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The role of loan portfolio losses and bank capital for Asian financial system resilience

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Abstract

This paper analyses the systemic risk in relation to bank lending for Asian economies. The methodology complements existing market-based systemic risk measures by providing measures based on accounting information that regulators typically collect. Loan loss provisions of banks are decomposed into (i) a prediction component that is based on observable bank characteristics, and (ii) two frailty components: a bank-specific systematic factor based on the assumption that a bank's asset portfolio is diversified and a systemic factor. Systemic risk is measured as the Value-at-Risk and Expected Shortfall of the financial system based on a simulation model that takes into account the current condition of banks in the financial system, the absolute size and the capitalisation of financial institutions, as well as the sensitivity to systematic and systemic frailty risk.

Keywords: Asia, Bank Capital, Bank Lending, Commercial Banks, Credit Portfolio Risk, Systemic Risk

JEL classification: G20, G28, C51

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1 Motivation

Bank lending is a major source for consumer and corporate finance and is the focus of prudential regulations as well as accounting standards to ensure system resilience. Asian banking systems have received very limited attention in literature during the recent years. These systems have continued to thrive while their US and South-European counterparts were exposed to severe economic stresses. This paper analyses this exciting intersection of bank lending and system resilience for Asian economies.

The extant literature analyses share returns and CDS spreads for the largest banks within developed Asian economies. For example, Fong et al. (2011) estimate systemic risk using equity returns for twelve Hong Kong banks and Wong et al. (2011) analyse systemic risk measures based on the distances to default for the largest banks (with equity returns) of ten Asian counties. Huang et al. (2012) compute stress insurance premiums from CDS spreads for 24 large Asian banks and relate systemic risk during the Global Financial Crisis (GFC) to risk aversion and liquidity crunches. Zhang et al. (2013) analyse market measures for systemic risk for 333 international banks (approximately a third of which is from Asia). Dungey et al. (2015) measure the systemic risk based on share prices for Australian firms including banks.[2]

Borio and Drehmann (2009) and Cerutti et al. (2012) argue that financial markets may be exposed to systematic under and/or over pricing which implies a higher degree of systemic risk than actuarial indicators may support. As an example, share prices jointly drop in times of financial crises as investors sell shares in a financial system. As a result, the systemic change in share prices is in part driven by investor behaviour, which may not reflect the real economy. Consistent with this view, Zhang et al. (2013) find that size-

[2] Prominent examples for US-based market-based systemic risk measures are Adrian and Brunnermeier (2011), Acharya et al. (2010) and Brownlees and Engle (2012).

based rankings dominate market-based measures as early-warning tools for systemic risk, and Snethlage (2015) applies a simulation-based approach for the New Zealand banking system and measures the risk associated with bank failure.

The literature on Asian banks has focused on market based measures for systemic risk. We extend this research to address regulatory concerns by providing an accounting-based model for financial system risk in bank lending and apply this methodology to Asian bank accounting data to complement market-based measures for systemic risk. We decompose banks' historic loss rates into multiple terms: the prediction term of bank losses based on risk factors observable by prudential regulators, a systematic frailty term and a systemic frailty term. Financial institutions fail when unexpected losses (i.e., frailty effects) exceed the capital. The paper analyses absolute loss exceedances for failed institutions, aggregates these for financial systems and reports moments of their distributions to determine the absolute size of systemic risk.

We focus on systematic risk of commercial loan portfolios of banks as (i) bank lending relates to the basic functions that financial institutions provide in economies, and (ii) hedging techniques are in short supply. This paper complements the existing literature on market-based systemic risk and on forms of connectedness other than bank lending, such as counterparty relationships in over-the-counter (OTC) transactions, borrower-lender relationships, or client-service provider relationships.

The contributions are as follows: Firstly, we provide cross-sectional systemic risk measures for bank lending in Asia. The Asian economic region is an important and fast growing economic region. We account for the historic cyclicality of loan losses, bank capitalisation and banking structure of Asian economies. The analysis is important as some Asian economies are currently discussing implementing deposit or bank liability insurance schemes and this paper may provide an input into the size requirements of such schemes.

Secondly, bank accounting data, readily available to regulators, is used to measure systemic risk, addressing the critique by Borio and Drehmann (2009) and Cerutti et al. (2012). The approach is independent from the efficiency of financial markets. The model is based on a structural economic model for bank default, where a bank default occurs if losses exceed capital. [3]

Thirdly, the size of financial system protection schemes is measured by computing the absolute losses in financial systems under distress and conditional on individual bank failures. The resulting risk measures enable the definition of minimum adequacy and hence the size of protection schemes for creditors in absolute terms and accounting data. The paper builds on Adrian and Brunnermeier (2011) who suggest the measurement of systemic risk by the conditional Value-at-Risk (CoVaR) and DeltaCoVaR for (relative) equity returns. [4]

Fourthly, the likelihood is derived for a model where loss rates are decomposed into an observable component, a systematic factor with regard to the bank portfolio and a systemic risk factor. We define **systematic risk** as the risk that relates to a bank portfolio and cannot be diversified. We further define **systemic risk** as risk that relates to a system of banks and can not be diversified. The measurement of systematic and systemic risk allows us to simulate distributions of bank losses and financial system losses for future time periods and to derive the size of financial system protection mechanisms.

The paper proceeds as follows: Section 2 presents the model framework and introduces a number of measures for systemic risk. Section 3 presents the empirical results and includes data description, the model estimation, the analysis of the impact of financial institutions on the system loss. Section 4 concludes.

[3] Acharya et al. (2010) and Brownlees and Engle (2012) acknowledge the role of leverage but do not control for the asset/credit risk.

[4] DeltaCoVaR is defined as an institution's contribution to systemic risk as the difference between (i) CoVaR of the financial system conditional on the institution being under distress, and (ii) the CoVaR of the financial system conditional on the median state of the institution.

2 A model for bank failure and financial system loss

In our contribution we isolate systematic shocks which are deviations of realised loss rates from loss rate predictions. Note that loss rate realisations aggregate over large banking portfolios and the idiosyncratic risks have been diversified. The remaining systematic risk will be decomposed into a systemic and a non-systemic component. To illustrate the diversification of idiosyncratic risks, we start on the borrower level, then aggregate risks to the bank level and finally to the system level.

The asset return of borrower i of bank j in period t $(i = 1, ..., I_j; j = 1, ..., J; t = 1, ..., T)$ is driven by a time-specific common risk factor X_{jt} and an idiosyncratic factor S_{ijt}:

$$R_{ijt} = \sqrt{\rho} X_{jt} + \sqrt{1-\rho} S_{ijt} \tag{1}$$

where X_{jt} and S_{ijt} are standard normally distributed and independent from each other, with standardised weights ρ and $\sqrt{1-\rho}$.

We decompose the risk factor X_{jt} further into a systematic component U_{jt} and a systemic component X_t^*, where both are i.i.d. standard normally distributed with standardised weights δ and $\sqrt{1-\delta}$:

$$X_{jt} = \sqrt{\delta} X_t^* + \sqrt{1-\delta} U_{jt} \tag{2}$$

The asset return process is then:

$$R_{ijt} = \sqrt{\rho\delta} X_t^* + \sqrt{\rho - \rho\delta} U_{jt} + \sqrt{1-\rho} S_{ijt} \tag{3}$$

A default event occurs when and if the asset return R_{ijt} falls below threshold c_{jt-1}. The borrower default is modelled by the indicator

$$D_{ijt} = \begin{cases} 1 & \text{borrower } i \text{ of bank } j \text{ defaults in period } t, \text{ for } R_{ijt} < c_{jt-1} \\ 0 & \text{otherwise, for } R_{ijt} >= c_{jt-1} \end{cases} \tag{4}$$

c_{jt-1} is a summary of all observable information on the borrower, the bank and the financial system. As we collect information on the bank level, we assume borrowers to be homogeneous for a given bank and heterogeneous for different banks. Bank regulators may extend the models by borrower-specific information (e.g., FICO scores and LTV ratios for mortgage borrowers or financial ratios for corporate borrowers) if available.

The conditional default probability, conditional on the systematic factor and systemic factor is given by:

$$\begin{aligned} P(D_{ijt} = 1 | X_t^*, U_{jt}) &= P(R_{ijt} < c_{jt-1} | X_t^*, U_{jt}) \\ &= P(\sqrt{1-\rho} S_{ijt} < c_{jt-1} - \sqrt{\rho\delta} X_t^* - \sqrt{\rho - \rho\delta} U_{jt} | X_t^*, U_{jt}) \\ &= \Phi\left(\frac{c_{jt-1} - \sqrt{\rho\delta} X_t^* - \sqrt{\rho - \rho\delta} U_{jt}}{\sqrt{1-\rho}} \right) \end{aligned} \tag{5}$$

where $\Phi(\cdot)$ is the cumulative density function (CDF) of the standard normal distribution.

A bank generally holds larger borrower portfolios and the portfolio default rate P_{jt}, which measures the ratio of defaulting borrowers divided by the total number of borrowers in a bank, converges in probability to the conditional default probability as idiosyncratic risk is diversified. In other words, given a granular credit portfolio, the default rate of bank j in time period t is:[5]

$$P_{jt} = \frac{\sum_{i=1}^{I_j} D_{ijt}}{I_j} \xrightarrow{p} \Phi\left(\frac{c_{jt-1} - \sqrt{\rho\delta}X_t^* - \sqrt{\rho - \rho\delta}U_{jt}}{\sqrt{1-\rho}}\right) \text{ as } I_j \to \infty \tag{6}$$

see e.g., Kupiec (2009). The right hand side of Equation (6) is the asymptotic default rate of bank j in period t. P_{jt} can be interpreted as the loss rate rather than the default rate of the portfolio if loss rates given default are equal to unity. Alternatively, one may assume higher default rates and lower loss rates given default resulting in comparable total loss rates.

We assume that the (implied default threshold and hence the) loss rate is a function of the probit transformed lagged loss rate p_{jt-1}[6], as well as bank characteristics $z_{k,jt-1}$ (with $k = 2, ..., K$) such as bank capital, profitability, liquidity, and credit growth. The bank-level controls define the bank lending standard and hence the loss rate:

$$c_{jt-1} = \beta_{0,j} + \beta_{1,j}\Phi^{-1}(p_{jt-1}) + \sum_{k=2}^{K} \beta_{k,j} z_{k,jt-1} \tag{7}$$

$\beta_{0,j}$ is a bank-level intercept, $\beta_{1,j}$ is the sensitivity of the probit transformed lagged loss rate and $\beta_{k,j}$, with $k = 2, ..., K$, are the sensitivities of the respective risk factors. Banks provision for expected credit losses. To the degree that credit losses can be explained by time lagged variables (p_{jt-1} and $z_{k,j,t-1}$), banks would anticipate economic shocks and allow for their impact on the loss rates through provisions. In this paper, we analyse the propensity of unexpected (random) shocks to draw on the bank capital. These random shocks are per definition independent from the deterministic time-lagged information.

