## SYSTEMIC RISK AND INTERCONNECTEDNESS ANALYSIS

Prepared By
**Monetary and Capital Markets Department**

This Technical Note was prepared in the context of an IMF Financial Sector Assessment Program (FSAP) in the United Kingdom in November 2015 and February 2016 led by Dimitri Demekas. It contains technical analysis and detailed information underpinning the FSAP findings and recommendations. Further information on the FSAP program can be found at http://www.imf.org/external/np/fsap/fssa.aspx

# CONTENTS

# Glossary

| | |
|---|---|
| BoE | Bank of England |
| CDS | Credit Default Swap |
| CET1 | Common Equity Tier 1 |
| CIMDO | Consistent Information Multivariate Density Optimization |
| DiDe | Distress Dependence Matrix |
| ES | Expected Shortfall |
| FE | Financial Entity |
| FSAP | Financial Sector Assessment Program |
| JPoD | Joint Probability of Distress |
| LGD | Loss Given Default |
| PMD | Portfolio Multivariate Density (of a financial system) |
| PoD | Probability of Distress |
| SA | Structural Approach |
| VAR | Vector Autoregression |

# EXECUTIVE SUMMARY[1]

**This note summarizes the assessment of interconnectedness and systemic risk undertaken for the United Kingdom (U.K.) financial system as part of the Financial Sector Assessment Program (FSAP).** It consists of three parts, focusing on the following: (1) motivation for monitoring cross-sector interconnectedness as part of the financial system's resilience assessment, (2) description of selected empirical methods that may be employed to analyze interconnectedness, and (3) an illustrative analysis conducted, based on a definition of the financial system that incorporates U.K. banking and life insurance sectors.

**Assessment of financial system resilience should account for the evolution of interconnectedness between firms and sectors.** Firm-by-firm or sector-by-sector approaches analyze the resilience of individual firms and sectors within the financial system, typically at a particular point in time. However, structural market changes continually giving rise to new channels of interconnectedness across firms and sectors may serve to transmit adverse shocks to the rest of the financial system. Analysis of interconnectedness and spillovers at various levels of granularity is thus an essential part of a comprehensive assessment of financial system resilience.

**Improved sector-specific resilience of the U.K. financial system is confirmed by the illustrative analysis undertaken, but evidence of still-significant cross-sector vulnerabilities is also found.** The main findings of the analysis utilizing essentially market-based data are summarized as follows:

- **Overall, systemic risk in the U.K. has declined to pre-crisis levels.** This reflects, to a significant degree, the improved sector-specific resilience established under sector-by-sector approaches applied in this FSAP.

- **Improved banking sector resilience is further verified using metrics spanning market-based as well as balance sheet information**. The likelihood of distress spilling over among individual banks is currently subdued, with little heterogeneity in this measure across banks.

- **Whereas interconnectedness within the banking sector has been declining over recent years, the comparable measure between banking and life insurance sectors has displayed more variability.** While this finding relies on quantifying interconnectedness as the likelihood of distress spillovers between sectors, evidence of steadily increasing interconnectedness between these sectors is also found using alternative methodologies based on analyzing spillovers of asset price volatility.

[1] This Technical Note was prepared by Sheheryar Malik.

# MONITORING CROSS-SECTOR INTERCONNECTEDNESS: SOME BACKGROUND

1. **Assessment of financial system resilience should account for the evolution of interconnectedness between firms and sectors.** Firm-by-firm or sector-by-sector approaches revolve around analyzing the resilience of individual firms and sectors within the financial system, typically at a particular point in time. However, structural market changes are continually giving rise to new channels of interconnectedness across firms and sectors. These can serve not only to transmit adverse shocks to the rest of the financial system, but may also amplify them. Therefore, analysis of interconnectedness and spillovers at various levels of granularity (that is, between firms and between sectors) is an essential part of a comprehensive assessment of financial system resilience.

2. **Interconnectedness in the financial system can potentially give rise to different channels of distress spillovers across sectors, with systemic risk implications.** Within- and cross-sector interconnectedness can be broadly classed as either "direct," due to direct counterparty transactions, or "indirect," as a result of exposures to common risk factors. An example of the former is interbank lending, which gives rise to counterparty credit risk. This would imply risk of an insolvent firm, imposing losses on firms with which it has outstanding obligations. Distress in these firms may possibly have knock-on effects to other related firms. On the other hand, in the case of indirect linkages due to common exposures, adverse shocks resulting in lower asset prices (a liquidity shock, for example) would hit all holders of those assets simultaneously, generating mark-to-market losses. Firms may attempt to cover losses, triggering asset fire sales. This would lead to further price declines, losses, asset price dislocations resulting in an amplification of market volatility, and general impairment of market-based financing mechanisms. The adverse feedback loop set in motion may result in system-wide spread of distress.

3. **Cross-sector interconnectedness can naturally arise due to participation in wholesale financing markets, via derivatives trading, securities lending, and repo transactions, for instance.** While transactions in these markets are typically collateralized—thus limiting direct losses from counterparty distress—an alternative channel of distress spillovers is created due to the "procyclical" nature of collateral, which may play out as follows: a market shock would lead to declines in asset values posted as collateral generating mark-to-market losses for the counterparty. Additional collateral would need to be posted to cover minimum margin requirements (so-called "margin call"). Reserves of liquid assets may be drained and asset fire sales may ensue to fulfill the requirements, triggering an adverse feedback loop described earlier. Moreover, amplification of shocks may result due to potentially procyclical investment behavior in certain sectors, for example, insurance and pension funds.[2]

[2] "Procyclicality and structural trends in investment allocation by insurance companies and pension funds," Bank of England Procyclicality Working Group Discussion Paper, 2014.

