

Credit Derivatives and the Default Risk of Large Complex Financial Institutions

Giovanni Calice¹ Christos Ioannidis² Julian Williams³

¹School of Management, University of Southampton, SO17 1BJ
G.Calice@soton.ac.uk

²Department of Economics, University of Bath, BA2 7AY
C.Ioannidis@bath.ac.uk

³Business School, University of Aberdeen
Julian.Williams@abdn.ac.uk

June 3, 2010

Executive Summary

- We develop a dynamic model of bank default risk utilizing the Merton approach as our underlying theoretical framework.
- For our empirical work we utilize a vector-autoregressive multivariate ARCH model to forecast direction and volatility of banks equity, co-evolving with two broad credit default swap indices, to proxy for factors affecting assets.
- Combining these two models we create a measure of bank default risk and test it over 16 systemically important large complex financial institutions (LCFIs).
- Finally we reverse engineer the model and back out a capitalization stress test based on future volatility scenarios generated from forward looking simulations.
- We conclude that bank re-capitalizations could be far larger than expected given even fairly benign future asset volatility.

Literature

- In the literature, there is no unambiguous answer to the question of whether these derivatives have a positive or negative effect on financial stability.
- Bystrom (2005), Stock price volatility is also found to be significantly correlated with CDS spreads and the spreads are found to increase (decrease) with increasing (decreasing) stock price volatilities. Furthermore, the other interesting finding in this paper is the significant positive autocorrelation present in all the studied iTraxx indices.
- Arping (2004), shows how CDs can facilitate banks' quest for more effective lending relationships. He argues that CDs can have ambiguous effects on financial stability, and that disclosure requirements can strengthen the efficacy of the CDs market.
- Verdier (2004), argues that, from a broader stability perspective, CDs in their current form increase the likelihood of future sovereign defaults.

Literature

- Instefjord (2005) analyzes risk taking by a bank that has access to CDs for risk management purposes. He finds that innovations in CDs markets lead to increased risk taking because of enhanced risk management opportunities.
- Wagner and Marsh (2004), These authors demonstrate that CRT mechanism, under certain conditions, is generally welfare enhancing.
- Wagner (2005), shows that the increased portfolio diversification possibilities introduced by CRT can increase the probability of liquidity-based crises.
- Rajan (2005), has suggested that the hedging opportunities afforded by CDs and other risk management techniques are transforming the banking industry.

Literature

- Partnoy and Skeel (2006), suggest that CDOs are too complex. The transaction costs are high, the benefits questionable. They conclude that CDOs are being used to transform existing debt instruments that are accurately priced into new ones that are overvalued.
- Wagner (2007), argues that new credit derivative instruments would improve the banks' ability to sell their loans making them less vulnerable to liquidity shocks. However, this again might encourage banks to take on new risks because a higher liquidity of loans enables them to liquidate them more easily in a crisis. This effect would offset the initial positive impact on financial stability.
- Wagner and Marsh (2006), on the other hand, argue that especially the transfer of credit risk from banks to non-banks would be beneficial for financial stability,

Literature

- A recent study by Hu and Black (2008), concludes that, thanks to the explosive growth in CDs, debt-holders such as banks and hedge funds have often more to gain if companies fail than if they survive.
- Allen and Gale (2006), develop a model of banking and insurance and show that, with complete markets and contracts, inter-sectoral transfers are desirable. However, with incomplete markets and contracts, CRT can occur as the result of regulatory arbitrage and this can increase systemic risk.
- Heyde and Neyer (2007), analyze the consequences of CDs contracts in which both the protection buyer and the protection seller is a bank for the stability of the banking sector. Overall, they show that in a macroeconomic downturn, CDs reduce the stability of the banking sector.

Credit Derivatives and Financial Stability

Table: Size of Global and UK CDs Market, Source: Fitch Global

Market	2002	2004	2006	2008 est.
Global Market	\$1,952B	\$5,021B	\$20,207B	\$33,120B
London Market	\$1,036B	\$2,450B	\$8,083B	

Table: Global Participants in the Credit Derivatives Market

Institution	2002	2006
Banks	39%	36%
Investment Companies	16%	17%
Hedge Funds	12%	13%
Insurance Companies	33%	34%

Methodology

- Merton (1974a) proposed the classic distance to default (D2D) approach to the pricing of corporate debt.
- The model treats equity, $V_E \in \mathbb{R}_+$, as a European call option on the value of the bank's total assets,
- which is assumed to follow a geometric Brownian motion

$$dV_A = V_A (\mu_A dt + \sigma_A dW_t) \quad (1)$$

- The model imputes the value, $V_A \in \mathbb{R}_+$, and volatility, σ_A , of assets from the equity market value and liabilities.
- Liabilities, $V_L \in \mathbb{R}_+$, of the firm are measured from the firm's balance sheet.