[5] In the empirical analysis, we model losses in relation to credit and trading portfolios including securities and derivatives.

[6] We choose the probit transformation in order to bring the endogenous variable to the same level of interpretation as the dependent variable.

The asymptotic cumulative density function of the loss rate conditional on the systemic factor is given by (see e.g., Bluhm et al., 2003):

$$
\begin{aligned}
L(p_{jt}) &= P(P_{jt} < p_{jt}) \\
&= P(\Phi\left(\frac{c_{jt-1} - \sqrt{\rho\delta}X_t^* - \sqrt{\rho - \rho\delta}U_{jt}}{\sqrt{1-\rho}}\right) < p_{jt}) \\
&= P(\frac{\sqrt{\rho - \rho\delta}}{\sqrt{1-\rho}}U_{jt} > \frac{c_{jt-1} - \sqrt{\rho\delta}X_t^*}{\sqrt{1-\rho}} - \Phi^{-1}\left(p_{jt}\right)) \\
&= 1 - \Phi\left(\frac{c_{jt-1} - \sqrt{\rho\delta}X_t^* - \sqrt{1-\rho}\Phi^{-1}(p_{jt})}{\sqrt{\rho - \rho\delta}}\right) \\
&= \Phi\left(\frac{\sqrt{1-\rho}\Phi^{-1}(p_{jt}) + \sqrt{\rho\delta}X_t^* - c_{jt-1}}{\sqrt{\rho - \rho\delta}}\right)
\end{aligned} \tag{8}
$$

The marginal density function given the threshold from Equation (7) and conditional on the systemic factor X^* is as follows:

$$
\begin{aligned}
l(p_{jt}) &= \frac{dL(p_{jt})}{dp_{jt}} = \frac{dL(p_{jt})}{d\Phi^{-1}(L(p_{jt}))}\frac{d\Phi^{-1}(L(p_{jt}))}{dp_{jt}} \\
&= \phi\left(\frac{\sqrt{1-\rho}\Phi^{-1}(p_{jt}) + \sqrt{\rho\delta}X_t^* - c_{jt-1}}{\sqrt{\rho - \rho\delta}}\right)\frac{\sqrt{1-\rho}}{\sqrt{\rho - \rho\delta}}\frac{1}{\phi\left(\Phi^{-1}(p_{jt})\right)} \\
&= \frac{\sqrt{1-\rho}}{\sqrt{\rho - \rho\delta}} \cdot exp\left(0.5\Phi^{-1}(p_{jt})^2 - \frac{0.5\left(\sqrt{1-\rho}\Phi^{-1}(p_{jt}) + \sqrt{\rho\delta}X_t^* - c_{jt-1}\right)^2}{\rho - \rho\delta}\right)
\end{aligned} \tag{9}
$$

where $\phi(\cdot)$ is the probability density function of the standard normal distribution.

One may worry whether our standard normal assumption is able to reflect tail risk in relation to the variable of interest – here the loss rate. Our methodology falls into the model class of non-linear mixture models which are able to model heavy tails. This model and some variants are common in the credit risk literature. The Gaussian factor model can also be interpreted in terms of a Gaussian copula for the borrowers' asset returns or their default times (see Li, 2000). These models have also found recognition in the supervisory rules for determining regulatory capital of banks (i.e., Basel II and Basel III). The assumptions of normal distributions relate to the risk factors and the implied asset returns. Conditional on these factors we receive symmetric probability distributions. Mixing (i.e., probability-weighting) these distributions over the factors results in a heavily fat tailed mixed distribution for the loss rate, which is consistent with our priors. In other words, the resulting loss rate distribution given a positive parameter for δ and ρ implies a right skew and a fatter tail compared with the normal distribution. Note that δ and ρ are bounded between zero and one and empirical estimates are significantly positive (compare Table 3 and Table 4). Furthermore, the model allows time varying parameters for the loss rate distribution. The standard deviation of loss rates is mean dependent. Hence, the resulting residuals have time-varying standard deviations with a greater standard deviation during an economic downturn than during an economic boom.

Figure 1 highlights this aspect by illustrating two densities with correlations $\rho = 0.2$ and $\rho = 0.5$ as an example.[7] The densities are more heavily skewed for higher parameters. This illustrates that the chosen model framework and distributional assumptions are capable of modelling heavy tailed empirical distributions. A concern may remain that mixtures of Gaussian distributions are restrictive. However, Schloegl and O'Kane (2005) show that the percentiles, such as a Value-at-Risk, obtained from a Gaussian copula credit model and a student-T copula credit model are comparable, provided that the parameters are estimated for the same empirical data.

[insert Figure 1 here]

We estimate the model parameters by maximising the logarithm of the unconditional

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[7] δ is reflects the fraction of systematic risk which is systemic and hence does not have an impact on the density for systematic risk. $\delta = 0$ for simplicity in both instances.

likelihood $L(\cdot|\beta_{0j}, \beta_{1j}, \delta_j, \rho_j)$ with regard to realisations x_t^* of X_t^* using the adaptive Gauss-Hermite-Quadrature and the Newton-Raphson method. This likelihood is:

$$l(\cdot|\beta_{0,j}, \beta_{1,j}, \delta_j, \rho_j) = \prod_{t=1}^{T} \int_{-\infty}^{\infty} l(p_{jt}|\beta_{0,j}, \beta_{1,j}, \delta_j, \rho_j, x_t^*) \cdot \phi(x_t^*) dx_t^* \tag{10}$$

The individual bank is required to hold capital in relation to the relative Credit Value-at-Risk based on a regulatory confidence level α_r ($CrVaR_{jt}^{\alpha_r}$, regulatory capital). In other words, the bank capital is based on the percentile of its loss distribution. Note that all banks hold capital not equal to but in excess of this level, i.e., based on a confidence level α_e with $\alpha_e > \alpha_r$ ($CrVaR_{jt}^{\alpha_e}$, economic capital) .

A bank default is indicated by D_{jt}:

$$D_{jt} = \begin{cases} 1 & \text{bank } j \text{ gets into financial distress in } t \\ 0 & \text{otherwise} \end{cases} \tag{11}$$

We assume that a bank default occurs if the unexpected loss rate exceeds the economic capital:

$$D_{jt} = 1 \Leftrightarrow \underbrace{P_{jt} - E(P_{jt})}_{\text{unexpected loss rate}} > \underbrace{CrVaR_{jt}^{\alpha_e}}_{\text{economic capital}} \tag{12}$$

The unexpected loss rate is the realised loss rate minus the loss rate that is expected based on the above factor models via integration over Equation (6) and Equation (7) [8] CrVaR represents the Credit Value-at-Risk, which is also the internal basis of a bank's economic capital. Generally speaking, economic capital is higher than regulatory capital as banks

[8] Equation (13) approximates a bank's provisioning level. Current provision rules are generally based on IAS 39, which applies an expected loss definition. Going forward, IAS 39 will be replaced by IFRS 9, which is also based on an expected loss definition (compare Gaston and Song, 2014).

apply greater confidence levels and provide for a safety buffer. Prudential regulators require banks to retain earnings or raise additional capital if banks are likely to be undercapitalised (i.e., have economic capital levels below regulatory capital levels) and generally do not allow undercapitalised banks to operate.

$$E(P_{jt}) = \Phi\left(\beta_{0,j} + \beta_{1,j}\Phi^{-1}(p_{jt-1}) + \sum_{k=2}^{K}\beta_{k,j}z_{k,jt-1}\right) \tag{13}$$

The relative loss exceedance M_{jt} is:

$$M_{jt} = max(P_{jt} - E(P_{jt}) - CrVaR_{jt}^{\alpha_e}, 0) \tag{14}$$

where $P_{jt} - E(P_{jt})$ is the unexpected loss.

Note that in extensions, one may consider taking the capital buffer, i.e., the difference between the economic and regulatory capital, as threshold. In a going concern scenario a bank is required to continue to meet the regulatory capital requirements. In other words, such a bank would have to rely on some sort of subsidy to remain active, which may include contributions from investors (e.g., via a merger where the acquiring bank makes a contribution), bondholders, or eventually the taxpayers (e.g., via a deposit insurance scheme). We did not follow this approach as it requires the regulatory capital requirement for every bank which we are unable to access.

The financial system is characterised by the sum of loss exceedance amounts in the system

$$L_t = \sum_{j=1}^{J} w_{jt} \cdot M_{jt} \tag{15}$$

with weight w_{jt} (e.g., total assets), relative loss exceedance M_{jt}, and distribution function $G(.)$.

The financial system moves into distress if its VaR_t^γ given by

$$G(VaR_t^\gamma) = P(L_t < VaR_t^\gamma) = \gamma \tag{16}$$

is exceeded. The threshold γ or the expectation of exceedances of γ may be linked to the size of a protection mechanism such as a deposit insurance scheme or taxpayers' willingness to fund.

We compute the following systemic risk measures:

- Unconditional Value-at-Risk: VaR;
- Unconditional Expected Shortfall, i.e., conditional Value-at-Risk: CVaR;
- Value-at-Risk conditional on the failure of bank j: CoVaR(j);
- Conditional Expected Shortfall conditional on the failure of bank j: CoCVaR(j);
- Difference between Value-at-Risk conditional on the failure of bank j and unconditional Value-at-Risk: DeltaCoVaR(j);
- Conditional Expected Shortfall conditional on the failure of bank j: CoCVaR(j) and unconditional Expected Shortfall: DeltaCoCVaR(j).

Given the parameter estimates for the individual banks, the loss distribution of the system is simulated. All results are based on an estimation of the parameters and a simulation with two million iterations of the risk factors X_t^* and U_{jt}.

To forecast the unconditional and conditional loss distributions for credit portfolios, it is common to apply Monte Carlo simulations (see e.g., Gupton et al., 1997). We have chosen this technique to match the structure of a risk mechanism that (i) decomposes systematic risk into systemic and non-systemic risk, (ii) nets it with the risk mitigation provided by bank capital, and (iii) conditions on bank default. A simulation is necessary as no analytical solutions or approximations are available for such a structural framework. Furthermore, simulations are able to provide scenarios based on model parameters estimated with historic data, but result in different, possibly more adverse realisations than those actually observed. Future research may develop new methodologies that enable the processing of data in a more efficient fashion, which may include analytical, semi-analytical, or selective approaches such as importance sampling.