**4. In order to complement the sector-by-sector assessments**, **various cross-sector approaches to analyzing interconnectedness and systemic risk were explored, focusing on the banking and insurance sectors.**[3] Numerous approaches have been proposed in the literature to analyze cross-sector interconnectedness and also systemic risk, for example, SRISK by Acharya et al (2012), CoVaR by Adrian and Brunnermeier (2016), Diebold and Yilmaz (2015), and Segoviano et al (2016b). In what follows, results across various methods were compared in order to ensure consistency. While advantageous in enabling analysis of spillovers between sectors over time, the aforementioned cross-sector approaches typically rely on market-based data. Notwithstanding their limitations, market-based data such as performance indices or CDS spreads are considered a useful complement to any regulatory and/or qualitative information on relevant financial entities.[4] These data may prove especially informative when detailed balance sheet data on cross-sector exposures are unavailable or scarce, and if a relatively higher-frequency assessment of market expectations and interconnectedness is required. The analysis conducted for the U.K. in the context of the FSAP is essentially illustrative and limits coverage to banking and insurance sectors. The time span for the analysis is August 2007–January 2016, and was chosen based on consistent availability of relevant historical time series across all entities considered.

# MODELING THE SYSTEM'S MULTIVARIATE DENSITY

**5. The core analysis conducted for the U.K. in the context of the FSAP conceptualizes the financial system as a portfolio of financial entities (FEs) spanning different sectors.** A structural approach (SA) for modeling portfolio risk[5] is a key ingredient here. Under the SA, a change in the value of a borrower's assets is related to the change in its credit risk quality. The basic premise of the SA is that a borrowing entity's underlying asset value evolves stochastically over time and distress is triggered by a drop in the firm's asset value below a threshold value (distress/default region), the latter being modeled as a function of the FE's financial structure.[6] Thus, it follows that the likelihood of the entity's asset value falling below the distress threshold is represented by the probability of distress (PoD) of the entity (Figure 1).[7]

**6. A portfolio multivariate density (PMD) describing the joint likelihood of distress of all FEs in a system is recovered.** Consistent with the basic premise of the SA to modeling portfolio

[3] Specifically, the group of banks included in the analysis includes Barclays, HSBC, RBS, Lloyd's, and Standard Chartered. Insurers (life only) include Aviva, Legal & General, Prudential Plc, and Standard Life. The insurance sector—as dealt with in this note—refers specifically to life insurers.

[4] Limitations of market-based data for such assessments, in general, may also encompass the role played by reduced trading volumes and liquidity. Such market conditions limit the extent to which asset prices reflect and reveal the fundamental information.

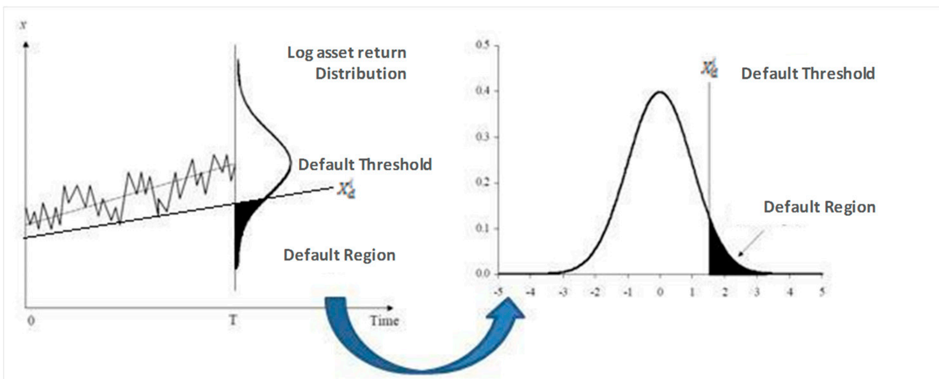
[5] Note that the SA is normally used to measure credit risk in portfolios of loans. In contrast, in this exercise we apply the SA to measure risk in a portfolio of FEs across sectors. Widely known applications of the structural approach include the Credit Metrics framework (Gupton et al., 1997) and the KMV framework (Crosbie et al., 1998).

[6] In what follows, *distress* and *default* are used interchangeably.

[7] The generalization of this approach includes, in addition to the distress/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.

risk, the PMD of the assumed system—constituted by FEs spanning multiple sectors—can be obtained via the method of Consistent Information Multivariate Density Optimization (CIMDO). Details are provided in Box 1. An important facet of the CIMDO method is the copula function describing distress dependence among FEs.[8] Given that density optimization is carried out over the cross section of all included FEs at each point in time, the dependence structure is allowed to dynamically adjust to changes in PoDs, with increases in PoDs being reflected in dependence increasing, potentially nonlinearly. Overall, the employed framework allows comprehensive coverage of the financial system by incorporating bank and nonbank sectors, while accounting for direct and/or indirect interconnectedness among sectors.[9]

**Figure 1. United Kingdom: Basic Premise of the Structural Approach**




Source: IMF staff.

Note: *Default* and *distress* are used interchangeably.

**7. Empirical measures of PoDs are required as inputs for PMD modeling.** It is important to emphasize that PoDs of individual FEs are exogenous variables in the CIMDO framework. Thus, it can be implemented with PoDs estimated with different approaches, including (1) Merton-type models, (2) credit default swaps (CDS), and (3) out-of-the-money option prices, or PoDs estimated based on supervisory information. The analysis provided for U.K. banks and insurers relies on PoD estimates backed out from five-year CDS spreads for each of the FEs in these sectors.[10] These data are available on a daily frequency.

[8] The distress dependence structure embedded in the multivariate 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 risk, dependence modeling becomes a daunting task. The CIMDO approach recovers the CIMDO-copula simultaneously when inferring the multivariate density. Thus, no additional modeling is required for the CIMDO-copula.