Solving for the Value and Volatility of Firm Assets I

- the value of the firm's equity is given as:

$$V_E = V_A \mathcal{N}(d_1) - \exp(-r_{t,T}) V_L \mathcal{N}(d_2) \quad (2)$$

- where,

$$d_1 = \frac{\log\left(\frac{V_A}{V_L}\right) + (r_{t,T} + \frac{1}{2}\sigma_A^2)(T-t)}{\sigma_A \sqrt{T-t}} \quad (3)$$

$$d_2 = \frac{\log\left(\frac{V_A}{V_L}\right) + (r_{t,T} - \frac{1}{2}\sigma_A^2)(T-t)}{\sigma_A \sqrt{T-t}} \quad (4)$$

$$= d_1 - \sigma_A \sqrt{T-t} \quad (5)$$

- here, $\mathcal{N}(z)$ is the evaluation of the standard cumulative normal distribution at z .
- $\mathcal{N}(\mu, \sigma^2)$ is the univariate normal probability density function, with mean μ and variance σ^2
- equation 2 has two unknowns, V_A , and σ_A , which must be jointly imputed.

Solving for the Value and Volatility of Firm Assets II

- The volatility of equity, σ_E using the following expression,

$$\sigma_E = \left(\frac{V_A}{V_E} \right) \frac{\partial V_E}{\partial V_A} \sigma_A \quad (6)$$

- this is effectively the delta of equity,

$$\frac{\partial V_E}{\partial V_A} \equiv \mathcal{N}(d_1) \quad (7)$$

- and the volatility of equity can be computed as:

$$\sigma_E = \left(\frac{V_A}{V_E} \right) \mathcal{N}(d_1) \sigma_A. \quad (8)$$

Solving for the Value and Volatility of Firm Assets III

- Rearranging and combining into a system of non-linear equations,

$$f = \begin{bmatrix} V_A \mathcal{N}(d_1) - \exp(-r_{t,T}) V_L \mathcal{N}(d_2) - V_E \\ \left(\frac{V_A}{V_E}\right) \mathcal{N}(d_1) \sigma_A - \sigma_E \end{bmatrix} \quad (9)$$

- and setting $f = \mathbf{0}$, the estimated value $\hat{V}_A$ and volatility $\hat{\sigma}_A$ of equity is computed using quadratic optimization or a similar technique,

$$f(\hat{V}_A, \hat{\sigma}_A) = \min_{V_A, \sigma_A} [e' f f' e | V_A, \sigma_A] \quad (10)$$

- where e is a 2-element unit vector. The expected number of standard deviations, $\eta_{t,T}$, from insolvency over the period, $t \rightarrow T$, is the d_2 of the call option of the value of assets over the value liabilities, i.e. the "distance" that this option is away from being *out-of-the-money*.

Finding the Distance to Default D2D

- The number of standard deviations from insolvency is therefore,

$$\eta_{t,T} = \frac{\log\left(\frac{\hat{V}_A}{V_L}\right) + \left(\mu - \frac{1}{2}\hat{\sigma}_A^2\right)(T-t)}{\hat{\sigma}_A\sqrt{T-t}} \quad (11)$$

- The market clearing probability of default is therefore,

$$\mathcal{P}(\eta_{t,T}) = \mathcal{N}(-\eta_{t,T}) \quad (12)$$

Forecasting Equity Volatility via Multivariate ARCH modelling

- Consider the co-evolution of the value of equity and the credit derivatives indices,

$$\mathbf{y}_t = [\Delta \log(V_{E,t}), \Delta \log(CDX_t), \Delta \log(ITRAXX_t)] \quad (13)$$

- The volatility of equity, may then be modeled as a multivariate ARCH type model,

$$\Sigma_{i,t} = \begin{bmatrix} \sigma_i^2 & \sigma_{i,CDX} & \sigma_{i,iTraxx} \\ \sigma_{i,CDX} & \sigma_{CDX}^2 & \sigma_{iTraxx,CDX} \\ \sigma_{i,iTraxx} & \sigma_{iTraxx,CDX} & \sigma_{iTraxx}^2 \end{bmatrix}_t \quad (14)$$

Multivariate-ARCH Specification I

- The system equation is,

$$\mathbf{y}_t = \mu_t + \Sigma_t^{\frac{1}{2}} \varepsilon_t \quad (15)$$

$$\varepsilon_t \sim \mathcal{N}(\mathbf{0}, \mathbf{I}) \quad (16)$$

- The evolution of the conditional covariance matrix is described by a BEKK type matrix autoregressive process,

$$\begin{aligned} \Sigma_{i,t} &= \mathbf{K}\mathbf{K}' + \mathbf{A}'\Sigma_{i,t-1}\mathbf{A} + \mathbf{B}' \left(\Sigma_{i,t-1}^{\frac{1}{2}} \varepsilon_t \left(\Sigma_{i,t-1}^{\frac{1}{2}} \varepsilon_t \right)' \right) \mathbf{B} \\ \theta &= [\text{ivech}\mathbf{K}', \text{vec}\mathbf{A}', \text{vec}\mathbf{B}']' \end{aligned} \quad (17)$$

- Maximum likelihood estimation is used to find the optimal parameter vector $\hat{\theta}$, the log likelihood function, $\mathfrak{F}(\cdot)$, is therefore,

$$\mathfrak{F}(\theta) = -\frac{1}{2} \left(n\tau \log(2\pi) + \sum_{t=1}^{\tau} \log |\Sigma_t| + (\mathbf{y}_t - \mu_t)' \Sigma_t (\mathbf{y}_t - \mu_t) \right) \quad (18)$$

Multivariate-ARCH Specification II

- The volatility of assets, σ_A , is restated as a dynamic process, conditional on the covariance process underlying the equity volatility,

$$\sigma_{A,t} = \psi(\sigma_{E,t} | \Sigma_{i,t}) \quad (19)$$

$$\sigma_{A,iTraxx,t} = \lambda(\psi(\sigma_{E,t}) | \Sigma_{i,t}) \quad (20)$$

- Once the implied asset volatility $\sigma_{A,t}$ has been computed, the implied covariation $\sigma_{A,iTraxx/CDX/Ratio,t}$ between the asset volatility and any one of the components of the MV-ARCH spec is found by simply nesting, 6, into the MV-ARCH structure.
- The model ascribes the contemporaneous and lagged dynamics of the credit indices endogenously within the volatility structure, making this model more flexible than a simple univariate GARCH-X type model.

