HONG KONG MONETARY AUTHORITY

Working Paper 19/2009
18 December 2009

MEASURING THE INTERDEPENDENCE OF BANKS IN HONG KONG

Prepared by Tom Fong, Laurence Fung, Lillie Lam and Ip-wing Yu[1]
Research Department
Hong Kong Monetary Authority

Abstract

This paper assesses systemic linkages among banks in Hong Kong using the risk measure "*CoVaR*" derived from quantile regression. The *CoVaR* measure captures the co-movements of banks' default risk by taking into account their nonlinear relationship when the banks are in distress. Based on equity price information, our estimation results show that the default risks of the banks were interdependent during the recent crisis. Although local banks are generally smaller, their systemic importance is found to be similar to their international and Mainland counterparts, which may be due to a higher degree of commonality in the risk profile of local banks. Regarding the impact of external shocks on the banks, international banks are more likely to be affected by the equity price fall in the US market, while local banks are relatively more responsive to funding liquidity risk.

JEL Classification Numbers: G21, G14
Keywords: Value-at-Risk, Systemic Risk, Risk Spillovers, Quantile Regression
Authors' E-Mail Addresses:
Tom_PW_Fong@hkma.gov.hk; Laurence_KP_Fung@hkma.gov.hk; lillie.lam@bis.org; Ip-wing_Yu@hkma.gov.hk

[1] The authors are grateful to Cho-hoi Hui and Hans Genberg for their useful comments.

Executive Summary:

- *The global banking problem during the financial crisis of 2007-2009 highlights the importance of monitoring the interconnectivity among financial institutions and financial systems. Such financial linkages can be assessed by estimating how the default risk of one financial institution affects the others using the information in their equity prices.*

- *This paper assesses the linkages among banks in Hong Kong using a CoVaR measure. The CoVaR methodology measures loss in extreme conditions and can be defined as the expected maximum loss (at the 99th percentile) in a bank's equity value (i.e. default risk), given that another bank's equity value falls substantially (at the 99th percentile).*

- *Empirical evidence suggests that, similar to other banking systems, there is significant risk interdependence among banks in Hong Kong. More importantly, although local banks are generally smaller, their systemic importance measured by the CoVaR, is found to be similar to their international and Mainland counterparts, which may be due to a higher degree of commonality in the risk profile of local banks.*

- *Regarding the impact of external shocks on the banks, international banks are more likely to be affected by the equity price fall in the US market, while local banks are relatively more responsive to the risk factor of funding liquidity in the Hong Kong dollar.*

- *The study shows that the CoVaR is a useful indicator of the extent of risk interdependence among banks and identifying systemically important banks, which is important in assessing the systemic risk and developing macro-prudential tools.*

I. INTRODUCTION

The global banking problem after the bankruptcy of Lehman Brothers in September 2008 demonstrates that default risks of financial institutions could be highly interdependent during times of financial crisis. This high interdependence underlies the importance of monitoring the interconnectivity among financial institutions and financial systems in conducting financial market surveillance. To extract the information on these financial linkages, many studies track the market perception, usually reflected in the equity prices of the financial institutions, of how the credit risk of one institution affects the others. As the financial linkages across institutions move together strongly and increase more than proportionally with the surge in the level of risk of each institution during a distress period, it is critical to capture such nonlinearity in their co-movement when assessing the systemic risk in the financial market.[2]

A quantile-regression analysis, which is a nonlinear methodology, models the nonlinear relationship among banks' credit risk at a higher quantile after correcting for common aggregate risk factors (such as market volatility, interbank liquidity, etc.). There are several advantages of using the quantile regression to capture this nonlinear relationship. First, it gives a more accurate estimation of co-movement of risk measures amid rapidly fall in security prices and increasing risk of financial institutions during a distress period. Secondly, by expressing the default risk of one bank as a function of another bank's default risk and common aggregate risk factors, the quantile regression can separately assess endogenous risks (i.e. shocks from other financial institutions) and exogenous shocks (i.e. shocks from the common risk factors). Thirdly, using a small sample in the quantile regression may also result in a better estimation of risk at a higher quantile because it uses all information available from the sample.[3]