[9] The PMD modeling undertaken has been shown to be robust under restricted data environments according to the probability integral transform criteria; see Segoviano (2006), and Segoviano and Espinoza (2016), forthcoming.

[10] For details on mapping CDS spreads into PoDs, see Hull, J., and A. White (2000), "Valuing Credit Default Swaps I: No Counterparty Default Risk," *Journal of Derivatives,* 8 (Fall), pp. 29–40.

## Box 1. Consistent Information Multivariate Density Optimization To Model Multivariate Densities

The more detailed formulation of CIMDO is presented in Segoviano (2006) and Segoviano and Espinoza (2016). CIMDO is based on the Kullback (1959) minimum cross-entropy approach. Suppose a portfolio contains two different types of assets (financial system's sectors in this application), whose logarithmic returns are characterized by the random variables *x* and *y*. Hence, we define the CIMDO-objective function as:

$$C[p,q] = \iint p(x,y)\ln\frac{p(x,y)}{q(x,y)}\,dxdy, \text{ where } q(.) \text{ and } p(.) \text{ are prior and posterior density functions.} \quad \text{(a)}$$

The *prior* distribution follows a parametric form $q(x,y)$; for example, a multivariate *t* distribution, that is consistent with economic intuition (that is, distress is triggered by a drop in the firm's asset value below a threshold value), and with theoretical models (the structural approach to model risk). However, the parametric density $q(x,y)$ is usually inconsistent with empirically observed measures of distress. Hence, information provided by empirical measures of distress of each FE in the system is of prime importance for the recovery of the *posterior* distribution. In order to incorporate this information into the *posterior* density, consistency-constraint equations are formulated 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:

$$\iint p(x,y)\chi_{[x_d^x,\infty)}\,dxdy = POD_t^x \qquad \iint p(x,y)\chi_{[x_d^y,\infty)}\,dydx = POD_t^y\,. \quad (b)$$

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

$$L[p,q] = \iint p(x,y)\,ln\,p(x,y)\,dxdy - \iint p(x,y)\ln q(x,y)\,dxdy + \lambda_1\left[\iint p(x,y)\chi_{[x_d^x,\infty)}\,dxdy - POD_t^x\right] + \cdots, + \lambda_2\left[\iint p(x,y)\chi_{[x_d^y,\infty)}\,dydx - POD_t^y\right] + \mu\left[\iint p(x,y)\,dxdy - 1\right], \quad (c)$$

where, $\lambda_1, \lambda_2$ represent the Lagrange multipliers of the consistency constraints, and $\mu$ represents the Lagrange multiplier of the probability additivity constraint. By using calculus of variations, the optimization procedure can be performed. The optimal solution is represented by a *posterior* multivariate density of the form,

$$\widehat{p(x,y)} = q(x,y)\exp\left\{-\left[1+\hat{\mu}+\widehat{\lambda_1}\chi_{[x_d^x,\infty)}+\widehat{\lambda_2}\chi_{[x_d^y,\infty)}\right]\right\}. \quad (d)$$

From the functional from (c), it is clear that the CIMDO recovers the distribution that minimizes the probabilistic divergence; that is, "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 to select a posterior that is closest to the prior (Kullback, 1959), thereby solving the under-identification problem of determining the unknown multivariate distribution from partial information provided by PoDs in its marginals.

**Simulation of systemic losses**

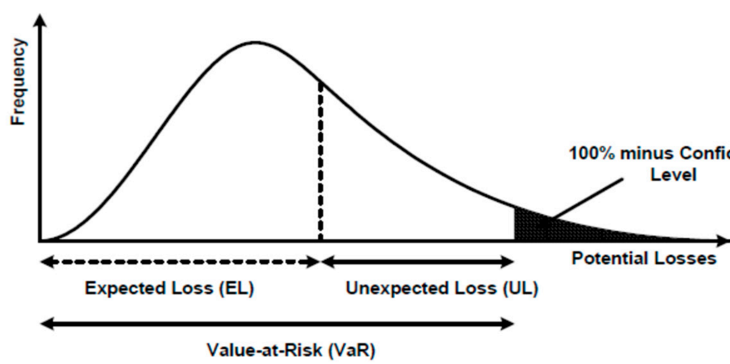
**8. Once the PMD is recovered, simulation of a systemic loss distribution can be conducted.** The simulation procedure is outlined in Box 2. From the resulting loss distribution, several systemic tail risk measures can be delineated, two of which are described as follows:

- **Value at risk:** The α-VaR of a loss distribution is given by the smallest number ξ such that the probability that the loss exceeds ξ is not greater then $(\mathbf{1-\alpha})$. Mathematically:

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

- **Expected shortfall (ES):** The α-ES of a loss distribution is the expected value of the α-tail distribution. This can be computed using the following proposition.

**Figure 2. United Kingdom: Distribution of Systemic Losses**




Source: Basel Committee on Banking Supervision, July 2005.

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 of $z_k$. Let $k_\alpha$ 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:

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

**9. The PMD and simulated systemic loss distribution allow the computation of several informative measures of systemic risk and interconnectedness, but for purposes of this analysis attention is restricted to the following subset.**[11]

- **Joint probability of distress (JPoD):** This describes the likelihood that all FEs in the portfolio/system are in distress. Suppose the financial system is comprised of two entities, then the CIMDO-density can be denoted by $p(x,y)$. Integrating this object yields the JPoD measure, such that:

  $$\int_{x_d^y}^{\infty}\int_{x_d^x}^{\infty} p(x,y)dxdy = \mathrm{JPoD},$$

  where, $x_d^x, x_d^y$ are the distress thresholds. In the empirical illustration, the distress thresholds delineate 1 percent tail of the distribution.