LCFIs Marsh and Stevens, BoE FSR (2003)

MORGAN STANLEY
GOLDMAN SACHS GROUP INC.
LEHMAN BROTHERS HOLDINGS INC.
DEUTSCHE BANK AG
BNP PARIBAS
SOCIETE GENERALE
BEAR STEARNS
HSBC HOLDINGS PLC ORD \$0.50 (UK REG)
BANK OF AMERICA CORPORATION
JP MORGAN CHASE & CO.
UBS AG
CREDIT SUISSE GROUP
BARCLAYS PLC ORD
THE ROYAL BANK OF SCOTLAND GROUP
CITIGROUP INC.
MERRILL LYNCH & CO., INC.

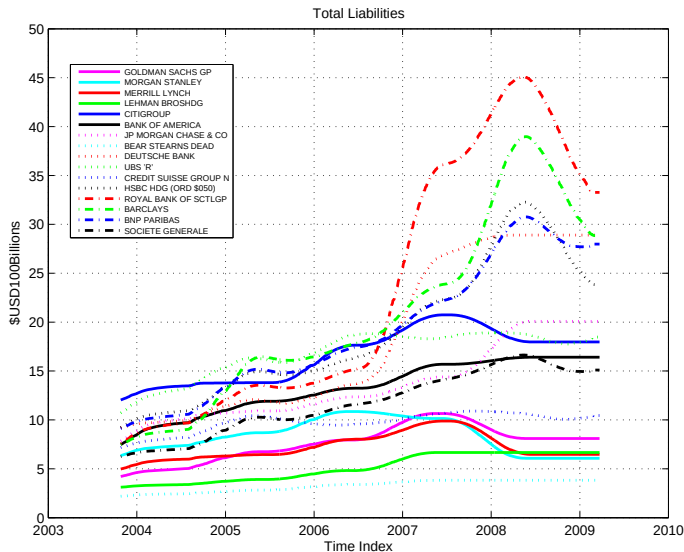
Banks' Financial Data

- The Dataset consists of daily closing observations running from Jan 4th 2005 to 31st April 2009.
- The dataset consists of individual financial institutions data drawn from the group of LCFIs as defined by the Bank of England (2001).
- To derive the value of liabilities V_L , the total liabilities excluding equity is collected for each quarter.
- The data is then interpolated to a daily frequency and matched to the market capitalization dates, using a cubic spline.

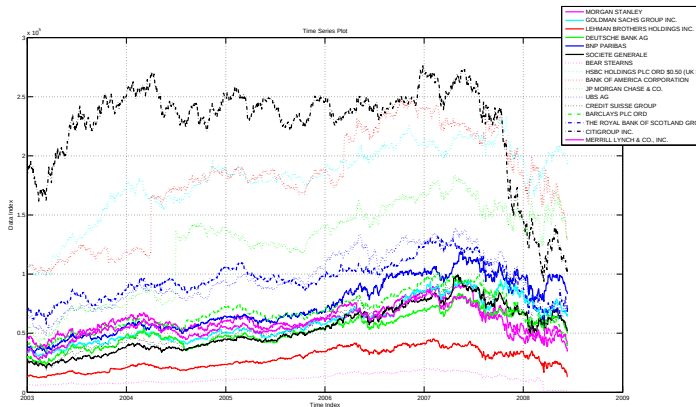
Credit Derivatives Data

- The most widely traded of the indices is the iTraxx Europe index composed of the most liquid 125 CDSs referencing European investment grade credits, subject to certain sector rules as determined by the IIC(International Investment Company).
- CDX is the brand-name for the family of Credit Default Swap Index products of a portfolio of 125 5-year default swaps, covering equal principal amounts of debt of each of 125 named North American investment-grade issuers.