As part of the efforts to assess the systemic risk for the Hong Kong banking

---

2 In the IMF's Global Financial Stability Report (April 2009), four different approaches including (i) the network approach, (ii) the co-risk model, (iii) the distress dependence matrix, and (iv) the default intensity model are mentioned. As discussed in the Report, each approach has its own merit and limitation but still they are an important set of tools that can provide the basis to address the spillover risk during the crisis. See details in IMF (2009a). Recent studies also discussed linkages of financial institutions, such as Bank of England (2009), IMF (2009b), Haldane (2009), and Brunnermeier et al. (2009).

3 Another commonly used method in tail analysis is the extreme-value theory. This method may give a poor estimate of risk because it takes only the tail realisation and ignores the information content of a large portion of data sample in the estimation.

sector, this paper estimates the risk linkages among banks in Hong Kong using the quantile regression analysis on the basis of the information in equity prices of Hong Kong banks.[4] Intuitively, a bank with a sharp fall in its equity price at the 99th percentile (i.e. a 1% probability of such extreme loss during the sample period) suggests that the bank may be in distress and has a high risk of default. A *CoVaR* measure derived from the quantile regression (namely the *CoVaR* method in this paper) is a value-at-risk (VaR) measure of a bank conditional on another bank being under stress on its equity price. Such influence can directly come from other banks, or arise indirectly from exposures to common risk factors (such as interbank claims, reliance on wholesales markets for funding and feedback from market volatility due to holding similar assets, etc.).[5] By estimating a *CoVaR* for each pair of banks, a matrix of banks' potential loss when other banks are under stress can be obtained.

As the Hong Kong banking sector is composed of both local and internationally active banks with different characteristics in terms of their market shares and business concentrations, we divide the banking sector into three bank groups: international banks, Mainland banks, and local banks to study their linkages in time of stress. Their *CoVaR* estimates help examine how default risks can spread from one bank group to another group and understand the extent of risk interdependence and systemic importance among banks.

The remaining parts of this paper are organised as follows. Section 2 reviews briefly the literature regarding the *CoVaR* measure. Section 3 introduces the *CoVaR* method. Data description is in Section 4. Section 5 discusses empirical results and Section 6 concludes.

II. LITERATURE REVIEW IN THE *COVAR* METHOD

The *CoVaR* measure derived from the quantile regression was first

[4] In the literature, both credit default swap (CDS) spreads and equity data are used to reflect banks' default risk. As the CDS information is only available for a small number of banks in Hong Kong, this study uses equity prices for estimation of *CoVaR*. It is noted that inferring default risk from equity prices is used in credit risk modelling. For example, Merton (1974) develops a structure model in which the equity price, equity volatility and liability of a company are the determinants of its default risk.

[5] Details can be found in Brunnermeier et al. (2009) and Chan-Lau (2008).

discussed by Adrian and Brunnermeier (2008).[6,7] Based on weekly market valued assets of 1,340 public financial institutions in the US[8], their study primarily focuses on marginal contribution of an institution to the overall systemic risk. Specifically, the *CoVaR* measure is defined as the VaR of a financial system conditional on the distress of a particular financial institution. In addition to using *CoVaR* measures to examine risk spillover, *CoVaR* can also be used to construct a countercyclical risk measure. The idea is that, given a sufficiently large cross-section of panel data, *CoVaR*s of financial institutions at each cross-section can help determine which characteristics of the financial institutions (such as average maturity mismatch, leverage, market-to-book, size, etc.) contribute to systemic risk over time. The panel regression coefficients can therefore be used to indicate how one should assign different weights to these characteristics in determining capital charge or tax imposed on different financial institutions.