- **Conditional probability of distress spillovers (across sectors):** Given that the PMD can be factored into conditional and marginal probabilities, construction of the distress dependence matrix (DiDe), at each point in time is enabled. The DiDe construct corresponding to $p(x,y)$ is depicted in Table 1, and reports the probability of the entity specified in the row falling into distress, given the entity specified in the column is in distress. Since the PMD and hence DiDe can be generalized to include more FEs, spanning multiple sectors, quantification of conditional probabilities at a sectoral level is possible. Importantly, while conditional probabilities do not necessarily imply causation, pair-wise conditional probabilities can provide important insights into interconnectedness between FEs and/or sectors constituting the system.

- **Tail risk index (TRI):** Using the system's simulated loss distribution, the "systemic" ES is recorded at each point in time.[12] The resultant series is then bound between zero and unity by deflating by the maximum ES recorded over the period (or sub-period). It is suggested that such a normalization is informative given it tracks the relative position of systemic risk (as measured by the systemic ES) with regard to a set reference point. In the analysis conducted, the peak level reached during the financial crisis is taken as the point of normalization.

[11] For details on the complete set of potential measures, please refer to Segoviano and Goodhart (2009).

[12] In the ES computation we set α=0.01 (1 percent).

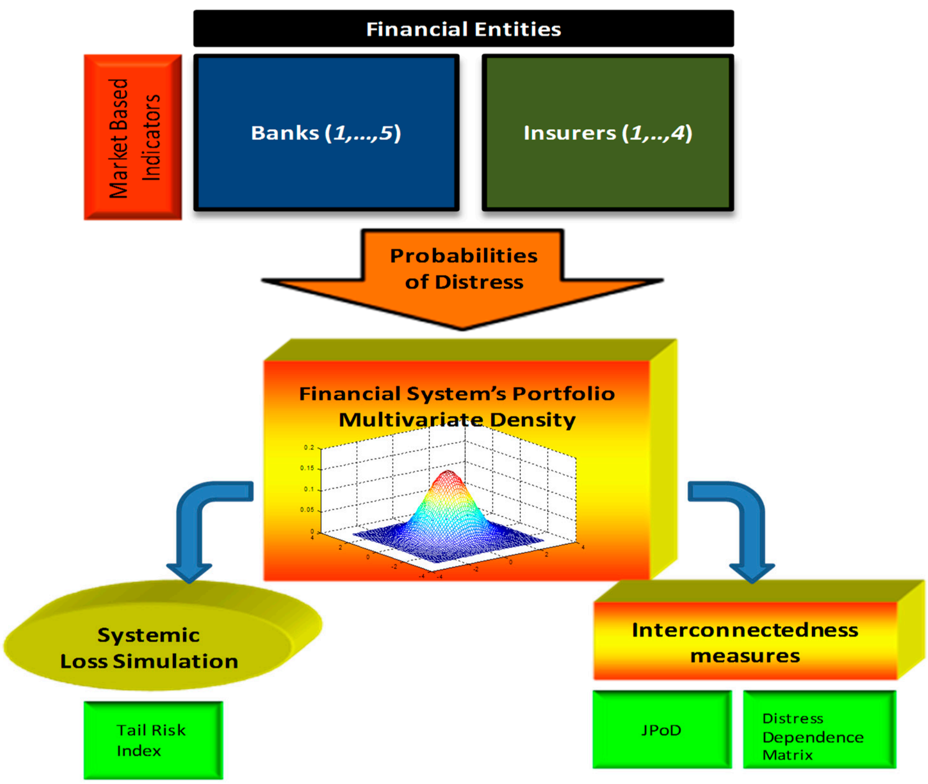
**Table 1. United Kingdom: Example—Distress Dependence Matrix**

| | Financial Entity X in Distress | Financial Entity Y in Distress |
|---|---|---|
| Financial Entity X in Distress | 1 | prob( X \| Y ) |
| Financial Entity Y in Distress | prob( Y \| X ) | 1 |

Source: Author's calculations.

Implementation of the analytical framework (described above) for the case for the U.K. is illustrated in Figure 3.

**Figure 3. United Kingdom: Implementation of the Analytical Framework—Stylized Representation**




Note: Banks included in the analysis are: Barclays, HSBC, RBS, Lloyd's, and Standard Chartered. Insurers (life only) include Aviva, Legal & General, Prudential Plc, and Standard Life.

## Box 2. Monte Carlo Simulation of Systemic Loss Distribution

Once the PMD is recovered, a Monte Carlo simulation is performed to generate the system's loss distribution. $\boldsymbol{X}$ random numbers are generated, and for every simulation $i$ two cases are considered:

If $X_i \leq K_i$ then the FE$i$ is in distress, and $\mathcal{X}_{\left(-\infty, X_d^i\right]} = 1$.

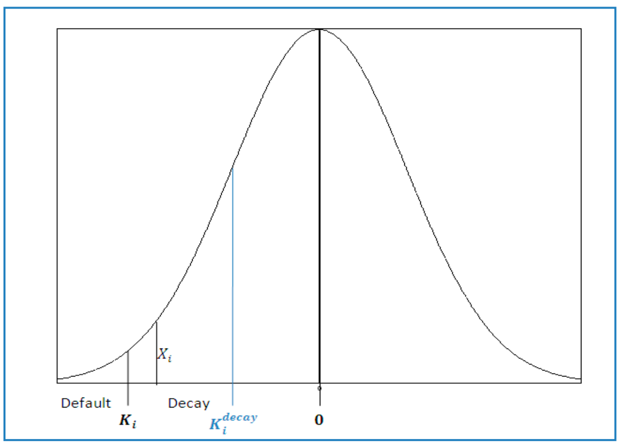
If $X_i > K_i$ then the FE$i$ is not in distress, and $\mathcal{X}_{\left(-\infty, X_d^i\right]} = 0$.