The simulation follows a number of steps for a single iteration after the parameters have been estimated. These steps are then repeated for two million iterations:

Step 1: Simulation of bank loss exceedances

In a first step, the systemic factor (one for all banks) and bank-systematic factors are simulated. The factors are assumed to be independent and standard normally distributed. The simulated future loss rates are then calculated based on the (i) the estimated parameters, (ii) observable time-lagged control variables for the last period of the data set, and (iii) simulated realisations of these random factors following Equation (6) and Equation (7). The unexpected losses are computed based on Equation (14) and the loss exceedences of unexpected losses relative to the capital levels of banks are computed following Equation (15).

Step 2: Aggregation to financial system losses

In a second step, the loss rates are weighted by gross loans to compute absolute losses per banks and the absolute losses are aggregated to the financial system by summing the realised losses for all banks in a financial system following Equation (14), which results in the distribution of financial system losses.

Step 3: computation of systemic risk measures

In a third step, the unconditional VaR and CVaR of the financial system are calculated by sorting the final system loss vector from low to high and recording the α-th percentile for VaR and the mean of losses in excess of this threshold for the Expected Shortfall CVaR. Then, iterations with losses exceeding the capital per bank are identified, collected and combined to a conditional loss vector. Furthermore, the conditional CoVaR and CoCVaR of the financial system per bank are computed by sorting the conditional loss vector from low to high and recording the α-th percentile for CoVaR and the mean of losses in excess of CoVaR for the Expected Shortfall CoCVaR. Lastly, DeltaCoVaR and DeltaCoCVaR are calculated for the financial system per bank as the difference between CoVaR and VaR, as well as, CoCVaR and CVaR.

3 Empirical Results

3.1 Data

We analyse the financial statements of Asian banks at the highest level of consolidation, generally bank holding companies for 17 economies: Australia, Bangladesh, China, Hong Kong, India, Indonesia, Japan, Korea (Republic of Korea), Malaysia, Pakistan, Philippines, Russia (Russian Federation), Singapore, Sri Lanka, Taiwan, Thailand and Vietnam. The reporting period covers the financial years from 1992 to 2010.

The bank financial data is from Bankscope. We filter the database for bank holding companies, commercial banks, cooperative banks, mortgage banks, and savings banks, confirming data consistency by manual reconciliation of annual reports and financial information collected from both Bloomberg and the Thomson Financial database. We take the bank financial statements of the greatest level of consolidation in the instance of multiple bank reports.

Note that exchange rates have a minor impact on the results as the model is based on financial ratios which are independent of exchange rates. Hence, the weighting of loss exceedances in Equation (15) is the only computation that is sensitive to the exchange rate. We convert the weight variable gross loans to USD using the exchange rate provided by Bankscope at the end of the 2009/2010 financial year, which is the last year in our study and basis for our simulation study. In total, our data covers almost $22 trillion in gross loans.

Some banks (generally smaller banks) may not have long time series to estimate bank-level parameters. We apply the parameters from an econometric model for all banks (see Table 3) but apply these parameters to all banks that we observe in the data for which we cannot estimate bank-level models in the last period.

We apply two filter rules:

- Filter Rule 1: We drop observations with missing values, and use this data set for our simulation study.
- Filter Rule 2: We drop banks which have fewer than ten observation periods.

Table 1 describes the number of banks before the application of filter rules and the total gross loans in 2010 by country before and after the application of the two filter rules.

[Table 1 about here.]

We report the fraction of gross loans for which we estimate a bank level model (see Filter 2 in Table 1, average over all countries: 72.9%) and the fraction of gross loans for which we are able to simulate and report systemic risk measures (see Filter 1 in Table 1, average over all countries: 94.9%). In summary, our economic findings should be interpreted with care. They apply to the majority of public banks that report financial accounts but not private banks and other financial service providers in a financial system. Private banks and lenders that do not have bank status as they are non-deposit-taking are not considered in this study.

We then calculate the loan loss provisions to gross loans (loss rate hereafter). We test bank charge-off rates with comparable results for the individual banks. We have a preference for loan loss provisions as this information is available for a greater number of (almost all) banks in our sample. Bank provisioning and capital allocation are subject to international standards (IAS 39/ IFRS9 for provisioning and the Basel regulations for capital). We confirm the validity of our models through statistical significance, economic plausibility and fit tests.

Figure 2 shows the mean loss rate per year (over all banks and countries) as well as the number of banks per year prior to the application of filter rules (compare Table 1 for the impact of filter rules). It is apparent that the South-East Asian Crisis in 1997 has lead to an increase in the average loss rate. Increases in the loss rates that exceed the expected loss rate based on a risk factor model explain the systemic risk in this paper. The number of banks has continuously increased over time. We include the size of banks in the financial system only for the last observation period. Therefore, changes in the number of banks and size of the financial system over time do not have, consistent with exchange rates, an impact on our estimation results. The GFC had no major impact on bank loss rates in Asia.

[Figure 2 about here.]

Table 2 shows in Panel A the descriptive statistics for the loss ratio, and bank fundamentals for all years. Panel B presents the Bravais Pearson correlation coefficients. Bank fundamentals include the capital ratio (total equity to total assets), liquidity (liquid assets to total assets), profitability (net income to shareholder equity), and loan growth (change of total loans relative over the past year) and real GDP growth pa.. The means and moments for loss rate and capital (e.g., mean for loss rate is 1.35% and the mean for capital is 13.84%) as well as the means and moments for other financial ratios are within our prior expectations.

The mean loan growth of developed economies and the credit growth of 14.05% is high and is a reflection of the economic growth in Asia relative to developed (Western) economies. [9] We have in total 5,462 annual bank observations in the sample. We note that all variables have low correlations.

[Table 2 about here.]

We include the probit transformed time-lagged loss rate so that the parameter estimates are on the same interpretation level and beta estimates between zero and one. All other financial ratios with the exception of the macro variable GDP are winsorised at the 5th and 95th percentile

3.2 Model estimation

The empirical model estimates parameters for the drivers of loss rates: the lagged loss rate, bank capital, liquidity, profitability, loan growth and real GDP. All covariates are lagged by one period to ensure that the models can provide forecasts. Furthermore, the parameters of frailty effects are estimated. Frailty is decomposed into a bank-systematic and a country-systemic component. This is economically sensible as banks provision for future losses and capital is allocated to cover unexpected losses, i.e., loss realisations in excess of provisioning. In essence, the systemic frailty is the co-variance of (i) the residual between the realised and the predicted loss rate, and (ii) the systemic factor, which is the average frailty effect for the financial system.

Table 3 shows the parameter estimates for the country-specific model. Table 4 shows the parameter estimates for the bank-specific model. In Table 4, Panel A shows the moments of the parameter distribution and Panel B the mean of the parameters by country. Bank-

[9] Note that the total assets and gross loans are reported on a bank level and differ from Table 1, which reports gross loans on the country level.

specific parameters can be estimated for 430 banks in the sample.

[Table 3 about here.]

[Table 4 about here.]

The parameter estimates fluctuate between the individual banks. We find that on average, banks' lagged loss rates have a positive impact and GDP a negative impact on the loss rates. The lagged loss rates are probit transformed as they enter a non-linear probit model and the resulting parameter estimates are bounded between zero and one, which reflects the degree to which past loss rate realisations are able to explain contemporary loss rate realisations.

The other risk drivers capital, liquidity profitability and loan growth are weaker. The number of available variables increases over time and more detailed financial ratios are often limited in availability over time. Fundamental factors need to be interpreted in relation to the lagged loss rate and real GDP growth which are the dominant factors and capture a large degree of loan portfolio specific risk characteristics and hence the realisation of historic business cycles. The signs of other variables is driven by inclusion/exclusion of these factors.

Figure 3, Figure 4 and Figure 5 show the average real fit diagrams, i.e., the average predicted, and average realised loss rate by country. In particular South-East Asian countries (i.e., Hong Kong, Indonesia, Korea, Malaysia, Philippines, Singapore and Thailand) experienced an increase in the loss rates during the South-East Asian crisis, which our models (mainly through the lagged loss rate) reflect with a lag. This is reasonable as banks increase provisions in the aftermath of financial crises. Other countries have experienced increases in loss rates in other years.

Note that the start year in terms of data availability is different across countries as a reflection of financial market development.

[Figure 3 about here.]

[Figure 4 about here.]

[Figure 5 about here.]

The systemic exceedance of the realised loss rate relative to the model-implied loss rate is measured by the ρ parameter for systematic risk and the δ parameter for the degree of systemic risk within systematic risk (see Equations (1) to (3)). Chart 6 shows the Bayes estimates of the systemic risk factor X^* by country. The Southeast Asian Crisis resulted in a negative factor for Southeast Asian countries and hence higher loss rates than implied by our models. Note that X^* enters in a negative fashion so that a smaller factor implies a higher loss rate (see e.g., Equation (6)).

[Figure 6 about here.]

3.3 Analysis of measures for systemic risk

We simulate two million iterations of the risk factors X_t^* and U_{jt}. These numbers are sufficient to ensure convergence.[10] Conditional on the simulated values, we compute the values for loss per bank and the loss of the financial system as the sum of all bank losses. We then compute the various measures for systemic risk by analysing moments of the simulated complete distributions or conditional distributions.

Figure 7 shows the cumulative loss distribution for a financial system and the system Value-at-Risk (VaR). We measure VaR unconditionally and conditionally on individual bank failures (CoVaR). In addition, we compute Expected Shortfall (CVaR) as the expected loss

[10] Our convergence criteria was a variation of less than 0.1% in both the Value-at-Risk and Expected Shortfall when doubling the number of iterations (i.e., from 250,000 to 500,000 to 1 million to 2 million).

in excess of VaR.

[Figure 7 about here.]

From these other absolute systemic risk measures will be derived. Firstly, we compute conditional measures: CoVaR and CoCVaR are system measures conditional on the loss exceedance of the respective bank. CoVaR is the VaR conditional on the default of a praticular bank and CoCVaR is the Expected Shortfall conditional on the default of a particular bank. The conditional risk measures are higher than the unconditional risk measures as they condition on an adverse economic state. Furthermore, conditional measures are bank-specific and we report the moments of the empirical distribution and the mean measure by country.