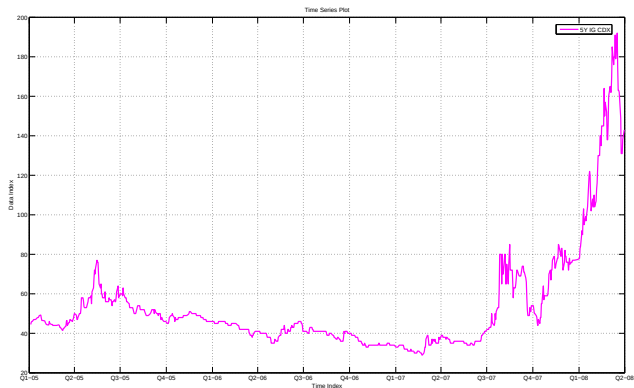
Total Liabilities



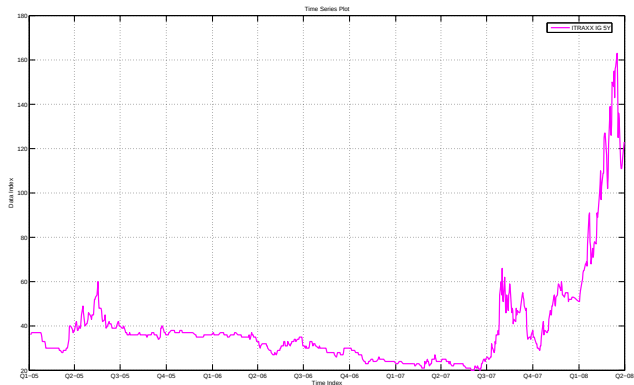
Equity, Market Capitalisation



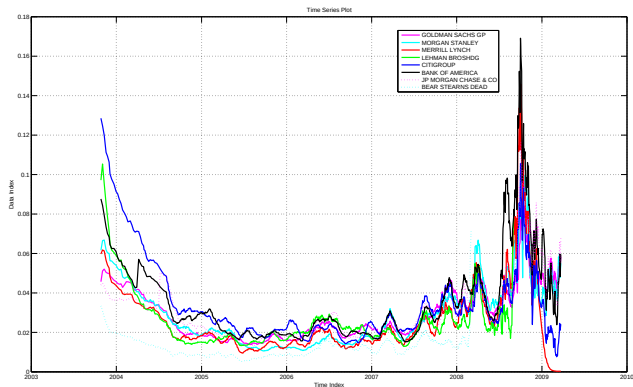
CDX Index Source: Thomson-Reuters



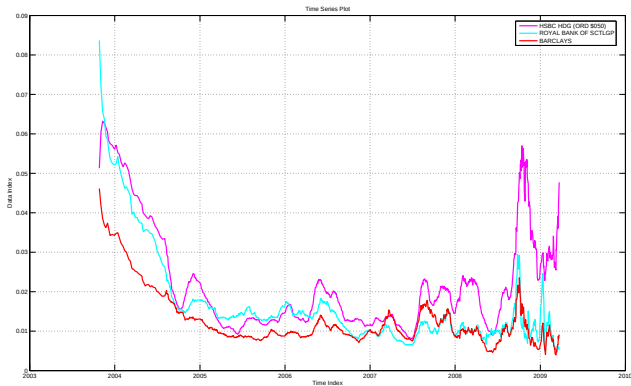
ITRAXX Index Source: Thomson-Reuters



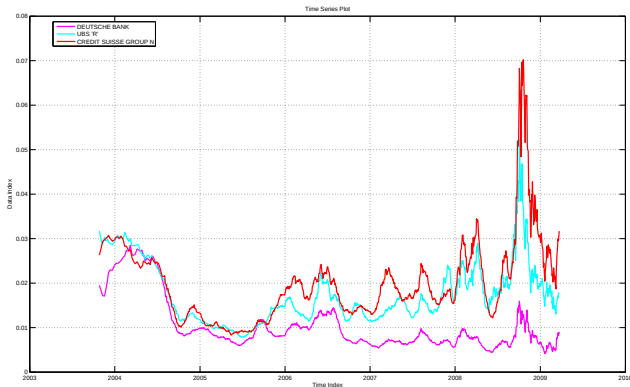
Volatility of Assets for US Banks



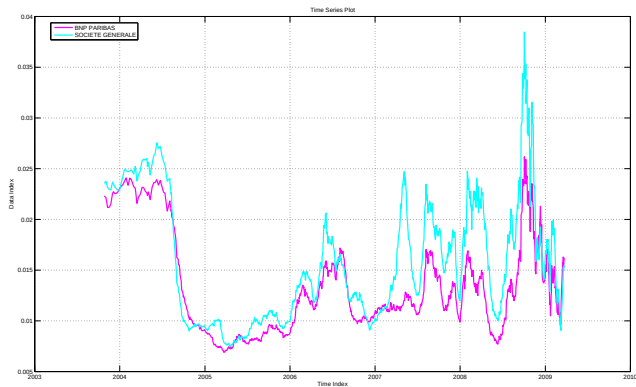
Volatility of Assets for UK Banks



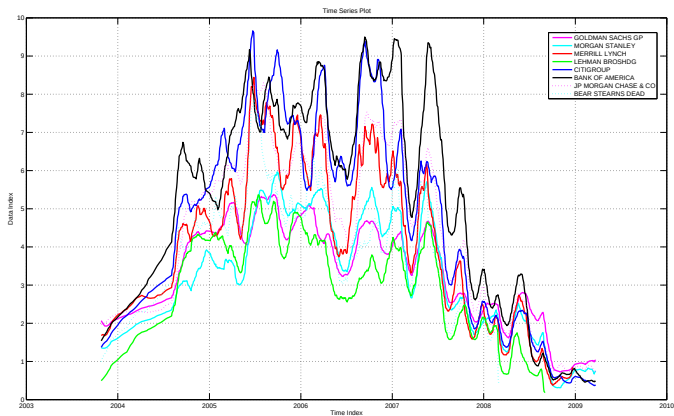
Volatility of Assets for Swiss/German Banks