Nevertheless, in addition to the binary case (distressed or not distressed), an FE can also experience losses if its risk quality deteriorates with respect to its current state. In order to capture this effect, losses are mapped to 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 the decay threshold for a given FE is defined as $K_i^{decay}$ then the random variable $Y_i$ can be assigned as follows:

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

Here, $\phi_i$ is the cumulative distribution function of the returns of the FE.

**Example: Loss threshold**




Then, for each FE$_i$ loss is defined as:

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

where $LGD_i$ is the loss given default, and $EAD_i$ represents the exposure at default of the system to a given FE$_i$. The $EAD_i$ is quantified by the total assets of each FE$_i$, at a given time *t*.

# CROSS-SECTOR INTERCONNECTEDNESS AND SYSTEMIC RISK: AN EMPIRICAL ILLUSTRATION

**10. Overall systemic risk has declined to pre-crisis levels, reflecting to a significant degree improved sector-specific resilience, also established in the context of the FSAP under sector-by-sector approaches.** As evidenced in Figure 4 (left panel), the systemic risk level, measured by the Tail Risk Index, is close to 40 percent of its peak value reached around the global financial crisis (GFC). By comparing contributions to this measure from banking and insurance sectors, we find that the former's contribution is the lowest it has been since 2008:Q1, with the peak reached during the euro area crisis.[13] This represents in large part improved banking sector resilience, in accordance with the findings of the banking sector stress tests undertaken as part of the FSAP. The observed decline in the systemic risk measure is in line with other measures of systemic risk, for example, SRISK,[14] which at the end of the sample period, stands around US$300 billion, close to half of its GFC level. Comparing changes in these measures from their GFC peaks to 2015:Q4, across the U.K. and U.S., indicates a similar magnitude of decline; (Figure 4, right panel).

**11. Increased banking sector resilience can be gauged by the reduction in likelihood of distress spilling over between banks.** Notwithstanding heterogeneity across individual banks, the (average) probability that distress in any one bank spills over to the rest of the banking sector is currently around four times less than peaks reached around the global financial crisis and also the euro area crisis (Figure 5).[15] Over this period, direct interconnectedness between banks' balance sheets has declined (Figure 6, left panel), while risk-based capital ratios, leverage ratios, and LCRs have all improved. The migration of over-the-counter derivatives to CCPs has reduced bilateral exposures between banks, but could have increased dependency on CCPs.[16] While not precluding the existence of still-significant indirect interconnectedness between bank and nonbanks, reductions in banks' reliance on wholesale funding has encompassed a winding down of banks' repo and securities lending transactions (Figure 6, right panel), implying banks should now be less exposed to risk of margin calls in these markets. Moreover, the likelihood of cross border spillovers of distress between the U.K., U.S., and euro area banking sectors is currently subdued relative to crisis periods (Box 3).

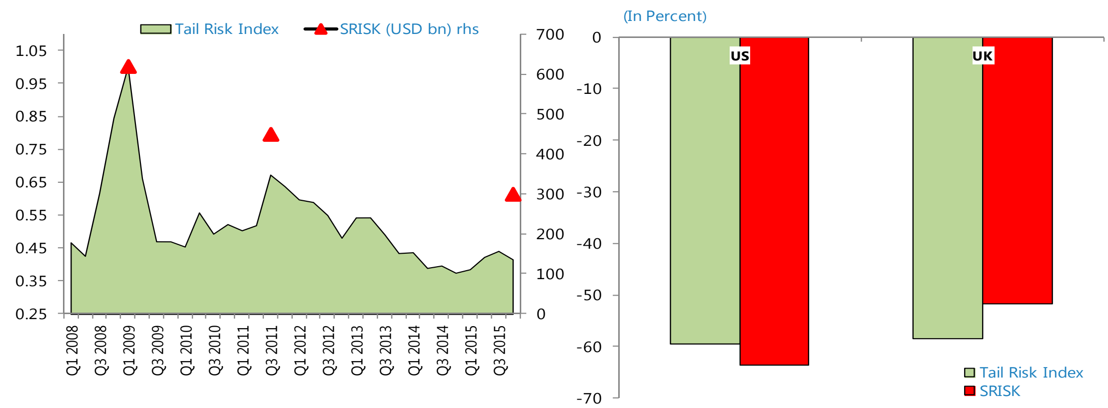
[13] The decline in the marginal contribution to overall systemic risk by the banking sector was ascertained using a Shapley value risk attribution methodology; see Tarashev et al. (2010) and Segoviano et al. (2016).

[14] SRISK measures the expected capital shortfall of the financial system, if equity values were to decline to global financial crisis levels. While computation of the Tail Risk Index focused on banks and insurers, the SRISK measure attributes more than 90 percent of variation in systemic risk to developments in these two sectors. The latter measure is available at V-Lab, http://vlab.stern.nyu.edu/en/.

[15] Similar periods of banking sector distress were indentified using a CoVaR approach.

[16] Banks may also be exposed to CCPs via equity ownership and contributions to default funds.