While the *CoVaR* method in Adrian and Brunnermeier (2008) focuses on how much an institution adds to overall systemic risk, Chan-Lau (2008) uses the *CoVaR* method to study the spillover effects among 25 financial institutions across the US, Europe and Japan, based on their CDS spreads. The *CoVaR* is defined as the VaR of one institution conditional on another institution being at a particular VaR level. The study shows the extent of risk interdependence among the financial institutions in both normal and stressful periods. In addition, by comparing the average risk spillover (in terms of average *CoVaR*) of each institution to the others, the study also sheds light on identifying systemically important institutions. Similar to the framework in Chan-Lau (2008), IMF (2009a) adopts the *CoVaR* method to assess the systemic linkages (namely, the co-risk in the study) in the US banking sector. Using the CDS spreads of 13 major US financial institutions, the study shows that the *CoVaR* method can help identify which institutions had higher default risk before the recent financial crisis emerged.

---

6 The quantile regression technique is first introduced by Koenker and Bassett (1978).

7 In their earlier work published in September 2008, they examined the spillover among the financial sectors including commercial banks, investment banks hedge fund and security broker dealer portfolio.

8 It covers four financial sectors including commercial banks, investment banks and other security broker-dealers, insurance companies, and real estate companies.

III. METHODOLOGY

We define VaR_q^j as the maximum loss in equity return of bank *j* at a confidence level of (1 - *q*) over *n* days. This unconditional loss can be statistically represented by $\Pr(R^j \le VaR_q^j) = q$, where R^j is the *n*-day return of the equity price of bank *j*.[9]

The measure of *CoVaR*, denoted by $CoVaR_q^{i|j}$, is defined as the *VaR* of bank *i* conditional on bank *j* at its level of VaR_q^j. Statistically, it can be specified as:

$$\Pr(R^i \le CoVaR_q^{i|j} \mid R^j = VaR_q^j) = q \,. \tag{1}$$

To estimate this conditional risk, a quantile regression is used to relate the equity return of bank *i* with that of bank *j*. Specifically,

$$R^i = \beta_{0,q}^{i|j} + \beta_{1,q}^{i|j} R^j + \beta_{2,q}^{i|j} R^{SPF} + \beta_{3,q}^{i|j} IVOL + \beta_{4,q}^{i|j} TED + \varepsilon_q^{i|j} \tag{2}$$

where R^{SPF} is the *n*-day return of the S&P 500 Financials Index to proxy the US stock market condition; *IVOL* is the *n*-day difference of the option-implied volatility of Hang Seng Index to proxy the Hong Kong stock market conditions; and *TED* is the *n*-day difference of the spread between 1-month HIBOR and 1-month Exchange Fund Bill yield to proxy the short term liquidity risk in the Hong Kong dollar. These risk factors in the quantile regression are used to help control for the market and economic conditions other than the shock from bank *j*.

In the quantile regression, the coefficients can be estimated by the minimisation of the sum of residuals $\sum_t (q - I_{\varepsilon \le 0}) \cdot \varepsilon_q^{i|j}$, and $I_{\varepsilon \le 0}$ is an indicator function which equals one if $\varepsilon_q^{i|j} \le 0$ and zero otherwise. After estimating coefficients

---

9 Specifically, the n-day return of the equity price of bank *j* is log (P_{t+n}/P_t) where P_t is the equity price of bank *j* on day *t*.

($\hat{\beta}$s) of the quantile regression, the $CoVaR_q^{i|j}$ can be obtained by substituting $\hat{\beta}$s into the following equation:

$$CoVaR_q^{i|j} = \hat{\beta}_{0,q}^{i|j} + \hat{\beta}_{1,q}^{i|j} VaR_q^{j} + \hat{\beta}_{2,q}^{i|j} R^{SPF} + \hat{\beta}_{3,q}^{i|j} IVOL + \hat{\beta}_{4,q}^{i|j} TED \quad (3)$$

The values of the common risk factors (i.e. R^{SPF}, *IVOL*, and *TED*) are those on the date when VaR_q^j is observed. If the VaR_q^j is a return between two dates, the values of the common risk factors are linearly interpolated by the values realised on the two dates. The linear interpolation is adopted with a ratio *r* calculated from $rVaR_{q,l}^j + (1-r)VaR_{q,u}^j = VaR_q^j$ where $VaR_{q,l}^j$ (and $VaR_{q,u}^j$) is the realised return of bank *j* just smaller (and larger) than VaR_q^j.