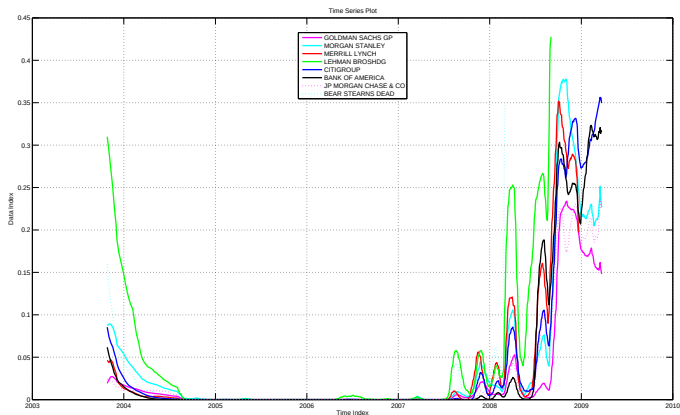
Volatility of Assets for French Banks



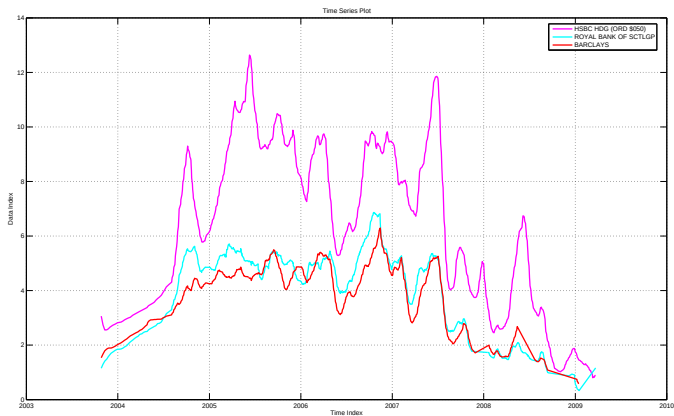
Distance to default for US Banks



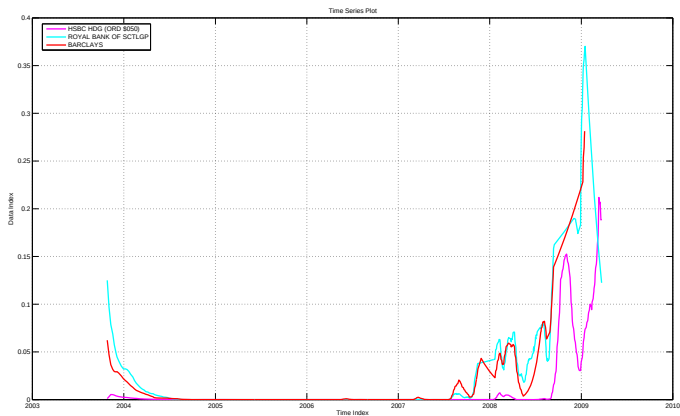
Historical Probability of default for US Banks



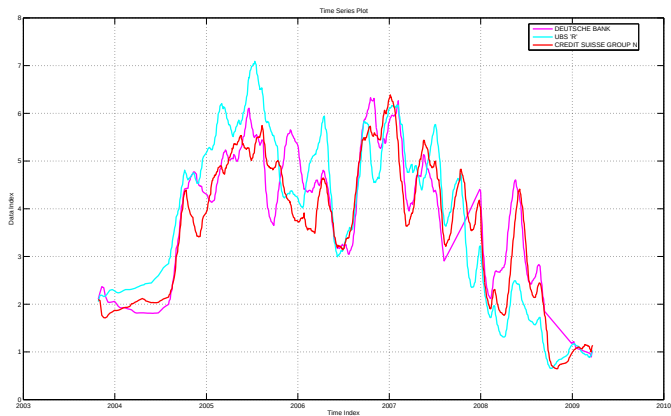
Distance to default for UK Banks



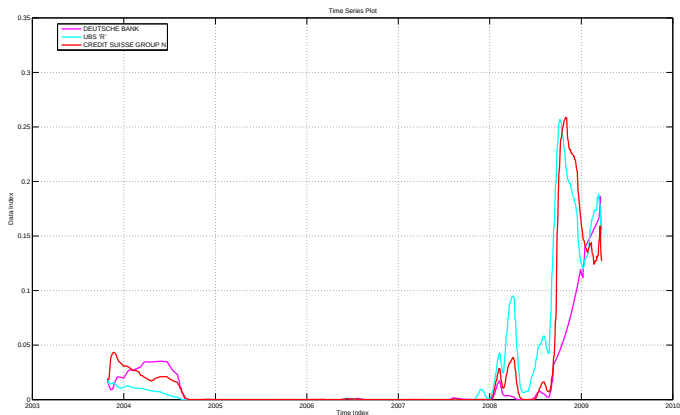
Historical Probability of default for UK Banks



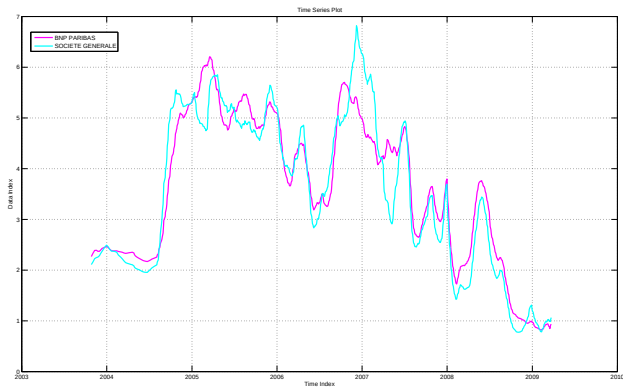
Distance to default for Swiss/German Banks