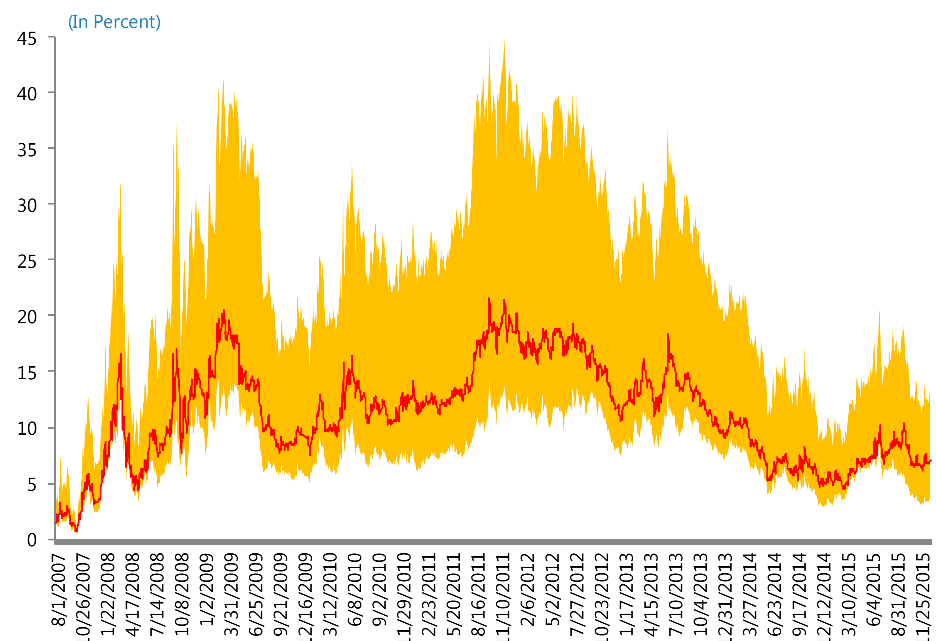
**Figure 4. United Kingdom: Systemic Risk Level (Left); Change Since Global Financial Crisis Peak (Right)**




Sources: Bloomberg, Bankscope, V-Lab (http://vlab.stern.nyu.edu/en/), and IMF staff estimates.

Note: The Tail Risk Index measures the expected shortfall from the system's simulated portfolio loss distribution, normalized by the historical maximum reached during the global financial crisis. This measure is bounded between zero and unity. SRISK measures the expected capital shortfall of the financial system, if equity values were to decline to crisis levels. rhs = right hand side axis.

**Figure 5. United Kingdom: Likelihood of Distress Spillovers within the Banking Sector**



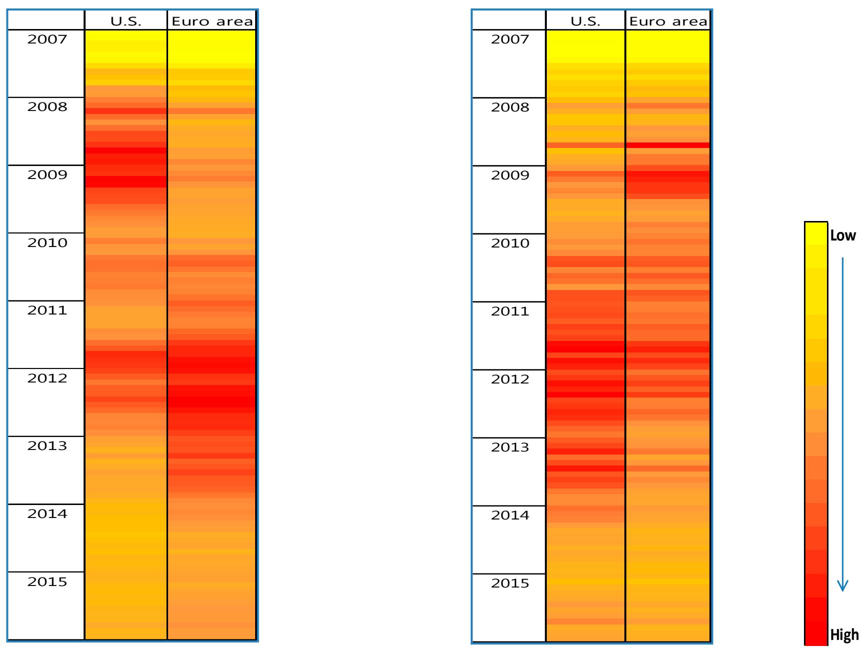

Sources: Bloomberg, Bankscope, and IMF staff estimates.

Note: The swathe represents heterogeneity across banks in the conditional probability of banking sector distress given distress in any one bank. The red line is the average of this measure across banks.

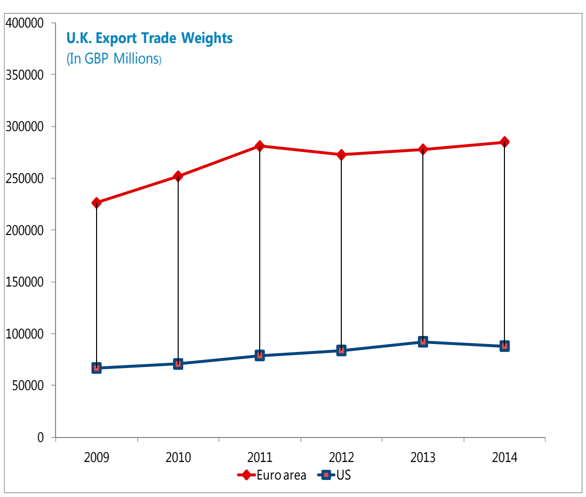
## Box 3. Likelihood of Cross-Border Distress Spillovers—Banking Sector

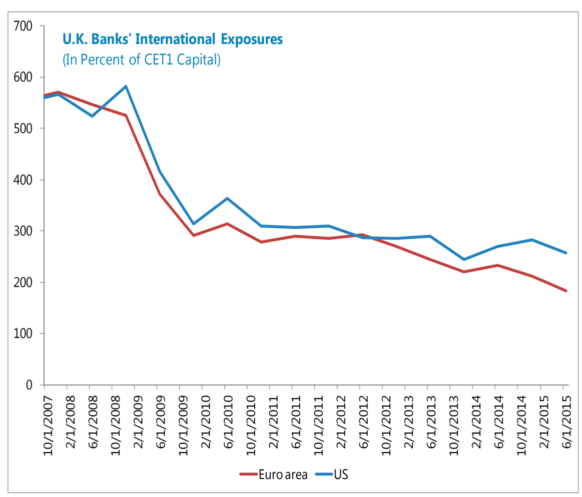
In broad terms, the likelihood of cross border spillovers of distress from the U.K. to U.S. and euro area banking sectors is currently subdued relative to crisis periods. After reaching elevated levels around the GFC and euro area crisis, the likelihood of distress spillovers as depicted in the heat map below is currently within relatively subdued range relative to historical crisis periods.