Secondly, we compute the differences between conditional measures and unconditional measures. DeltaCoVaR and DeltaCoCVaR is the difference between the conditional and unconditional risk measure. [11] These measures are, like the underlying conditional measures, bank-specific and we report the moments of the empirical distribution and the mean measure by country.

Table 5 describes the empirical distribution for the exceedance ratio and the systemic risk measures by country (Panel A) and the mean values by country (Panel B) for one-year loss rates. The exceedance ratio is the numbers of loss exceedances over the number of iterations. The ratio is on average 1.05% (with the 1st percentile of zero and the 99th percentile of 18.51%).

The systemic risk measures are based on the 99th percentile. In the tables, Panel A describes the moments for all banks and Panel B the mean systemic risk measures by country.

[Table 5 about here.]

[11] Adrian and Brunnermeier (2011) propose the CoVaR given the median state of a financial institution. We follow this approach but assume that CoVaR given the median state of a financial institution is equal to the unconditional VaR of the financial system.

The number of observations represents the number of banks that experience a positive loss exceedance (relative to economic capital) and is smaller than the total number of banks. Systemic risk may be measured by the system Value-at-Risk (VaR) or Expected Shortfall (Conditional VaR) which is the mean of all losses exceeding the VaR. For example the VaR of China is \$86 billion and the Expected Shortfall (CVaR) is \$142 billion based on a confidence level of 99%. These numbers may be interpreted as the size of a financial protection scheme that ensures that all loss exceedances are covered up to the 99th percentile. The VaR and CVaR for countries may be interpreted analogously. Potential applications may be the definition of minimum fund sizes for deposit insurance schemes and fees to protected banks by prudential regulators. Also, the size and economic value of explicit and implicit government guarantees (i.e., for too-big-to fail institutions) may be assessed as a basis for potential levies.

Furthermore, the CoVaR measures the VaR of the financial system if a particular bank has experienced a loss exceedance. It is a measure of co-movement of the particular bank and the financial system and bank-specific. DeltaCoVaR is the difference between the CoVaR and the VaR of the financial system and describes the degree by which a bank's loss exceedance increases the system VaR. We report average CoVaR and DeltaCoVaR for countries throughout the paper. For example the CoVaR for China is \$150 billion and the DeltaCoVar follows with \$64 billion (i.e., \$150 billion less \$86 billion). These measures are analogous for Expected Shortfall (CVaR) and indicate the systemic risk of individual financial institutions or the appropriate size of a financial protection scheme that ensures that all loss exceedances are covered up to the 99th percentile conditional on a bank's failure.

In our view, financial system protection schemes may be based on the VaR or CVaR measure as these are unconditional (ex-ante) measures for future absolute loss levels. The bank-specifc systemic measures CoVaR and CoCVaR, DeltaCoVaR and DeltaCoCVaR may serve regulators as bank-specific measures of systemic risk and the formulation of bank-specific policies. Such bank-specific measures are generally confidential due to their impact on competition in financial markets.

Note that whilst the Expected Shortfall (CVaR) is equal or greater than VaR and the conditional measures (CoVaR and CoCVar) are asymptotically always equal or greater than the unconditional measures (VaR and CVaR), while the difference between conditional and unconditional measures may be lower or greater than the constituents. VaR and CVaR are identical for all banks of a system (here a country) and the conditional measures (CoVaR, CoCVar, DeltaCoVaR and DeltaCoCVar) are bank-specific as they condition on the loss exceedance of the individual bank.

Table 6 shows the systematic risk if losses accumulate over a three year period. Panel A shows the moments of systemic risk measures Panel B the mean systemic risk measure by country. The analysis of a three year period is interesting from a financial system resilience perspective as banks may be unable to recapitalise for such an extended period during economic downturns and capital should be able to cover such multi-period losses. We compute the three year loss rate by assuming that the one-year loss rate is persistent over three consecutive years. The three year scenario may be interpreted as a stress test to test the degree to which current capital levels provide coverage under a severe adverse loss scenario. As a result, the systemic risk measures increase. For example the VaR of China is $371 billion (an increase of 431% relative to the one-year loss scenario) and the Expected Shortfall (CVaR) is $142 billion (an increase of 380% relative to the one-year loss scenario).

[Table 6 about here.]

In summary, the exceedance ratios and systemic risk measures are substantially higher if loss rates accumulate over three consecutive periods and banks are not able to recapitalise.

In aggregate, the sum of the value at risk measures is $127 billion (i.e., the sum over all values in the VaR column, in Table 5, Panel B, assumptions one-year loss rate and 99% confidence level). These numbers may be interpreted as being consistent with the Global

Financial Crisis in the US where the Federal Deposit Insurance Corporation (FDIC) covered losses of approximately $70 billion. The relation of system losses of $127 billion to the US realised number of $70 billion may be explained by the greater size of the aggregate Asian banking system (approximately $21 trillion in gross loans, see Table 1) than the US (approximately $10 trillion in gross loans). Whilst there are many differences between the US and Asia, we consider this to be anecdotal evidence for the model's reliability and an appropriate benchmark for further research on Asian banking systems.

This ad hoc comparison should be read with some care. First, every crisis is a non-reoccurring event and it is difficult to attach a likelihood for the GFC. Laeven and Valencia (2008) and Bordo et al. (2001) identify a number of major crises in the past one hundred years and the frequency of a major crisis may be higher than one percent, which is the value that we have based our simulation study on. Second, the risk horizon of the crisis (two years) may be offset by a greater financial system in Asia (about twice the size of the US). Our assumption of loss rate persistency over longer periods of time is empirically untested. In severe economic downturns, capital markets may remain severely constrained for multiple periods and it is likely that capital may have to cover the losses of multiple periods before a bank recapitalisation may occur (we analyse the role of multi-year losses above). Third, we assume that economic capital is available to cover losses, which assumes bank liquidation to cover losses. It is likely in severe economic downturns that losses that do not exceed the economic capital but exceed the capital buffer are passed on to a safety net to ensure that banks continue to provide financial services to an economy. In other words, actual losses may be higher as only a fraction of bank capital may be available for risk cover. We are unable to analyse capital buffers (i.e., the difference between economic and regulatory capital) as we do not have robust data for regulatory capital.

Furthermore, we are interested in analysing the drivers for systemic risk and regress the ratio of our systemic risk measures to total gross loans of a country on the input factors to analyse the direction and relative importance of their economic impact. The input factors are the various exogenous variables that generate the systemic risk measure. Table 6 shows the results of this analysis:

[Table 7 about here.]

The systemic measures VaR, CVaR, CoVaR, CoCVaR, DeltaCoVaR, DeltaCoCVaR are included relative to the total gross loans to control for size. The unconditional systemic risk measures VaR and CVaR increase with the loss rate as the overall loss risk is higher. However, the conditional systemic measures DeltaCoVaR and DeltaCoCVaR decrease with the loss rate as a lower loss rates implies that if a bank fails it is more likely that the economy is experiencing a major downturn and that (many) other banks will fail at the same time. Capital has as expected a negative effect on the VaR and CVar and a positive effect for the conditional bank-specific systemic risk measures CoVaR, CoCVaR, DeltaCoVaR, DeltaCoCVaR. The explanation for the latter is similar in nature to the one of the loss rate as it provides coverage for losses: if capital levels are exceeded it is likely that the economy is experiencing a major downturn and that many other banks will fail at the same time. The parameters ρ and δ have a positive impact on all systemic risk measures.

4 Conclusion

This paper develops a bank model for systemic risk in bank lending. The model analyses the impact of financial institutions' failure on the distribution of losses in the financial system. Financial institutions fail when unexpected losses exceed the capital. Failed financial institutions pass these loss exceedances on to creditors, deposit insurance schemes and the general public. The benefits of the presented model framework are (i) the measurement of systemic frailty, and (ii) the measurement of the size of safety nets in terms of attachment likelihood and expected losses given attachment. The model is generally applicable as it does not rely on financial market data. The parameter estimation is based on a novel maximum likelihood technique to derive the parameters in a non-linear mixed model with multiple random effects.

The key findings of this paper are that bank loss rates can be decomposed in observable fundamental and macroeconomic factors, as well as systematic and systemic frailty. Banks' loss rates tend to co-move with the time lagged loss rate and in opposite with real GDP growth. The other variables of capital, liquidity, profitability and loan growth, are of a lower importance.

Cerutti et al. (2012) and others point out that systemic risk may be driven by many institutional characteristics, which implies that the systemic risk measures derived in this paper should be interpreted in conjunction with other systemic relevant information such as counterparty relationships in over-the-counter (OTC) transactions, borrower-lender relationships, or client-service provider relationships.

These results need to be read with care. Whilst simulation studies such as ours are able to simulate economic downturn events that are more severe than the ones observed in the training sample, the parameters that we base our conclusions on are estimated from historic data. Some countries in our study have experienced a severe economic downturn (i.e., the South-East Asian crisis) while others have not. The results are based on the assumption that historic observations are representative for future economic outcomes and further research may verify this assumption.

For the implementation of the proposed models, regulators may formulate confidence levels and potentially refine the models outlined in this paper by a more sophisticated differentiation of bank capital (Tier 1, Tier 2 and capital buffer) that we are unable to provide due to data limitations on regulatory capital.

Going forward, financial institutions may be asked to disclose and hedge such exposures. For example, counterparty credit risk in OTC transactions will be mitigated through centralised clearing systems. However, the systematic and systemic nature of bank lending is difficult to mitigate directly through regulation as it relates to the basic functions financial institutions provide in economies and hence the reason for their existence. Banks are exposed and likely to remain being exposed to systemic risk through similar asset portfolio characteristics and related exogenous shocks.

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Figures

Fig. 1. Portfolio default rate distribution resulting from the Gaussian Copula model

This figure shows the densities of the portfolio default rates for a default probability of 5% and asset correlations $\rho = 0.2$ and $\rho = 0.5$. The densities are more skewed for higher correlation. This illustrates that the chosen model framework and distributional assumptions are able to model heavy tailed empirical distributions (here with positive skew).