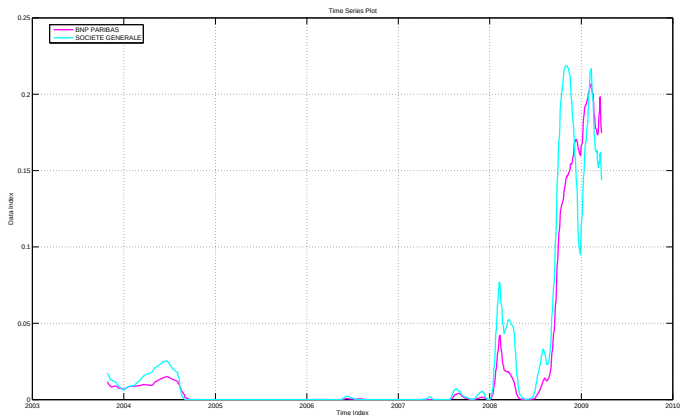
Historical Probability of default for Swiss/German Banks



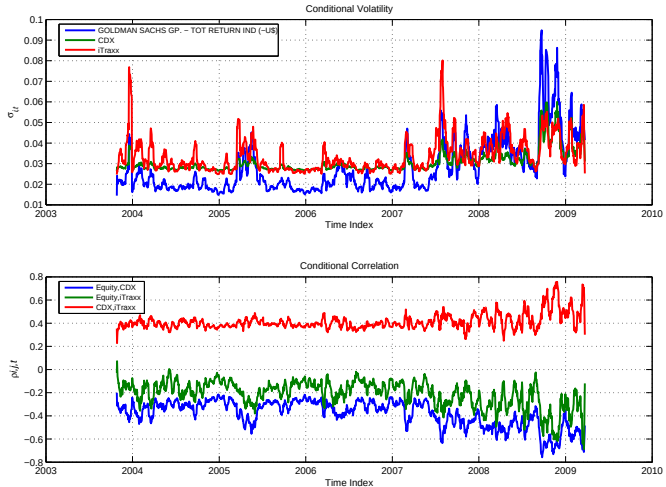
Distance to default for French Banks



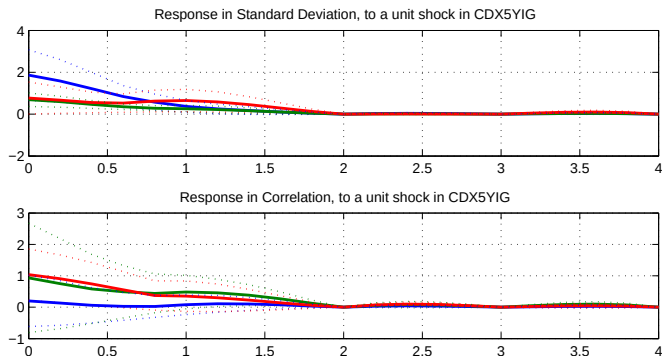
Historical Probability of default for French Banks