**Spillover to the U.K. from:** **Spillover from the U.K. to:**




Direct cross border interconnectedness has declined, as reflected in the declining percentage of CET1 capital corresponding to U.S. and euro area exposures of U.K. banks. However, macroeconomic linkages, such as fairly stable export trade weights, may keep indirect channels of spillovers non-negligible, via effects on the rest of the financial sector.

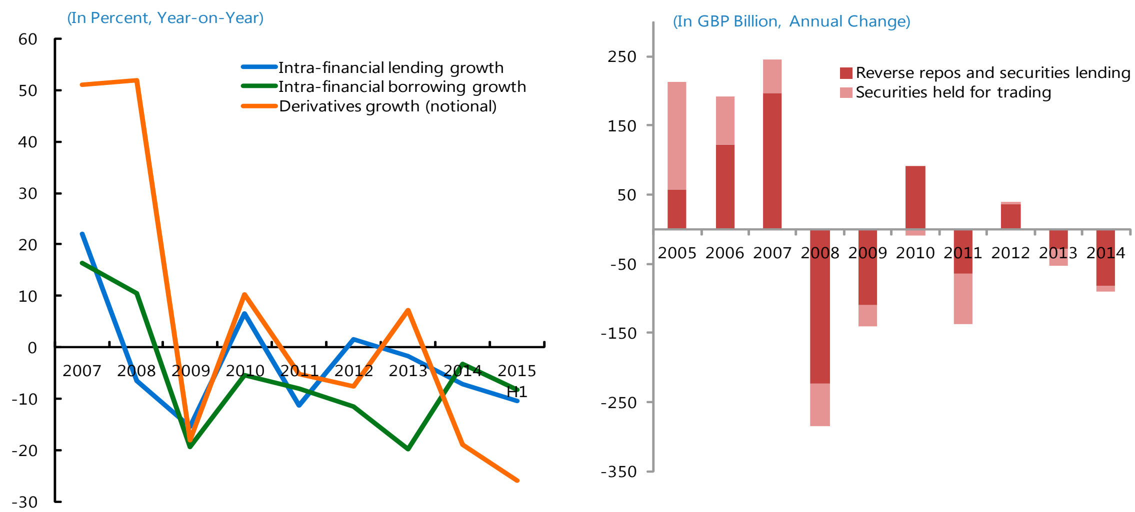



Sources: Bank of England, Office of National Statistics, Bloomberg, Bankscope, and IMF staff estimates.

**12. The insurance sector's vulnerability to distress spilling over from the banking sector has remained stable over recent years.** The likelihood of the insurance sector going into distress given distress in the banking sector has remained roughly stable over the past five years, after peaking during the global financial crisis (Figure 7, left panel). The insurance sector is a provider of funds to the banking sector through outright holding of bank debt (also via investment funds) and financing operations through securities lending markets (in which U.K. insurers are active participants).[17] At end-2013, the share of securities issued by banks represented 16 percent of (life) insurers' corporate bond portfolios and 10 percent of their equity portfolio. However, direct holding of bank debt by U.K. insurers was much higher around the crisis (according to market intelligence). This would have contributed to the peak witnessed in 2008:Q4–2009:Q1. Also, banks' interaction with insurers in securities lending markets has witnessed a decline over the same period.

**Figure 6. United Kingdom: Banks' Balance Sheet Interconnectedness (Left); Securities Financing Transactions (Right)**



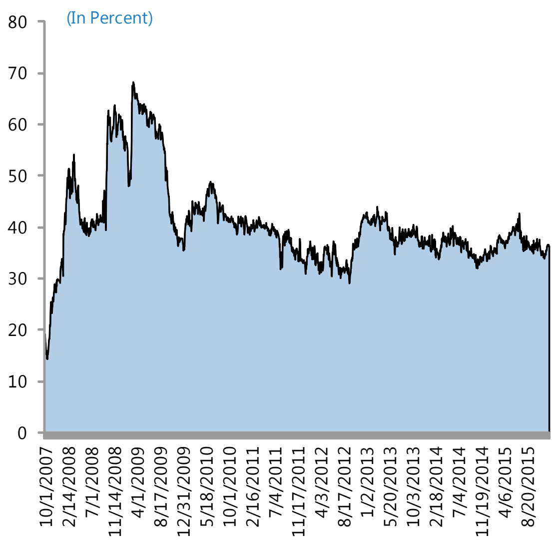

Source: Bank of England.

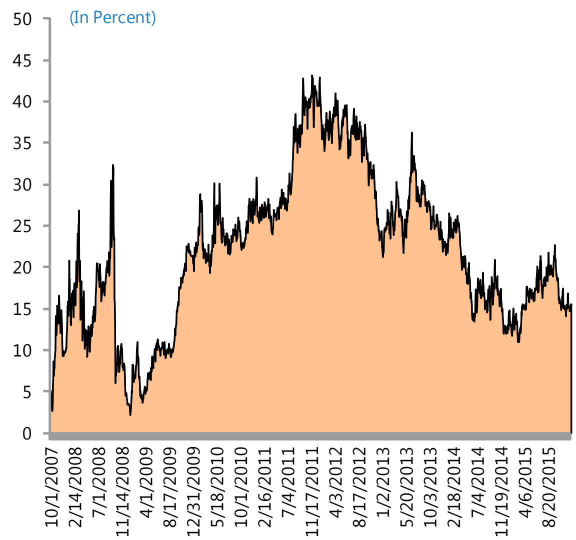
**13. The vulnerability of the banking sector to distress spilling over from the insurance sector has displayed considerable variability since the financial crisis.** The likelihood of the banking sector going into distress is conditional on the distress in the insurance sector, which peaked around the euro area crisis (Figure 7, right panel). While the downward trend observed may reflect increased resilience of the banking sector to shocks from other sectors in general, it is noted that distress dependence vis-à-vis the insurance sector may continue to display variability going forward. This may tentatively, and in part, be a result of the gradual convergence of business models of insurance with banking. U.K. insurers are increasingly engaging in activities such as direct lending