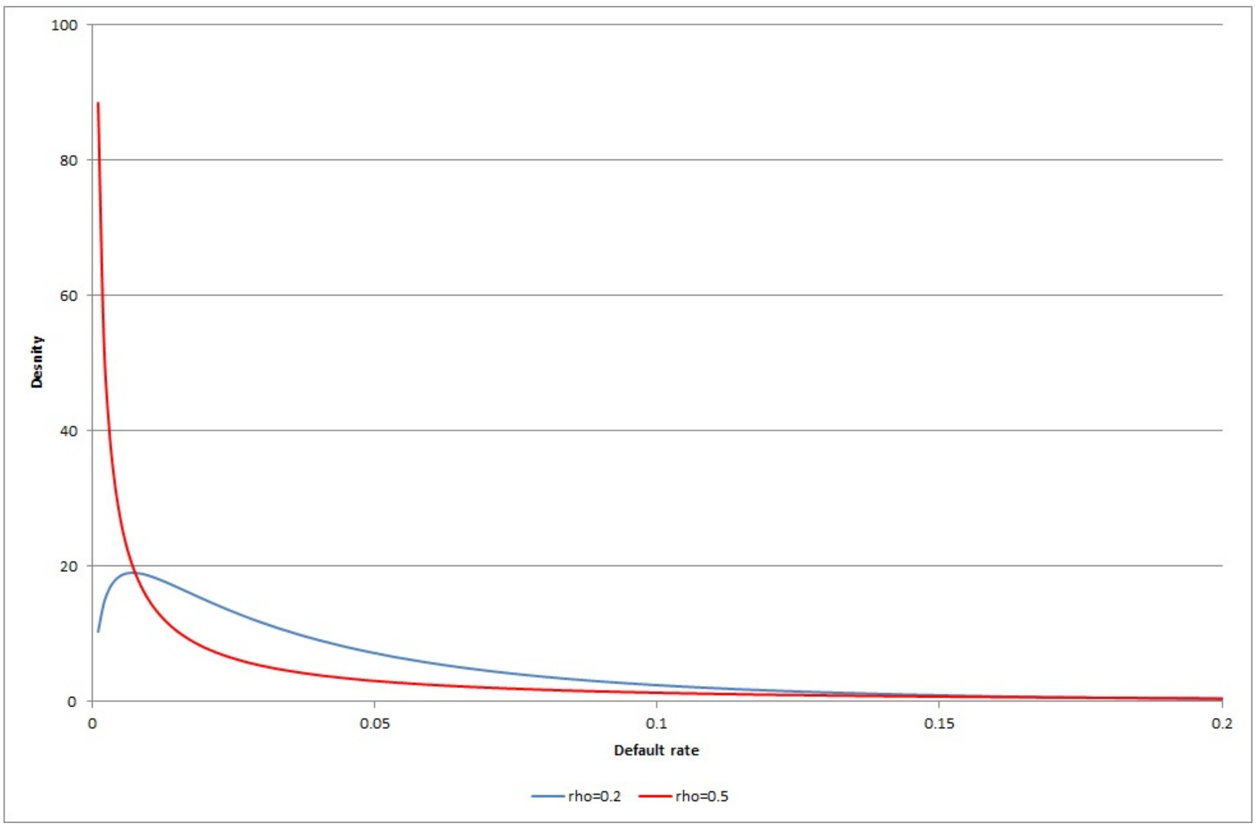


Fig. 2. Average loss rate and number of banks over time

This chart shows the loss rate and number of banks over time. The Southeast Asian crisis led to an increase of bank losses in 1998 while the Global Financial Crisis in 2008/2009 had no impact on Asian banks. The number of banks is based on the raw data prior to the application of data filters (Filter Rule 1 and Filter Rule 2).

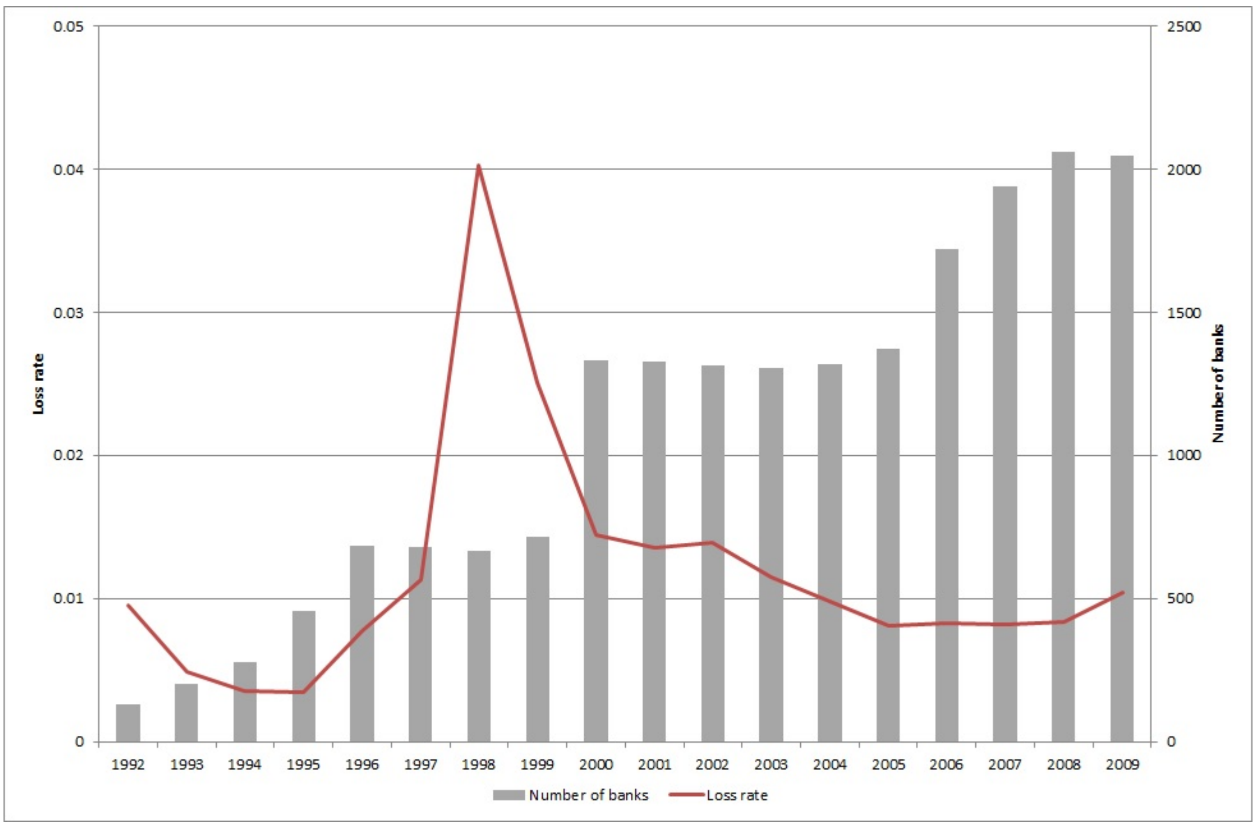


Fig. 3. Real fit diagrams: average predicted and average realised loss rate, by country

These charts show the real fit diagrams, i.e., the average predicted, and average realised loss rate by country using the country level models (see Table 3). Predicted loss rates fall short of realised loss rates during major economic downturns, in particular during the Southeast Asian Crisis in 1997/98 for Southeast Asian countries.

Fig. 4. Real fit diagrams: average predicted and average realised loss rate, by country (cont.)

These charts show the real fit diagrams, i.e., the average predicted, and average realised loss rate by country. Predicted loss rates fall short of realised loss rates during major economic downturns, in particular during the Southeast Asian Crisis in 1997/98 for Southeast Asian countries.

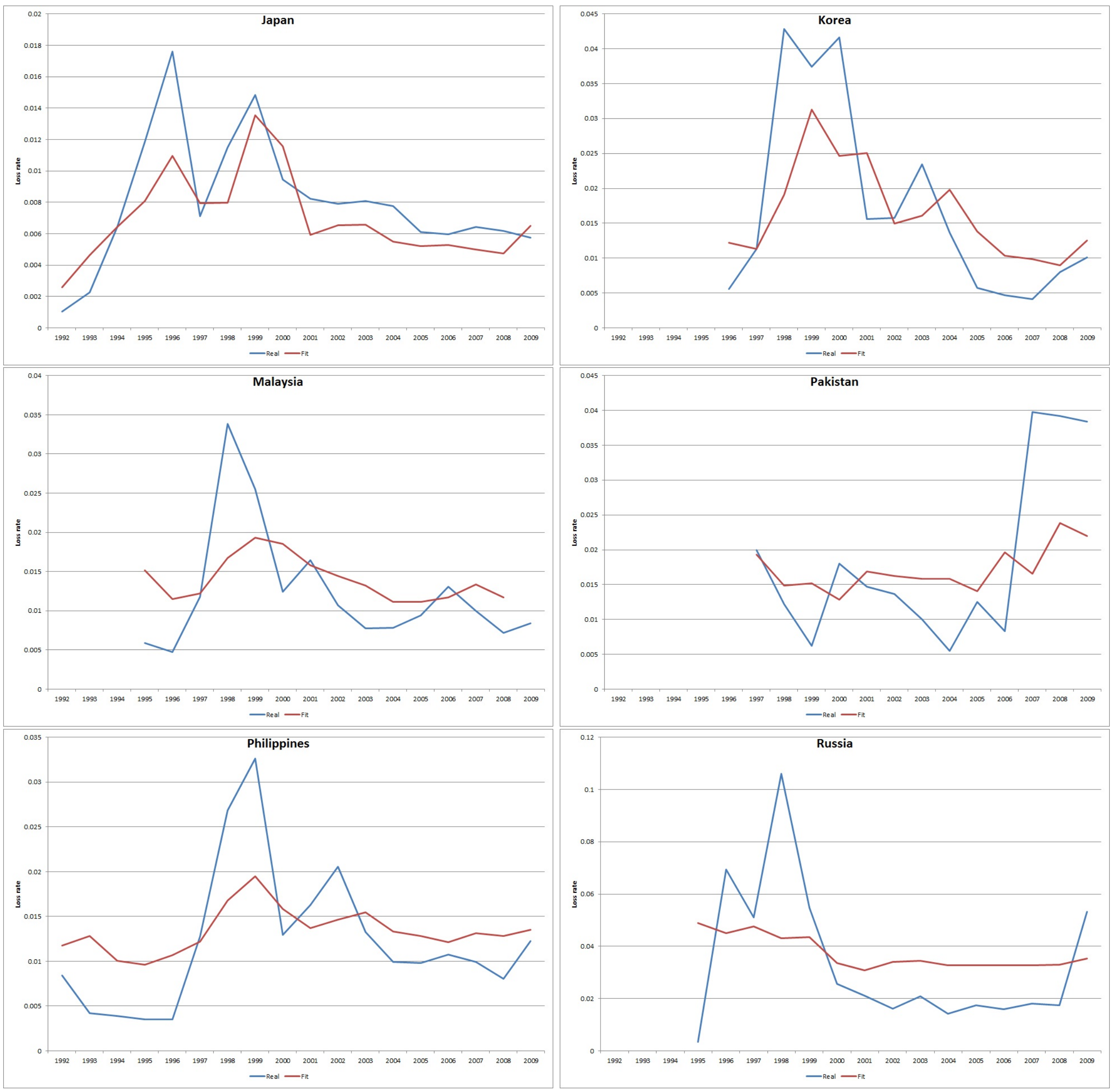


Fig. 5. Real fit diagrams: average predicted and average realised loss rate, by country (cont.)