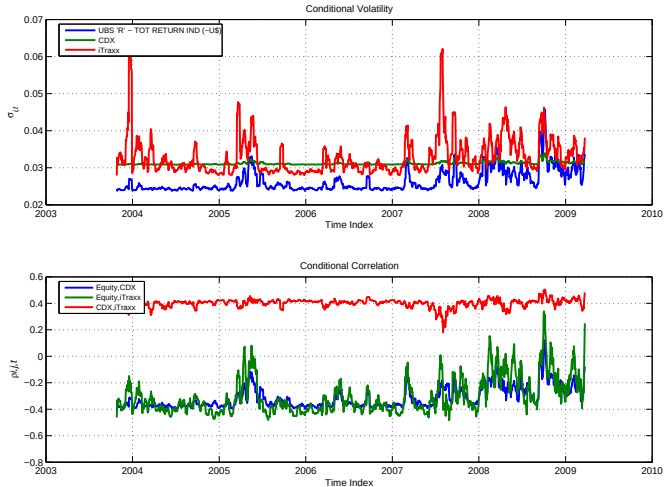
Example Covariance Analysis of GS



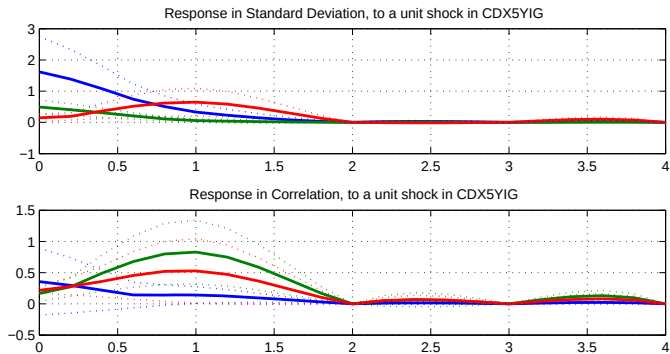
Example Impulse Response Analysis of GS



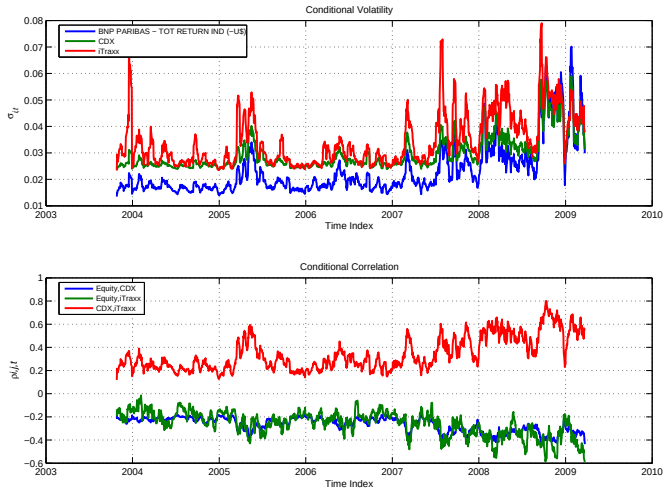
Example Covariance Analysis of UBS



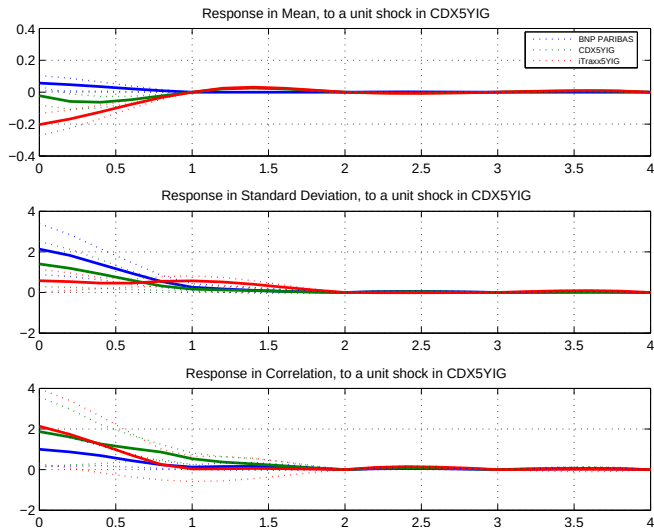
Example Impulse Response Analysis of UBS



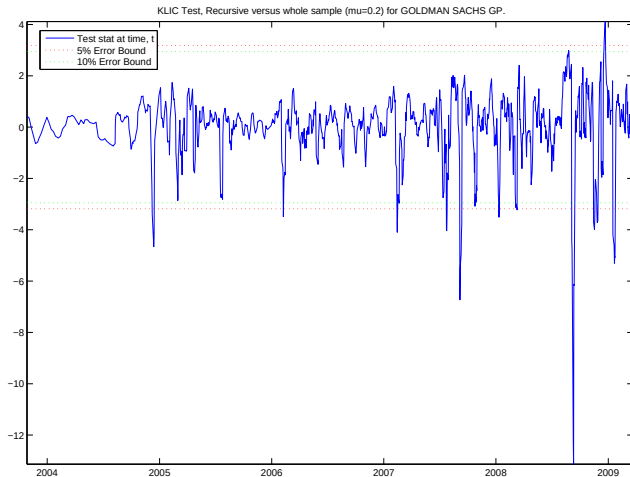
Example Covariance Analysis of BNP Paribas



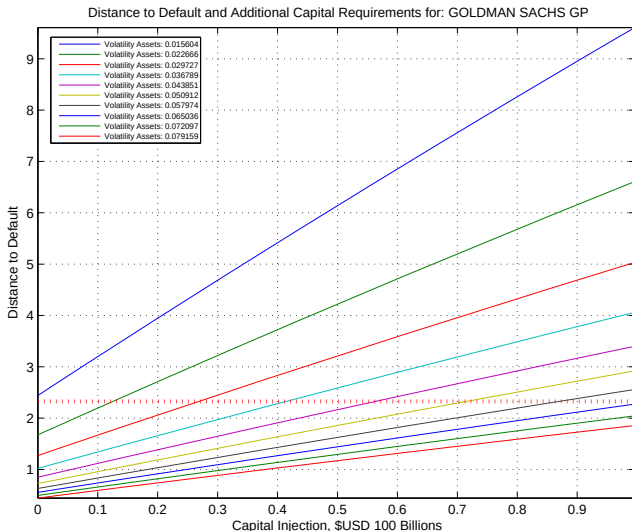
Example Impulse Response Analysis of BNP Paribas



