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Cross-Border Direct Bank Exposures in Asian Economies: A Counterparty Risk Ranking Assessment

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Abstract

This paper develops and applies a portfolio-based framework for assessing systemic risk in cross-border banking networks. Relying on three complementary measures, it captures distinct risk dimensions related to diversification, institution-specific shocks, and contagion potential. Despite limitations stemming from indirect exposures and the lack of bank-level bilateral data, the approach remains informative for surveillance, enabling the identification of jurisdictions that warrant closer supervisory attention. The empirical application shows that systemic risk profiles vary significantly across banking systems, with diversification offering resilience in some cases and concentrated exposures amplifying vulnerabilities in others. The results underscore the importance of adopting multi-pronged analytical methods in supervisory practice to better target scarce monitoring resources toward emerging systemic vulnerabilities.

Keywords: bank exposures, ASEAN economies, credit risk models, probability of default.

JEL codes: F3, G01, G15, G21.

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1 Introduction

Cross-border banking offers significant benefits, including the facilitation of international trade and investment, enhanced credit allocation, and improved funding access for firms and sovereigns. However, this interconnectedness also creates vulnerabilities, as it enables shocks to spill over across countries, a phenomenon that was evident during the 2008 global financial crisis. Consequently, it is of great importance for systemic risk regulators and financial stability overseers to identify the foreign banking jurisdictions that could pose the greatest risk to their domestic economies and financial systems.

Identifying which banking jurisdictions pose the most risk requires assessing two elements: a economy's exposure to them and the jurisdictions' inherent risk. Exposure can be direct, such as the domestic banking sector's claims on foreign entities, which face default risk in a crisis. Inherent risk reflects the probability of default, that a jurisdiction's banks will be unable or unwilling to honor their liabilities. Both exposure and inherent risk can also be indirect. For instance, this is the case when problems in one jurisdiction spill over to others even without direct claims, often due to shared economic factors, interdependent asset prices, or non-fundamental based contagion (Forbes and Rigobon 2002).

While conventional approaches often rank counterparties by exposure size alone, such rankings overlook critical risk factors including default probabilities, interconnectedness, and co-dependence among financial institutions. This paper introduces a practical methodology for ranking a economy's counterparty banking systems according to the risks they pose to that economy, building upon three complementary credit portfolio–based systemic risk approaches developed in the aftermath of the 2008 global financial crisis. These approaches include the marginal contribution to systemic risk (MCSR), which captures risks under current conditions (Acharya et al. 2017); the distressed insurance premium (DIP), which reflects idiosyncratic or firm-specific shocks (Huang, Zhou, and Zhu 2012); and the incremental contribution to systemic risk (ICSR), which accounts for system-wide shocks (Chan-Lau 2010).

We illustrate the methodology by ranking the counterparty banking systems of four Asian economies: Hong Kong China, Japan, Korea, and the Philippines. Our analysis demonstrates that systemic risk rankings derived from these three distinct methodological approaches, focused on measuring diversification effects, idiosyncratic shocks, and spillover potential respectively, differ from simple exposure-based rankings across all jurisdictions analyzed. These findings highlight the importance of adopting multiple perspectives that explicitly model interconnectedness to provide more comprehensive assessments of systemic risk in cross-border banking.

Key economy-specific findings emerge from this analysis. First, Hong Kong China and Japan benefit from diversified cross-border exposures that reduce systemic risk under normal conditions, while Korea and the Philippines show limited diversification benefits. Second, during global distress events, spillover effects are primarily driven by advanced economies in Europe and the United States rather than regional counterparties. Third, at the regional level, Singapore illustrates how exposure size alone does not determine systemic risk: despite being an important cross-border banking counterparty with large regional liabilities, Singapore does not rank as a major risk contributor due to the low credit risk and resilience of its banking system to global shocks.

The remainder of this paper is organized as follows: Section 2 provides a concise overview of related work, section 3 to 5 describe the data used to implement the methods and discusses the results. Finally, section 6 presents the conclusions of this study.