These charts show the real fit diagrams, i.e., the average predicted, and average realised loss rate by country. Predicted loss rates fall short of realised loss rates during major economic downturns, in particular during the Southeast Asian Crisis in 1997/98 for Southeast Asian countries.

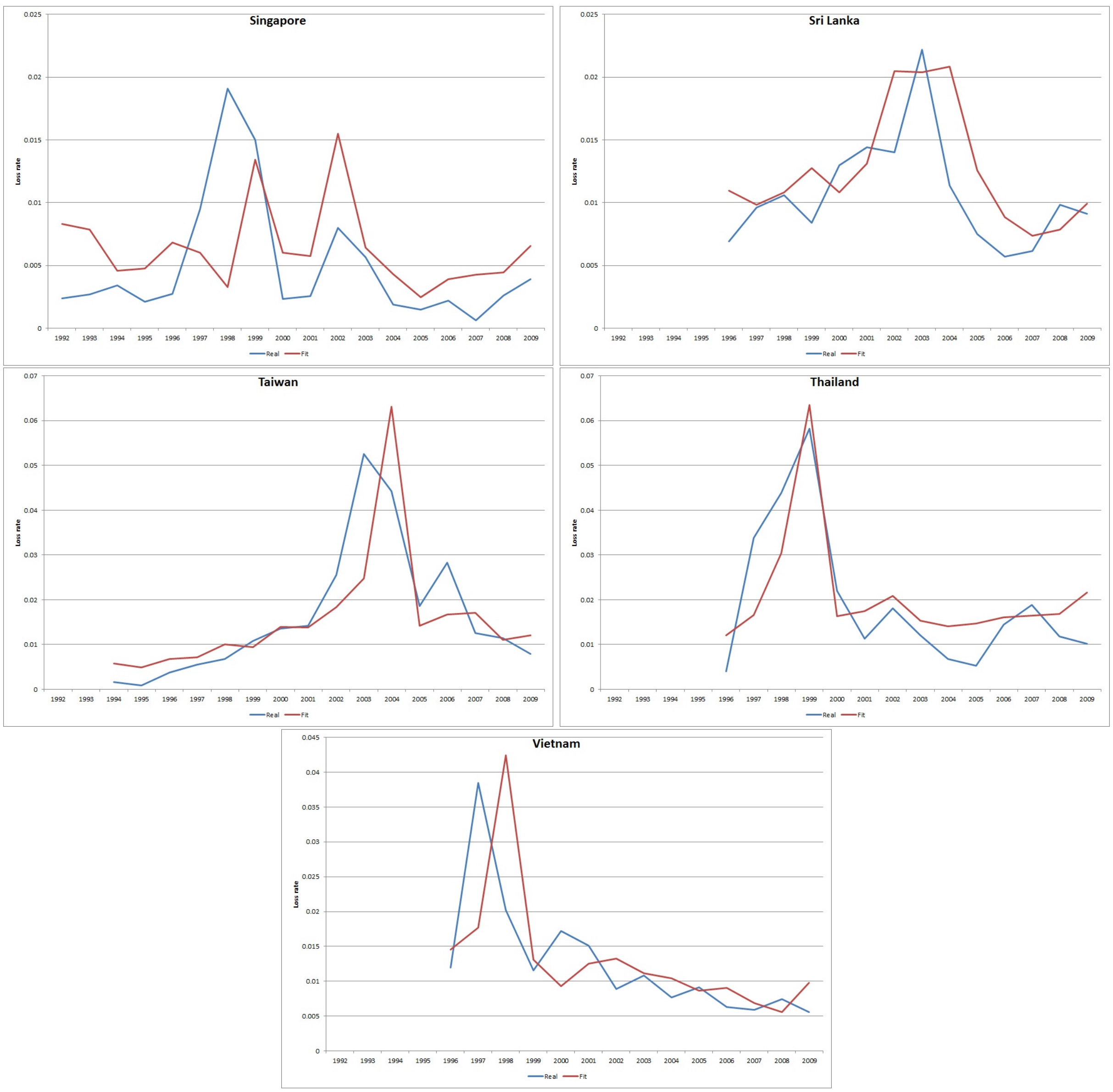


Fig. 6. Systemic factors by country

This chart shows the systemic factors by country. The Southeast Asian Crisis resulted in a positive factor for Southeast Asian countries. Systemic risk is measured by the exposure to systemic frailty, i.e., the systemic deviation of bank loss rates from predicted loss rates. This in essence is the co-variance of the residual between the realised and predicted loss rate and the systemic factor which is the average frailty effect for the financial system.

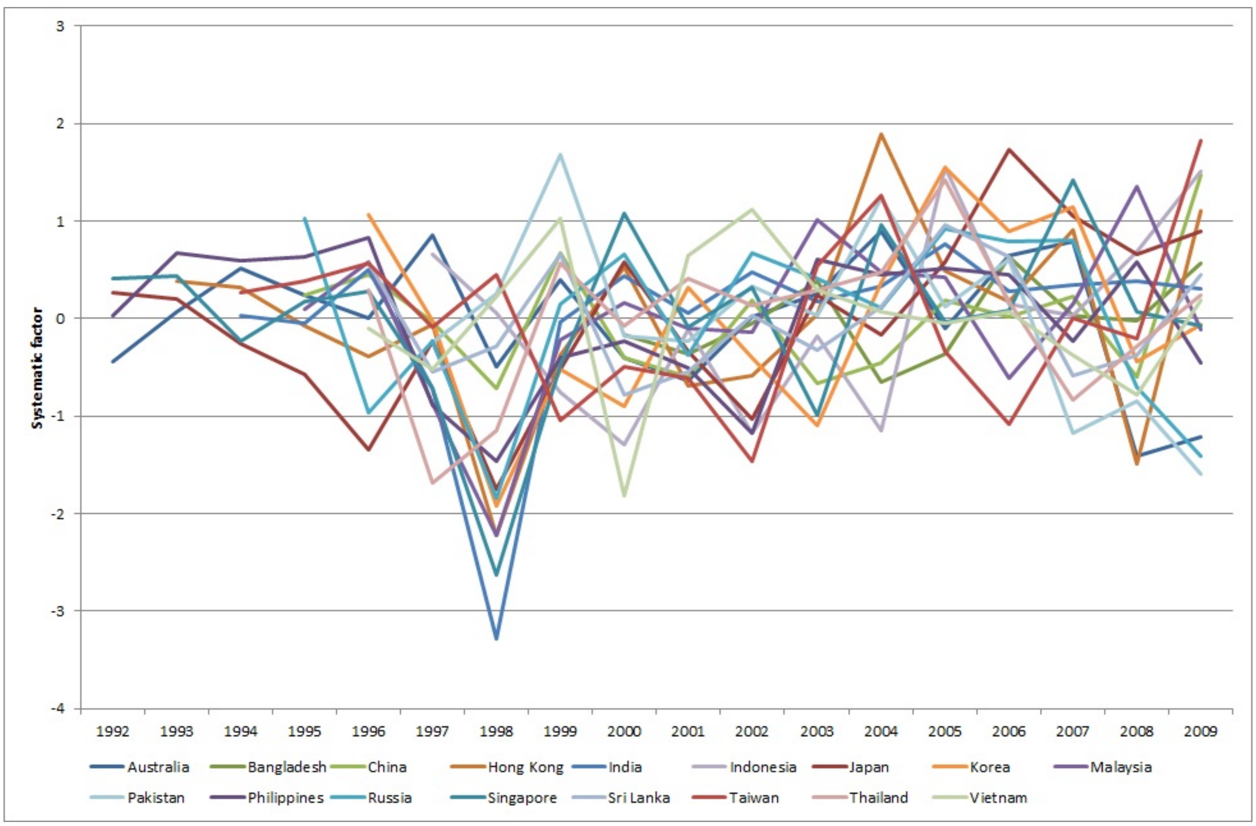
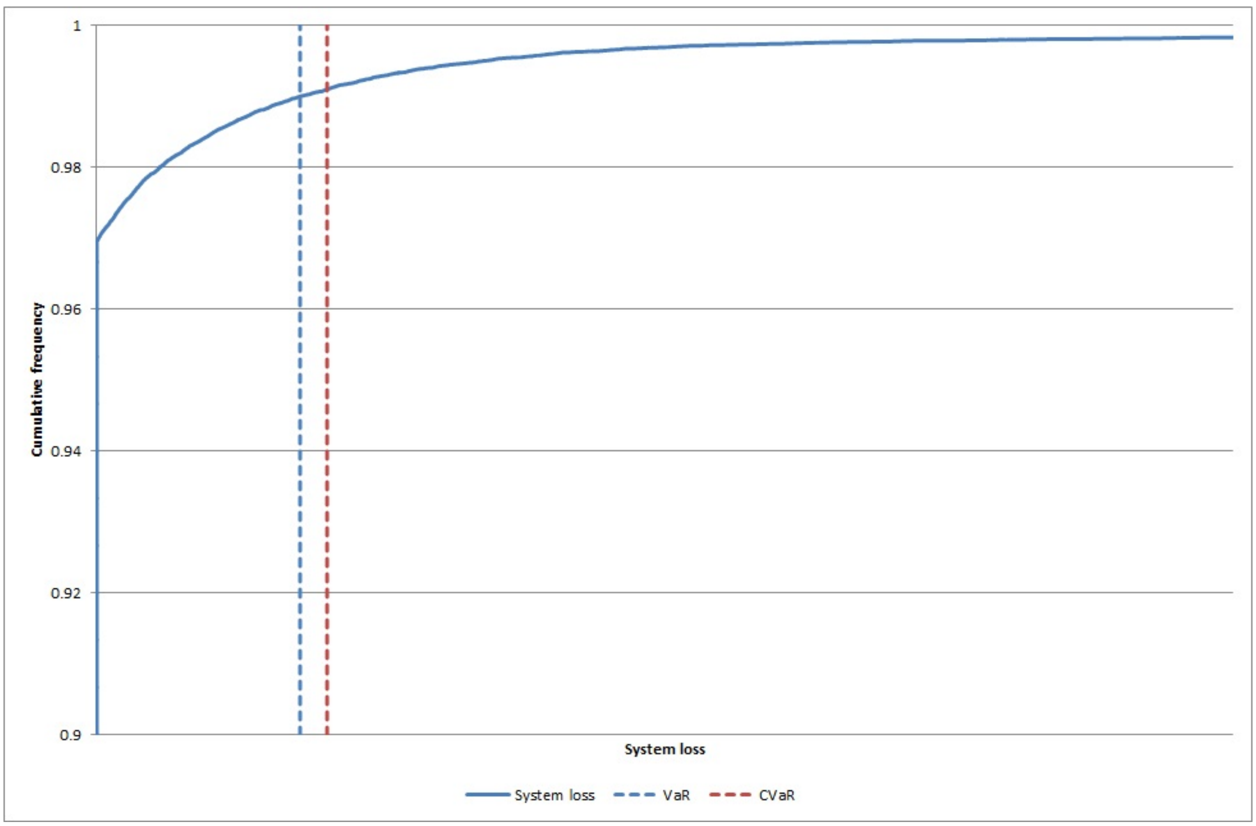


Fig. 7. System loss, Value-at-Risk and Expected Shortfall

This chart shows the cumulative frequency for the system loss, VaR and Expected Shortfall (CVaR) and conditional on a bank's default. System losses are based on a Monte Carlo simulation.