The *CoVaR* method can also be used to evaluate which banks are more at risk when the common risk factors are stressed. The corresponding measures can be estimated by

$$CoVaR_q^{i|j,SPF} = \hat{\beta}_{0,q}^{i|j} + \hat{\beta}_{1,q}^{i|j} R_q^{j} + \hat{\beta}_{2,q}^{i|j} VaR^{SPF} + \hat{\beta}_{3,q}^{i|j} IVOL + \hat{\beta}_{4,q}^{i|j} TED \quad (4)$$

$$CoVaR_q^{i|j,IVOL} = \hat{\beta}_{0,q}^{i|j} + \hat{\beta}_{1,q}^{i|j} R_q^{j} + \hat{\beta}_{2,q}^{i|j} R^{SPF} + \hat{\beta}_{3,q}^{i|j} VaR^{IVOL} + \hat{\beta}_{4,q}^{i|j} TED \quad (5)$$

$$CoVaR_q^{i|j,TED} = \hat{\beta}_{0,q}^{i|j} + \hat{\beta}_{1,q}^{i|j} R_q^{j} + \hat{\beta}_{2,q}^{i|j} R^{SPF} + \hat{\beta}_{3,q}^{i|j} IVOL + \hat{\beta}_{4,q}^{i|j} VaR^{TED} \quad (6)$$

where $CoVaR_q^{i|j,SPF}$, $CoVaR_q^{i|j,IVOL}$, and $CoVaR_q^{i|j,TED}$ are *VaR*s conditional on R^{SPF}, *IVOL* and *TED* at their *VaR* levels respectively; and VaR_q^{SPF}, VaR_q^{IVOL} and VaR_q^{TED} are unconditional *VaR*s of R^{SPF}, *IVOL* and *TED* respectively.

The absolute level of *CoVaR* reveals the vulnerability of a bank when another bank is in distress. In other words, the larger the estimated *CoVaR* (in absolute term) of a bank, the larger spillover effect is. Apart from the measure in absolute level, an excess of the *CoVaR* over the *VaR* is also derived to examine the responsiveness of a bank to another distressed bank:

$$\Delta CoVaR_q^{i|j} = CoVaR_q^{i|j} - VaR_q^i . \tag{7}$$

If banks' risks are significantly interdependent, $\Delta CoVaR$ will be different from zero. This is an essential indicator to reflect the extent of banks' risk interdependence and systemic importance.

IV. DATA

Twelve banks that are listed in the Hong Kong Stock Exchange and have substantial business in Hong Kong are selected in this analysis. These banks are grouped into (1) international banks; (2) local banks; and (3) Mainland banks, according to the business coverage of the banks and the countries where their parent companies are incorporated in.

The estimation uses daily information for the period from 4 January 2006 to 22 May 2009.[10] This sample period is selected because it covers the distress period during the global financial crisis of 2007-2009. To be consistent with the market practice in calculating banks' market risk, we examine a 10-day return of banks' equity prices and the maximum loss of the prices at 99% confidence level. In other words, n is set as 10 and q is set as 1%.

V. EMPIRICAL RESULTS

The $CoVaR$ and $\Delta CoVaR$ of the three bank groups are presented in Tables 1 and 2 respectively. Bank group listed in the first row of the tables are the "source" of stress. Each cell in Table 1 represents the $CoVaR$ of the bank listed in the first column at the 99th percentile conditional upon the VaR of another bank at the 99th percentile. Similarly, each cell in Table 2 represents the excess of $CoVaR$ over VaR ($\Delta CoVaR$) of the bank listed in the first column at the 99th percentile conditional upon another bank being in distress. For instance, when a Mainland bank comes under stress

[10] Due to data availability, the sample period starts from 4 January 2006. The data used are obtained from Bloomberg.

(depicted by having its VaR of its equity value at the 99th percentile), an international bank's VaR at the 99th percentile increases by 10.6 percentage points on average compared with its unconditional VaR. This is not necessarily symmetric. In case an international bank is in trouble, a Mainland bank's VaR at the 99th percentile only rises by 8 percentage points.