2 Literature review

The 2007-2009 global financial crisis underscored the inadequacies of traditional microprudential regulation, which focuses on the soundness of individual institutions, and highlighted the need for a macroprudential approach that addresses system-wide risks and interdependencies (Crockett 2000; Borio 2003). A key strand of this literature examines how to measure systemic risk in banking portfolios and attribute it to individual institutions to inform regulatory interventions, such as capital surcharges. The following three studies, which serve as the backbone of this study, share a portfolio view of the banking system and advocate attributing systemic risk to internalize externalities, but differ in their methodological approaches.

The three foundational studies employ distinct methodological approaches to systemic risk measurement and attribution. Huang, Zhou, and Zhu (2012) propose a “distress insurance premium" (DIP) using CDS spreads and dynamic conditional correlation models to estimate joint default probabilities and quantify institutions’ marginal contributions to systemic risk. Tarashev, Borio, and Tsatsaronis (2010) introduce a game-theoretic methodology using the Shapley value to attribute aggregate systemic risk to individual institutions, ensuring additivity where contributions sum to total risk while accounting for size, risk profiles, and common exposures. Finally, Chan-Lau (2010) focus on “too-connected-to-fail" institutions, proposing regulatory capital charges based on network models and CoRisk analysis (Chan-Lau 2009) to capture how interconnected failures amplify default probabilities across the system.

Several studies share the same foundational approaches in these studies, namely, the use of market-based measures of default risk, the focus on financial network, and the calculation of risk contributions.[1] Adrian and Brunnermeier (2016) introduce the conditional risk measure CoVaR and use it to rank U.S. financial institutions based on their systemic risk attributions. Acharya et al. (2017)

1. For a more comprehensive overview of the systemic risk literature, see the surveys of Bisias et al. (2012), Brunnermeier and Oehmke (2013), Acharya, Brunnermeier, and Perret (2024), and Benoit et al. (2016); and the textbooks of Chan-Lau (2019), Fouque and Langsam (2013), and Gai (2013),

propose the systemic expected shortfall (SRISK) measure to evaluate the potential capital shortfalls financial institutions face. Gauthier, Lehar, and Souissi (2012) assesses systemic risk in the Canadian banking system by calibrating different risk attribution methods using network simulations. Drehmann and Tarashev (2013) propose measures accounting for the possibility that a bank is both a source of shocks and vulnerable to them. Finally, Zedda and Cannas (2020) introduce the leave-one-out approach, which evaluates the systemic risk contribution on a stand-alone basis and as a source of contagion risk.

Implementing many of these systemic risk measures requires information on cross-border banking exposures, for which the BIS international banking statistics provide one of the most comprehensive sources and have been widely used to analyze vulnerabilities in the global banking system, as reviewed by Hardy, McGuire, and von Peter (September 2024). Among these studies, Avdjiev, Berger, and Shin (2018) find that the data available at the time of run-up to the 1997 Asian financial crisis would have alerted observers about the rapid build-up of vulnerabilities in the financial sector. Doerr and Schaz (2021) used the data to classify banks according to the geographic diversification of their syndicated loan portfolio and show that the most diversified among them play a stabilizing role by maintaining their loan supply during a banking crisis. Aldasoro, Hardy, and Jager (2022), using the data, construct a measure of geographic coverage and complexity for 96 global bank holding companies. They find that higher geographic complexity makes banks more resilient to local shocks but makes them riskier as they are able to arbitrage prudential regulation.

Beyond banking risk, BIS statistics also offer additional perspectives on currency and institutional exposures. Hardy, McGuire, and von Peter (September 2024),shows how the currency dimension of these data makes it possible to track the role of major currencies across international markets, highlighting in particular the outsized role of the U.S. dollar in offshore finance and its implications for external debt, bank funding, and FX-derivative obligations. McGuire, von Peter, and Zhu (March 2024) demonstrate how moving from the standard residence-based reporting to a nationality view—grouping balance sheets by banks' or firms' headquarters—reveals the central role of multinational institutions and financial centres, and provides new insights into countries' foreign currency debt, financial openness, and the drivers of cross-border positions.