[17] Insurers invest indirectly in banks' debt and equity through investment funds, and also place deposits (albeit small amounts) with banks. Large exposure data collected from U.K. banks show that a few insurers lent large enough amounts through repo markets to appear in banks' top 20 counterparties.

to households and corporates. This may render the credit cycle more sensitive to insurers' activities. An example of this is the growth in direct lending to the commercial real estate sector.[18] In addition to both sectors being increasingly exposed to common shocks due to business model convergence, an overarching structural factor binding together distress dynamics of both banks and insurers is the prolonged low interest rate environment. This would serve to compress net interest margins and also render both sectors vulnerable to asset price adjustments if interest rates rise.

**Figure 7. United Kingdom: Likelihood of Distress Spillovers—Banks to Insurers (Left); Insurers to Banks (Right)**




Sources: Bloomberg, Bankscope, and IMF staff estimates.

Note: The above measure is the conditional probability of a particular sector *x* going into distress, given distress in sector *y*, and vice versa.

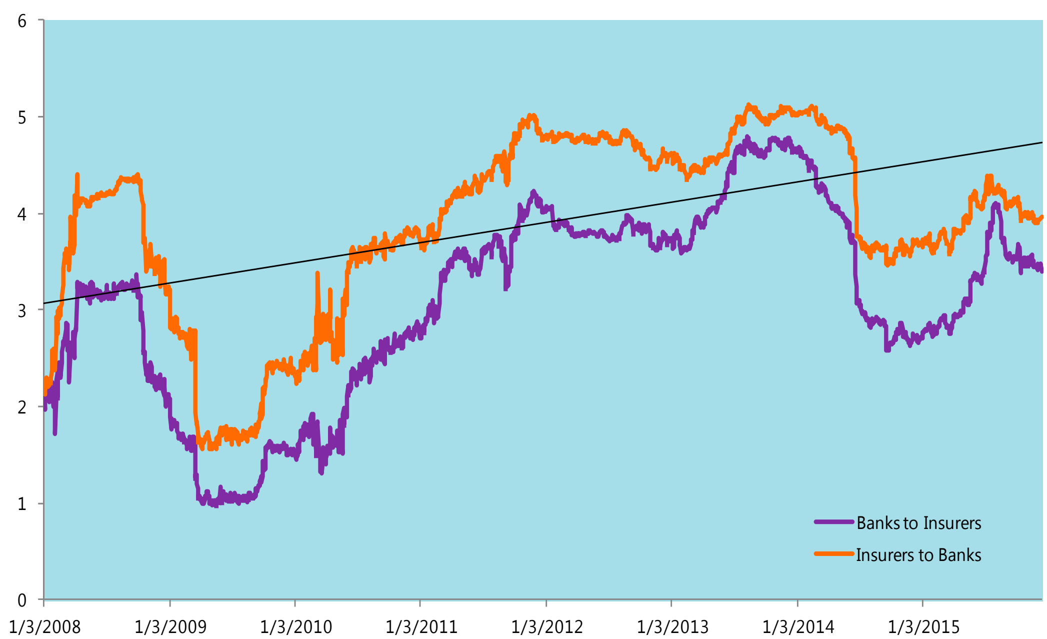
14. **Increasing volatility spillovers between banking and insurance sectors provide evidence of a potential upward trend in cross-sector interconnectedness.** Using the framework developed by Diebold and Yilmaz (2015) based on network connectivity measures, spillovers of volatility of distress dynamics between sectors is analyzed. In brief, within this framework, connectedness assessment relies on an approximating high-dimensional vector autoregression (VAR), estimated via "shrinkage" methods, which facilitate recovery of degrees of freedom. The VAR is estimated on a rolling window basis, and forecast error variance decompositions conducted for each run allow quantification of directional spillovers over time. In this particular example, distress dynamics are captured by time series of CDS spreads of banks and insurers. The input measure used is the associated volatility in distress dynamics, which is proxied by daily changes in these spreads. As shown in Figure 8, the percentage of forecast error variation of this volatility (proxy) measure for the banking (insurance) sector explained by shocks to distress dynamics of the insurance (banking)

[18] See French et al. (2015).

sector has been trending upward over time. A similar upward trend was found using daily log returns in equity prices as inputs for this framework.

**Figure 8. United Kingdom: Banking and Insurance Sectors—Volatility Spillover Analysis Using CDS Spreads**

(In Percent)




Sources: Bloomberg, Bankscope, and IMF staff estimates.

Note: The y-axis measures the percentage contribution to the forecast error variance of the U.K. banking (insurance) sector's asset price volatility (as measured by daily changes in CDS spreads in this example) from shocks emanating in the insurance (banking) sector. This analysis is based on the framework detailed in Diebold and Yilmaz (2015). The rolling window length for the VAR (one lag) was set at 252 days. The input series encapsulating distress volatility are measured as daily changes in banks' and insurers' CDS spreads. The VIX index was included as an exogenous control variable in the VAR. The particular estimator used for the VAR is a variant of Lasso, namely "elastic net" by Zou and Hastie (2005). A "generalized" forecast error variance decomposition (see Koop et al, 1996; Pesaran and Shin, 1998) was employed to quantify directional spillovers.

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