Tables

Table 1
Asian financial systems

This table shows the number of banks and gross loans as well as the relative gross loans included in this study after filtering rules. Filter Rule 1 is applied to the simulation analysis and Filter Rule 2 is applied to the model estimation.

Country	**Banks**	**Gross loans**	**Gross loans (filter 1)**	**Gross loans (filter 2)**
Australia	30	1,824,528,900,000	99.7%	94.1%
Bangladesh	32	30,727,446,821	81.6%	46.8%
China, People's Republic	96	5,164,222,700,000	99.0%	72.1%
Hong Kong	29	554,334,904,032	95.4%	71.6%
India	65	654,358,056,081	83.6%	65.3%
Indonesia	52	138,302,920,246	97.0%	70.9%
Japan	585	9,236,636,700,000	98.2%	50.4%
Korea, Republic of	19	1,226,339,500,000	99.9%	65.0%
Malaysia	36	375,871,073,855	99.9%	84.5%
Pakistan	24	37,092,467,122	100.0%	89.7%
Philippines	27	51,325,393,609	99.6%	93.5%
Russian Federation	923	687,880,425,606	62.3%	42.4%
Singapore	13	331,899,558,261	99.8%	96.7%
Sri Lanka	13	11,756,169,249	100.0%	89.5%
Taiwan	51	951,326,311,123	93.3%	58.2%
Thailand	20	235,740,703,935	100.0%	96.1%
Vietnam	32	65,590,984,975	98.8%	48.5%
Sum/average	2,047	21,577,934,214,915	94.6%	72.7%

Table 2
Variable description

This table shows descriptive statistics (Panel A) and Bravais Pearson correlations (Panel B) for key variables.

Panel A: Descriptive statistics							
Moment	**Loss rate**	**Capital**	**Liquidity**	**Profitability**	**Loan growth**	**GDP**	**Gross loans**
Mean	0.0135	0.1384	0.1639	0.0788	0.1405	0.0369	20,139,029,484
P1	0.0001	0.0399	0.0382	-0.2485	-0.0877	-0.0736	16,063,009
P25	0.0030	0.0676	0.0781	0.0255	0.0020	0.0169	1,064,190,404
P50	0.0065	0.1010	0.1287	0.0761	0.0683	0.0389	4,848,509,087
P75	0.0137	0.1669	0.2246	0.1597	0.2312	0.0614	14,600,128,221
P99	0.1247	0.4402	0.4344	0.2870	0.6738	0.1073	308,295,865,341
N	5,462	5,462	5,462	5,462	5,462	5,462	5,462
Panel B: Correlations							
Variable	**Loss rate**	**Capital**	**Liquidity**	**Profitability**	**Loan growth**	**GDP**	**Gross loans**
Loss rate	1.0000	0.0931	0.1176	-0.1094	-0.0226	-0.0352	-0.2496
Capital	0.0931	1.0000	0.5658	0.2148	0.2645	-0.1347	0.1739
Liquidity	0.1176	0.5658	1.0000	0.2655	0.2964	-0.1065	0.2230
Profitability	-0.1094	0.2148	0.2655	1.0000	0.3584	-0.0436	0.3473
Loan growth	-0.0226	0.2645	0.2964	0.3584	1.0000	-0.0923	0.3561
GDP	-0.0352	-0.1347	-0.1065	-0.0436	-0.0923	1.0000	0.0161
Gross loans	-0.2496	0.1739	0.2230	0.3473	0.3561	0.0161	1.0000

Table 3

Parameter estimates for the system-level model

Table 3 shows the parameter estimates for financial systems. Significance levels are *** significant at 1%, **: significant at 5% and *: significant at 10%.

System	**Intercept**	**Loss rate**	**Capital**	**Liquidity**	**Profitability**	**Loan growth**	**GDP**	**delta**	**rho**
Australia	-1.7396***	0.4686***	1.6937**	1.9344***	0.5456**	0.0863	-3.742*	0.0631	0.0725***
Bangladesh	-1.2975***	0.3169***	-0.8961	-0.3694	-0.0308	0.1077	-2.0045	0.0142	0.0813***
China	-1.7016***	0.2982***	-0.6343*	0.2952	-0.1524	-0.2424*	0.7978	0.0522	0.0681***
Hong Kong	-0.9662***	0.5896***	-0.1127	0.3676	-0.6181*	0.088	0.0105	0.3582***	0.1251***
India	-0.874***	0.4251***	0.3555	-1.0275**	-0.2617	-0.094	-3.7214*	0.1632**	0.1072***
Indonesia	-1.1672***	0.2121***	-0.4071	-0.3147	-0.55*	0.2264	0.1771	0.2587***	0.401***
Japan	-1.245***	0.3849***	-1.6652***	-0.526***	0.2625**	0.3243**	-4.2384**	0.0706**	0.11***
Korea	-1.3754***	0.3644***	-0.4727	0.6778	-0.3444*	0.3803**	-0.6348	0.418***	0.0753***
Malaysia	-1.0094***	0.4512***	-0.52*	-0.4655	0.2639	0.0436	0.6479	0.0891*	0.1696***
Pakistan	-1.5189***	0.2864***	0.107	0.0747	-0.2579	-0.0934	2.2911	0.1565*	0.2193***
Philippines	-1.1034***	0.3309***	-0.8764***	-0.3806	0.0379	0.0187	-0.3193	0.0512	0.1686***
Russia	-1.6019***	0.0721	0.2598	-0.3338	0.2706	-0.0511	-0.6504	0.1662**	0.3369***
Singapore	-2.757***	0.0128	-0.0561	0.9345*	3.2212*	0.3277	-4.804**	0.449***	0.1362***
Sri Lanka	-1.2082***	0.4679***	0.0748	0.5312	-0.5712*	0.1833	-1.7051	0.0474	0.1012***
Taiwan	-0.5776***	0.6787***	-0.2213	-0.3025	0.8905***	0.1733	-1.2289	0.1082**	0.1045***
Thailand	-1.7155***	0.0678	-0.3368	0.0567	0.4558	-0.2965	-3.8924***	0.0849	0.2315***
Vietnam	-0.826	0.3321***	-1.0875*	-0.5088	-0.5714	-0.3608*	-2.461	0.1752	0.1415***

Table 4
Parameter estimates for the bank-level model

This table shows the parameter estimates for the bank-specific model. Panel A shows the moments of the parameter distribution and Panel B the mean of the parameters by country. Bank-specific parameters can be estimated for 430 banks in the sample.

Panel A: Moments of parameter estimates

Parameter	Intercept	Loss rate	Capital	Liquidity	Profitability	Loan growth	GDP	delta	rho
Mean	-1.7691	0.2586	0.0349	0.6475	0.1564	0.2865	-2.7060	0.4648	0.1197
P1	-7.2477	0.0000	-35.1578	-13.6773	-17.0130	-7.9507	-27.5475	0.0000	0.0050
P25	-2.4907	0.0000	-3.0853	-1.6370	-1.1896	-0.6521	-5.6922	0.0061	0.0321
P50	-1.8472	0.1358	0.4819	0.6214	0.4902	0.1658	-1.5987	0.5567	0.0739
P75	-0.8779	0.4372	2.4106	2.1618	1.5534	0.9841	1.0022	0.7767	0.1638
P99	2.7415	1.0000	46.6036	20.1026	11.0440	10.3081	20.7816	0.9939	0.6660
N	430	430	430	430	430	430	430	430	430

Panel B: Mean parameter estimates by country

Parameter	Intercept	Loss rate	Capital	Liquidity	Profitability	Loan growth	GDP	delta	rho
Australia	-2.0436	0.3099	1.9182	1.405	0.265	0.1438	-5.6169	0.489	0.06389
Bangladesh	-0.6514	0.349	-7.0639	0.1339	-1.4873	0.07007	1.2076	0.5011	0.09917
China	-2.4841	0.1685	-0.26	0.7589	-0.5284	0.2716	5.1853	0.5302	0.09348
Hong Kong	-2.4837	0.4194	1.6177	1.8708	-0.5785	0.2022	-1.0537	0.626	0.0786
India	-1.2414	0.3796	-0.4533	-0.3142	-0.07395	0.04625	-2.2163	0.5486	0.07959
Indonesia	-1.484	0.1654	-1.3701	0.5819	-1.2452	0.4809	-0.5295	0.6045	0.3178
Japan	-2.0023	0.2347	0.859	0.6007	0.6668	0.5504	-5.0948	0.3344	0.08115
Korea	-1.149	0.3892	-2.3634	0.5501	-0.213	0.256	-1.0945	0.7492	0.07088
Malaysia	-2.6927	0.205	2.7388	1.5356	-0.2512	0.1711	-0.3992	0.5004	0.1012
Pakistan	-1.7474	0.24	-0.7359	0.9035	-0.5115	0.1861	0.4702	0.6182	0.1536
Philippines	-1.3879	0.1623	-1.5377	-0.3639	1.4244	0.03822	-3.5938	0.414	0.1502
Russia	-1.9833	0.1024	0.05778	0.4993	0.2664	0.04924	0.321	0.4931	0.2148
Singapore	-2.8656	0.2073	1.3081	0.1523	5.0583	0.4719	-4.0878	0.7961	0.1382
Sri Lanka	-1.3078	0.4186	0.3681	0.1915	-1.2893	0.2467	-0.4967	0.5522	0.1165
Taiwan	-1.6554	0.3881	1.1915	1.7743	0.537	0.3741	-0.386	0.4161	0.07796
Thailand	-1.4046	0.1333	-0.9717	-0.8274	1.4826	-0.6708	-6.0034	0.3507	0.1516
Vietnam	0.8988	0.4649	-4.0655	2.2174	-3.1562	0.09397	-16.8344	0.6139	0.2201

Table 5

Systemic risk measures

The systematic risk measures are computed for the 99th percentile and two million iterations. Panel A shows the moments of systemic risk measures Panel B the mean systemic risk measure by country. The exceedance ratio is the number of loss exceedances over the number of iterations. VaR is the Value-at-Risk, CVaR is the Expected Shortfall, VaR and CVaR are unconditional measures. CoVaR and CoCVaR are conditional on the loss exceedance of the respective bank (the table shows the distribution over all banks). DeltaCoVaR and DeltaCoCVaR is the difference between the conditional and unconditional risk measure.