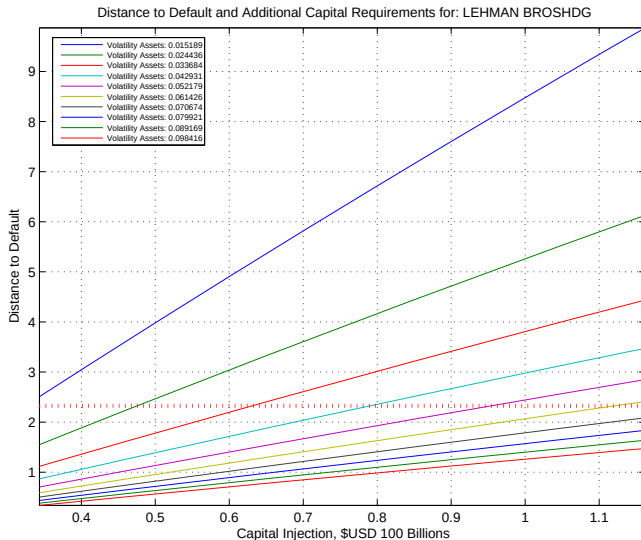
KLIC Test of GS Model Stability



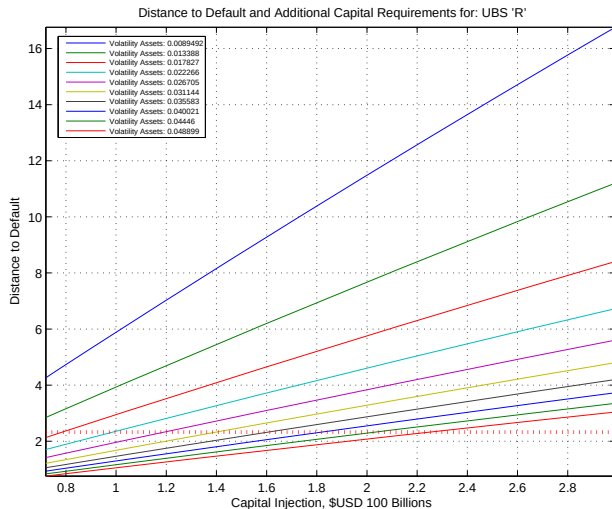
Capital Injections for Goldman Sachs



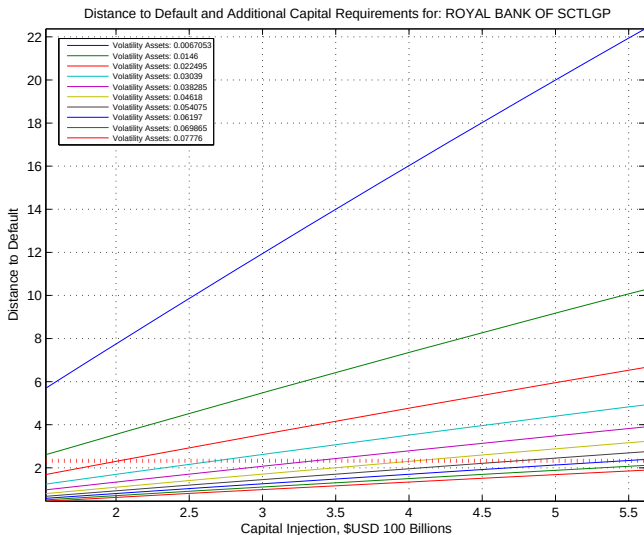
Capital Injections for Lehman Brothers



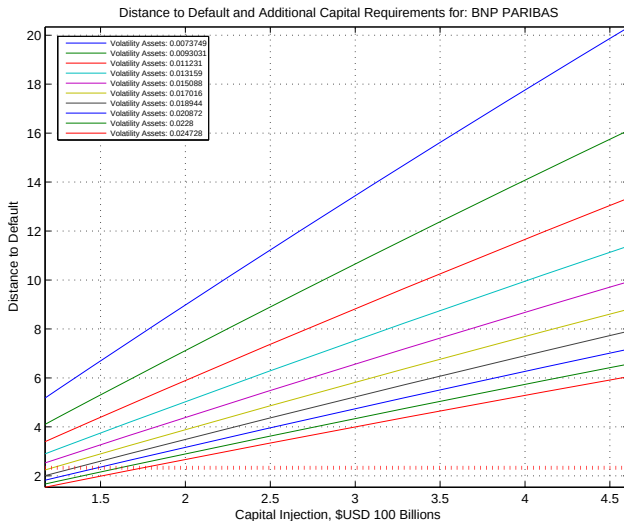
Capital Injections for UBS



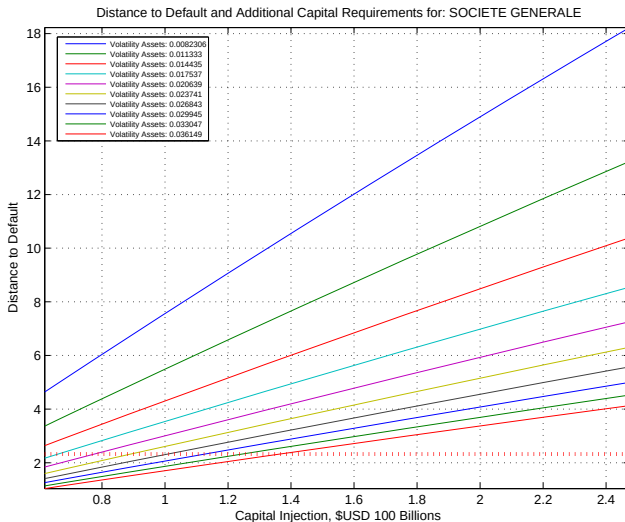
Capital Injections for Royal Bank of Scotland



Capital Injections for BNP Paribas



Capital Injections for Société Générale



Concluding Remarks

- At present this paper demonstrates a distance to default model with some striking results regarding the potential default risk of several international LCFIs.
- Our preliminary results suggest that default risk is highly correlated across international boundaries and that information contained in the market prices of Credit Derivatives impacts the equity and asset volatilities of LCFIs.
- Given this transmission mechanism we suggest that there is significant evidence that large default events can propagate across institutions and that this shock propagation to the collective asset volatility is enough to create significant default events in those institutions heavily exposed in these markets.
- We believe that credit default swap index factor augmented models of default risk will be a major area of risk analysis for future research.