The main findings of the empirical results are summarised as follows:

(i) Table 1 shows that the expected maximum losses in equity value of banks (as reflected by averages of banks' *CoVaR* s) are significantly larger than their corresponding *VaR* estimates as shown in the last column. Table 2 demonstrates that the expected maximum loss in a bank's equity value increases by about 10.1 percentage points on average when another bank is in distress, revealing that banks in Hong Kong were generally interconnected with each other during the sample period.

(ii) The extent of risk interdependence among banks is found to be the highest for local banks, followed by international banks and Mainland banks. Chart 1 shows that when a bank suffers from an extreme equity loss, the expected maximum losses in equity value in a 10-day horizon of local banks, on average, would increase by 11.3% to 43.4%, and that of international banks would increase by 10.8% to 38.9%. For Mainland banks, the expected maximum loss would increase by 8.1% to 35.7%.

(iii) Chart 2 indicates that different groups of banks being in distress affect the extent of risk interdependence differently. When a local bank is in distress, it would on average increase other banks' expected maximum losses by 11.8%. The effects due to a distressed international bank and a distressed Mainland bank are estimated to be 9.4% and 8.5% respectively. This suggests that although local banks are generally smaller in size, their systemic importance is found to be similar to or even greater than their international and Mainland counterparts.

(iv) Chart 3 shows the average $\Delta CoVaR$ s of the three bank groups conditional on changes in the common risk factors including the US equity market performance, funding liquidity in the Hong Kong dollar and local stock market condition (represented by R^{SPF} , *TED* and *IVOL* respectively). The estimation results show that the expected maximum losses in equity value of local banks are more responsive to the funding liquidity risk, while those of international banks is more responsive to a sharp fall in the US equity prices. When *TED* is stressed at its 99% *VaR*, the *VaR* of local banks is estimated to increase by 7.6 percentage points to 39.7% on average. When R^{SPF} is stressed at its 99% *VaR*, the *VaR* of international banks increase by 6.5 percentage points to 34.6%.

VI. CONCLUSIONS

This paper measures the risks of different bank groups in Hong Kong by employing the *CoVaR* method to take account of banks' interdependence under extreme conditions based on their equity prices. The empirical results suggest that, similar to other banking systems, there is significant risk interdependence among banks in the Hong Kong banking sector. More importantly, although local banks are generally smaller in size, their systemic importance measured by the *CoVaR* is found to be similar to their international and Mainland counterparts, which may be due to a higher degree of commonality in the risk profile of local banks. Regarding the impact of external shocks on the three bank groups, international banks are more likely to be affected by the equity price fall in the US market, while local banks are relatively more responsive to the risk factor of funding liquidity in the Hong Kong dollar.

The study shows that the *CoVaR* is a useful indicator of measuring the extent of risk interdependence among banks and identifying systemically important banks, which is important in assessing the systemic risk and developing macro-prudential tools.

Table 1. *CoVaR* for the Crisis Period from 4 January 2006 to 22 May 2009

Bank at risk under the following bank group	Source of stress: *International*			*Mainland*			*Local*			Row average (Vulnerability): All Groups			Average VaR
	Min	Max	Average	Min	Max	Average	Min	Max	Average	Min	Max	Average	
International	0.276	0.467	0.375	0.263	0.554	0.387	0.273	0.526	0.396	0.263	0.554	0.389	0.281
Mainland	0.265	0.429	0.356	0.284	0.391	0.335	0.274	0.488	0.370	0.265	0.488	0.357	0.276
Local	0.258	0.546	0.426	0.268	0.571	0.409	0.346	0.668	0.464	0.258	0.668	0.434	0.320
Column average (Systemic importance)	0.258	0.546	0.391	0.263	0.571	0.383	0.273	0.668	0.411	0.258	0.668	0.397	0.296