Panel A: Moments of systemic risk measures							
Parameter	**Exceedance ratio**	**VaR**	**CVaR**	**CoVaR**	**CoCVaR**	**DeltaCoVaR**	**DeltaCoCVaR**
Mean	0.0113	17,435,942,696	30,580,526,710	54,268,379,109	68,118,454,130	36,832,436,414	37,537,927,420
P1	0.0000	-	7,294,758	83,288,833	83,288,833	- 41,138,137,064	- 97,401,849,804
P25	0.0000	5,191,739,837	8,505,379,406	9,381,432,118	11,518,555,629	3,693,003,448	2,360,284,548
P50	0.0004	23,081,967,728	41,390,268,177	45,018,119,258	51,758,417,673	27,672,584,727	28,840,774,978
P75	0.0049	23,081,967,728	41,390,268,177	74,909,117,295	103,059,759,722	51,494,799,266	60,548,182,070
P99	0.1995	85,970,210,948	142,233,923,689	317,793,840,740	317,793,840,740	294,711,873,012	269,448,246,174
N	708	708	708	708	708	708	708
Panel B: Mean systemic risk measures by country							
Parameter	**Exceedance ratio**	**VaR**	**CVaR**	**CoVaR**	**CoCVaR**	**DeltaCoVaR**	**DeltaCoCVaR**
Australia	0.0034	1,245,487	9,479,923	566,867,392	612,515,865	565,621,905	603,035,943
Bangladesh	0.0182	1,233,988,731	1,440,122,715	1,483,369,320	1,512,736,592	249,380,589	72,613,877
China	0.0018	85,970,210,948	142,233,923,689	139,476,336,872	149,791,334,481	53,506,125,924	7,557,410,792
Hong Kong	0.0000	-	7,294,758	2,972,460,048	3,202,474,683	2,972,460,048	3,195,179,925
India	0.0102	1,644,571,754	2,936,066,539	8,060,066,273	9,008,055,209	6,415,494,520	6,071,988,670
Indonesia	0.0359	5,523,409,124	8,505,379,406	19,539,434,358	22,712,229,282	14,016,025,234	14,206,849,877
Japan	0.0067	23,081,967,728	41,390,268,177	79,574,648,428	101,777,590,052	56,492,680,700	60,387,321,874
Korea	0.0006	-	833,345,474	31,312,073,254	37,032,419,530	31,312,073,254	36,199,074,056
Malaysia	0.0029	558,028,513	1,090,355,012	2,275,437,894	2,689,910,932	1,717,409,381	1,599,555,920
Pakistan	0.0820	148,407,271	220,481,895	622,641,751	723,966,689	474,234,479	503,484,794
Philippines	0.0023	56,073,236	133,236,614	256,602,762	288,182,945	200,529,526	154,946,331
Russia	0.0128	5,191,739,837	9,118,924,760	25,012,886,192	35,143,428,066	19,821,146,355	26,024,503,306
Singapore	0.0002	-	40,446,329	11,901,779,159	14,123,859,930	11,901,779,159	14,083,413,600
Sri Lanka	0.0043	57,641,509	138,068,463	348,334,047	385,552,765	290,692,538	247,484,302
Taiwan	0.0010	296,653,632	1,189,269,979	3,679,632,691	4,332,466,097	3,382,979,059	3,143,196,118
Thailand	0.0159	2,514,935,514	3,886,296,761	6,541,785,316	7,443,642,631	4,026,849,801	3,557,345,871
Vietnam	0.0236	1,705,216,645	2,018,016,561	2,491,821,964	2,622,761,280	786,605,320	604,744,719

Table 6

Systemic risk measures, three year persistent loss rate scenario

The systematic risk measures are computed for the 99th percentile and two million iterations. Panel A shows the moments of systemic risk measures Panel B the mean systemic risk measure by country. The exceedance ratio is the number of loss exceedances over the number of iterations. VaR is the Value-at-Risk, CVaR is the Expected Shortfall, VaR and CVaR are unconditional measures. CoVaR and CoCVaR are conditional on the loss exceedance of the respective bank (the table shows the distribution over all banks). DeltaCoVaR and DeltaCoCVaR is the difference between the conditional and unconditional risk measure.

Panel A: Moments of systemic risk measures							
Parameter	**Exceedance ratio**	**VaR**	**CVaR**	**CoVaR**	**CoCVaR**	**DeltaCoVaR**	**DeltaCoCVaR**
Mean	0.0346	159,201,666,153	228,473,780,060	310,975,726,248	381,300,094,321	151,774,060,095	152,826,314,261
P1	0.0000	366,891,037	870,393,688	759,952,499	1,242,123,473	- 101,981,200,000	- 207,396,600,000
P25	0.0007	13,526,025,923	20,081,516,358	50,520,158,201	61,012,516,374	23,039,952,586	22,116,751,757
P50	0.0087	250,802,747,418	356,218,154,656	378,151,544,745	488,236,971,720	132,085,780,153	138,808,969,668
P75	0.0478	250,802,747,418	356,218,154,656	472,300,154,047	589,518,844,751	218,160,006,414	230,649,632,597
P99	0.3465	370,667,184,273	539,801,462,368	1,310,207,800,000	1,391,698,700,000	1,015,447,600,000	994,751,153,917
N	925	925	925	925	925	925	925
Panel B: Mean systemic risk measures by country							
Parameter	**Exceedance ratio**	**VaR**	**CVaR**	**CoVaR**	**CoCVaR**	**DeltaCoVaR**	**DeltaCoCVaR**
Australia	0.0087	366,891,037	1,298,499,912	5,004,513,293	6,169,710,158	4,637,622,257	4,871,210,246
Bangladesh	0.0320	4,157,008,577	4,777,365,544	4,752,889,147	5,030,623,557	595,880,570	253,258,013
China	0.0079	370,667,184,273	539,801,462,368	719,911,932,681	852,238,707,509	349,244,748,408	312,437,245,141
Hong Kong	0.0019	477,620,551	6,336,035,307	84,803,945,008	97,528,857,756	84,326,324,457	91,192,822,450
India	0.0389	13,526,025,923	20,081,516,358	47,738,085,026	54,928,579,409	34,212,059,102	34,847,063,051
Indonesia	0.0795	31,131,313,591	43,110,660,415	67,864,858,924	81,310,796,292	36,733,545,333	38,200,135,876
Japan	0.0306	250,802,747,418	356,218,154,656	475,280,713,279	585,379,528,328	224,477,965,861	229,161,373,672
Korea	0.0199	23,512,307,589	44,462,611,489	129,324,487,719	158,538,218,521	105,812,180,130	114,075,607,032
Malaysia	0.0207	5,327,106,905	7,306,149,474	11,703,952,660	13,564,609,097	6,376,845,755	6,258,459,623
Pakistan	0.0818	1,030,574,228	1,476,683,683	3,570,888,494	4,226,357,133	2,540,314,266	2,749,673,450
Philippines	0.0177	612,545,143	870,393,688	1,420,397,515	1,585,723,360	807,852,372	715,329,671
Russia	0.0662	52,443,450,706	87,323,423,994	132,092,971,593	176,850,724,718	79,649,520,888	89,527,300,723
Singapore	0.0039	813,784,640	8,885,757,158	52,791,657,506	61,802,700,236	51,977,872,866	52,916,943,078
Sri Lanka	0.0284	719,382,969	1,022,760,007	1,648,299,351	1,918,886,532	928,916,382	896,126,525
Taiwan	0.0166	8,026,111,865	11,568,040,639	20,706,687,380	24,424,759,101	12,680,575,515	12,856,718,461
Thailand	0.0519	12,849,810,919	18,215,791,083	26,265,819,572	31,315,004,895	13,416,008,653	13,099,213,813
Vietnam	0.0486	7,854,880,092	9,220,961,011	11,813,284,111	12,970,762,066	3,958,404,019	3,749,801,055

Table 7
Regression analysis for input factors on systemic risk measures

This table shows the impact of the input factors on systemic risk. The systematic risk measures are computed for the 99th percentile and two million iterations. Significance levels are *** significant at 1%, **: significant at 5% and *: significant at 10%.

Variable	**VaR**	**CVaR**	**CoVaR**	**CoCVaR**	**DeltaCoVaR**	**DeltaCoCVaR**
Intercept	0.0707***	0.1014***	0.0157	0.0587**	-0.0551***	-0.0426***
Std. Err	0.01	0.0134	0.0233	0.0274	0.0158	0.0165
c	0.0237***	0.0356***	0.0071	0.0252**	-0.0166***	-0.0104*
Std. Err	0.0037	0.0049	0.0085	0.01	0.0058	0.006
Capital	-0.0081	-0.0136*	0.1077***	0.0968***	0.1158***	0.1104***
Std. Err	0.0057	0.0076	0.0132	0.0155	0.0089	0.0093
delta	0.2682***	0.4023***	0.4631***	0.6341***	0.195***	0.2318***
Std. Err	0.0163	0.0219	0.038	0.0446	0.0257	0.0268
rho	0.0113	0.031**	0.1837***	0.2071***	0.1724***	0.1761***
Std. Err	0.0111	0.0149	0.0258	0.0304	0.0175	0.0183
R-sq.	0.3635	0.4256	0.3608	0.3943	0.3549	0.3592
Obs.	925	925	925	925	925	925