Note: A positive figure indicates a loss in equity return

Table 2. Δ*CoVaR* for the Crisis Period from 4 January 2006 to 22 May 2009

Bank at risk under the following bank group	Source of stress: *International*			*Mainland*			*Local*			Row average (Vulnerability): All Groups		
	Min	Max	Average	Min	Max	Average	Min	Max	Average	Min	Max	Average
International	0.030	0.198	0.094	0.017	0.284	0.106	-0.020	0.257	0.115	-0.020	0.284	0.108
Mainland	-0.004	0.164	0.080	-0.024	0.124	0.059	0.007	0.221	0.094	-0.024	0.221	0.081
Local	-0.022	0.227	0.106	-0.012	0.175	0.089	0.013	0.260	0.144	-0.022	0.260	0.113
Column average (Systemic importance)	-0.022	0.227	0.094	-0.024	0.284	0.085	-0.020	0.260	0.118	-0.024	0.284	0.101

Chart 1. *CoVaR*s and *VaR*s estimates of the three bank groups

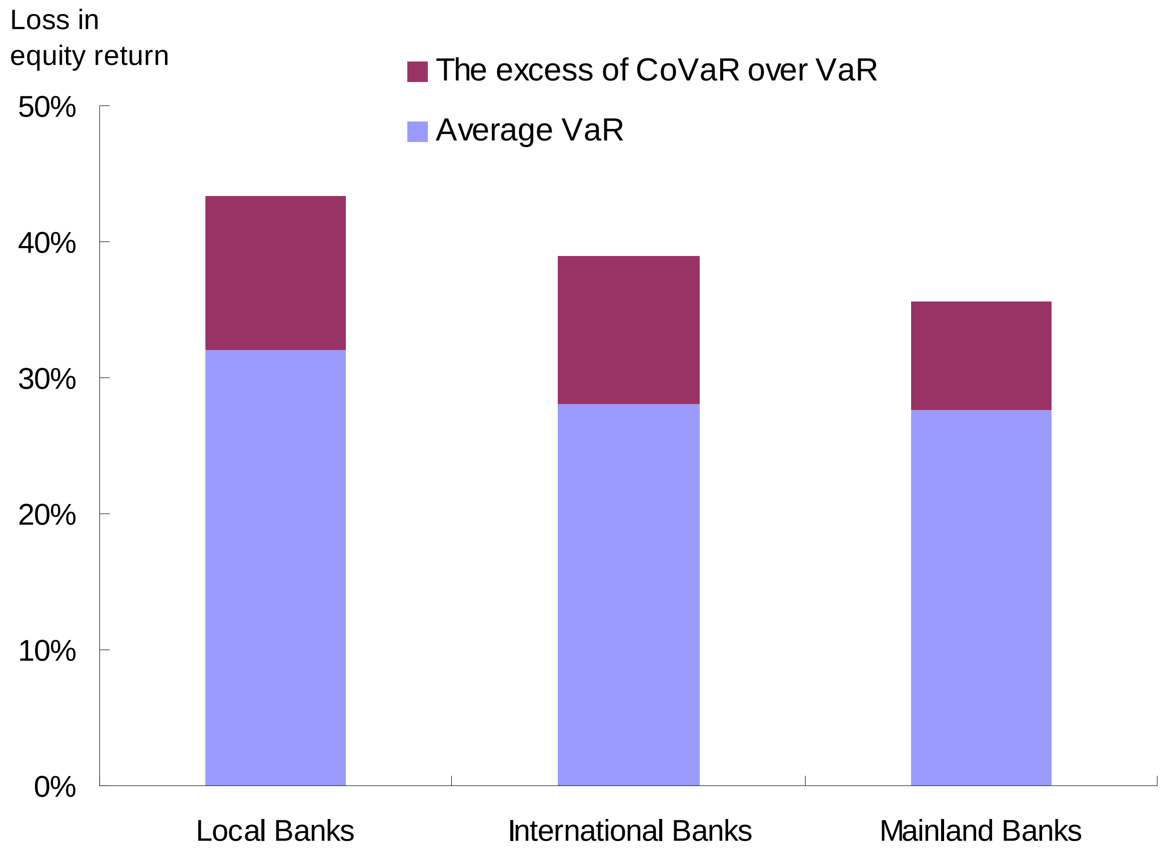
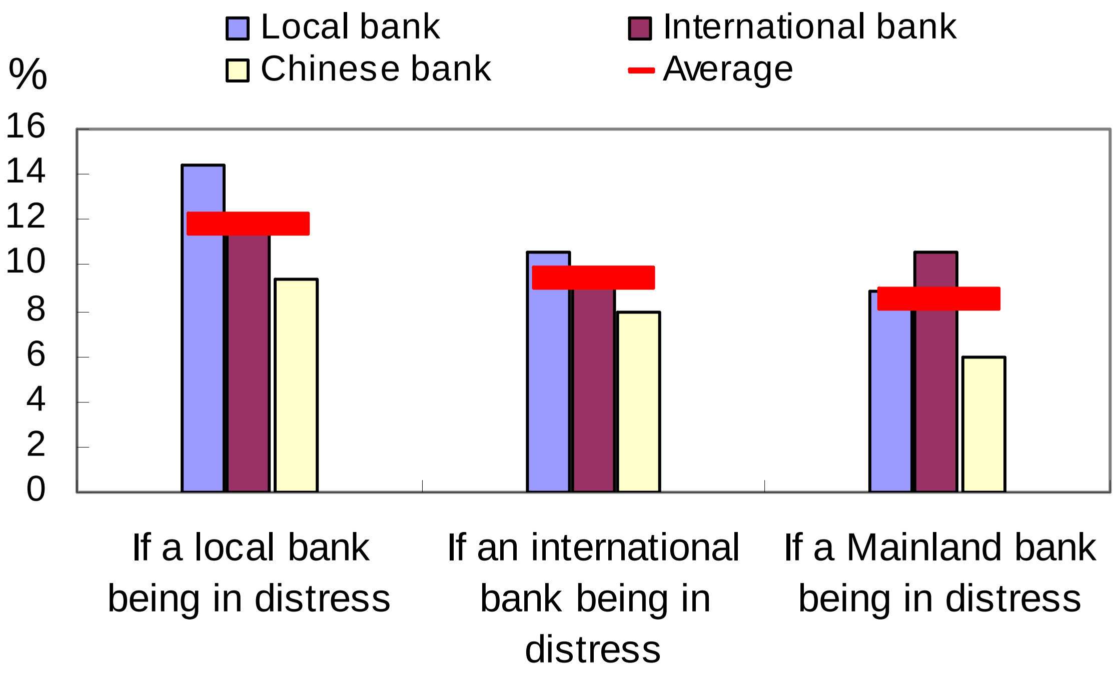
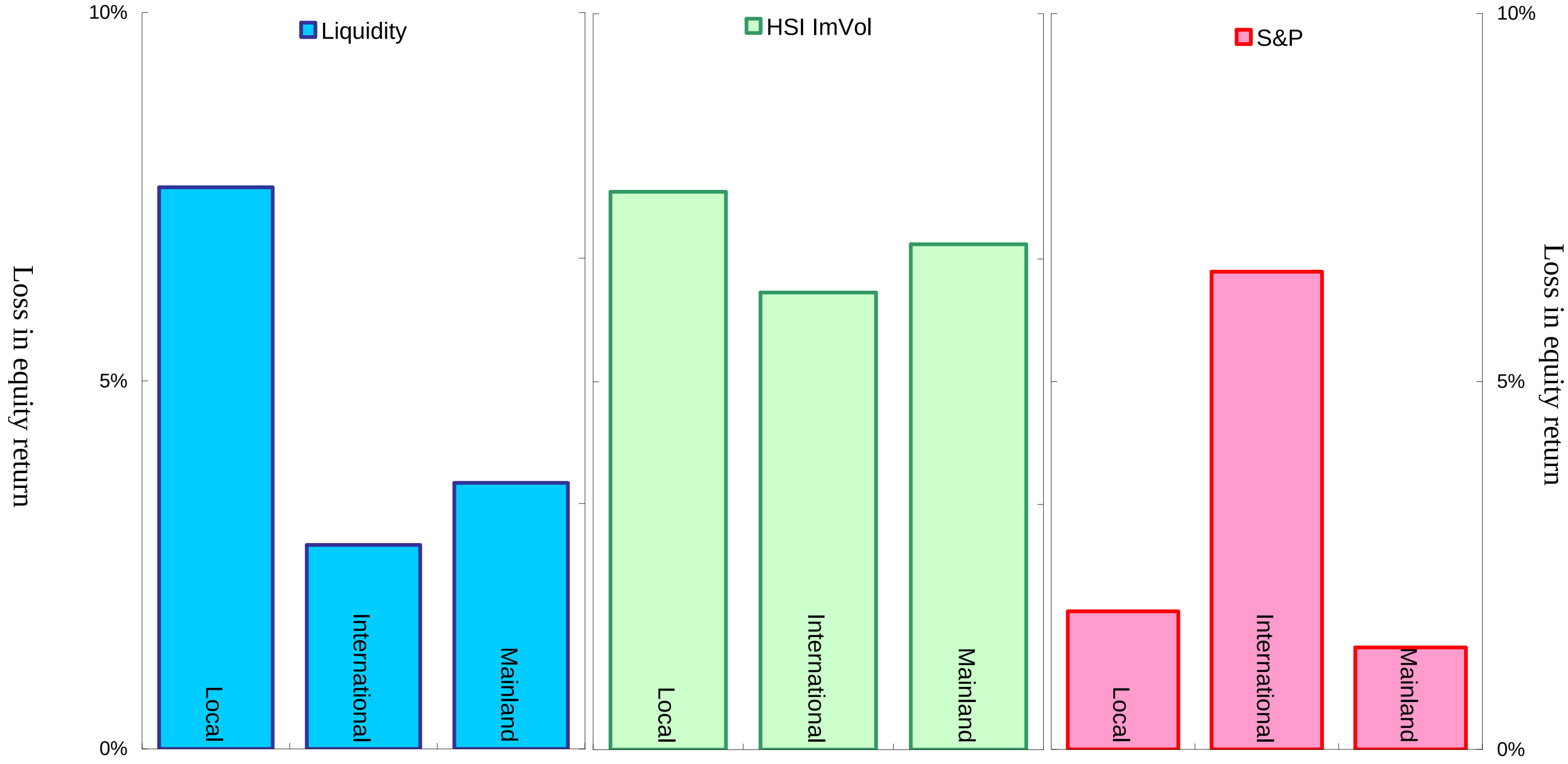


Chart 2. Increases in the expected maximum losses in equity value of other banks given a bank being in distress (measured by $\Delta CoVaR$)



Note: A positive figure indicates a loss in equity return

Chart 3. Responsiveness to common risk factors (measured by row averages of *ΔCoVaR* conditional on common risk factors)



REFERENCES

Adrian, T. and Brunnermeier, M.K. (2008): "CoVaR", Federal Reserve Bank of New York Staff Report, No.348, September.

Bank of England (2009): "Building a More Resilient Financial System", Bank of England Financial Stability Report, Chapter 3, June.

Brunnermeier, M., Crockett, A., Goodhart, C., Persaud, A.D., and Shin, H. (2009): "The Fundamental Principles of Financial Regulation", Geneva Reports on the World Economy 11, Preliminary Conference Draft. Available at www.voxeu.org/reports/Geneva11.pdf.

Chan-Lau, J.A. (2008): "Default Risk Codependence in the Global Financial System: Was the Bear Stearns Bailout Justified?". Available at http://www.bcentral.cl/conferencias-seminarios/seminarios/pdf/Chan-Lau.pdf

Haldane, A. (2009): "Why Banks Failed the Stress Test", Speech delivered at the Marcus-Evans Conference on Stress-Testing, Bank of England, London. Available at http://www.bankofengland.co.uk/publications/speeches/2009/speech374.pdf.

IMF (2009a): "Assessing the Systemic Implications of Financial Linkages", Global Financial Stability Report, Chapter 2, April.

IMF (2009b): "IMF: Prevent Institutions Becoming Too Connected to Fail". Available at http://www.imf.org/external/pubs/ft/survey/so/2009/RES042109B.htm.

Koenker, R. and Bassett, G. (1978): "Rregression Quantiles", Econometrica, 46(1), 33-50.

Merton (1974), “On the pricing of corporate debt: the risk structure of interest rates”, Journal of Finance, Vol. 29, pp. 449-470.