3 Methodology

Banking jurisdictions typically hold claims on foreign counterparties, which can be assessed using standard credit portfolio models. Our methodology evaluates systemic risk through three measures—DIP, MCSR, and ICSR—each defined as the difference in expected shortfall (ES) between a baseline and a stressed portfolio. While the computation principle is common, the choice of baseline–stressed pairs differs across measures, capturing distinct dimensions of systemic risk. We refer to these systemic risk portfolios as the DIP, MCSR, and ICSR portfolios.

The methodology is developed in three steps: first, we characterize the counterparties by their risk parameters; second, we construct the systemic risk portfolios; and third, we model the corresponding loss distributions.

3.1 Counterparty characteristics

Let $\{N\}$ denote the set of bank jurisdictions, with each jurisdiction $B \in N$ is characterized by the following parameters:

- baseline probability of default, $PD(B)$;
- unconditional stressed probability of default, $PD^S(B)$;
- conditional stressed probability of default, $PD^S(B|A^S)$, when jurisdiction $A \in N$ is stressed;
- exposure at default, EAD_B, the total claims on B not honored in default;
- loss given default, LGD_B, the share of EAD_B lost in default;
- asset correlation, ρ_B, the sensitivity of B to a systematic factor.

where all PDs are defined over the time horizon H.

Baseline PDs are typically obtained from commercial or public data providers, while unconditional stressed PDs are set equal to a high percentile (e.g., 90th or 95th) of the empirical distribution. EAD and LGD are usually calibrated from default studies or regulatory benchmarks. The remaining parameters, conditional stressed PDs and asset correlations, require additional modeling assumptions as described in Section 3.3 below.

3.2 Systemic risk portfolios

This methodology implements the three approaches within simplified portfolio settings, enabling the use of standard credit portfolio methods to compute loss distributions and to illustrate how each risk contribution captures a distinct dimension of systemic risk. In general, systemic risk measures are defined as the difference in a tail risk measure—expected shortfall—between two portfolios: a "stressed" portfolio and a baseline portfolio:

- For the MCSR, the stressed portfolio includes all counterparty banking systems, while the baseline excludes the counterparty under assessment, and probabilities of default (PDs) are taken at their current levels.
- For the DIP, the stressed and baseline portfolios have the same composition, but the PD of the assessed counterparty is stressed in the stressed portfolio.
- For the ICSR, the stressed and baseline portfolios again have the same composition as in the DIP, but stress spills over from the assessed counterparty to others in proportion to its stressed PD.

Formally, let $I \in \{N\}$ be the jurisdiction under analysis and $J \in \{N^I\}$ the counterparty whose systemic risk contribution is being evaluated, where $\{N^I\}$ as the set of all counterparties of I, and $\{N^I_{-J}\} \triangleq \{N^I\} \setminus \{J\}$ as the set of counterparties excluding J. The systemic risk portfolios pairs and corresponding PDs are shown in Table 1.

Table 1: Systemic risk portfolios

Method	Portfolios Baseline	Portfolios Stressed	Probability of Default Baseline	Probability of Default Stressed
MCSR	$\{N^I_{-J}\}$	$\{N^I\}$	$PD(B),\ B \in \{N^I_{-J}\}$	$PD(B),\ B \in \{N^I\}$
DIP	$\{N^I\}$	$\{N^I\}$	$PD(B),\ B \in \{N^I\}$	$PD^S(J);\ PD(B),\ B \in \{N^I_{-J}\}$
ICSR	$\{N^I\}$	$\{N^I\}$	$PD(B),\ B \in \{N^I\}$	$PD^S(J);\ PD^S(B \mid PD^S(J)),\ B \in \{N^I_{-J}\}$

Note: $\{N^I\}$ is the set of the counterparties of jurisdiction i; $\{N^I_{-J}\}$ excludes counterparty J; PD is the baseline PD, and PD^S is the stressed PD.
Source: the Authors.

From an economic perspective, each of the three approaches captures a distinct dimension of systemic risk. The MCSR highlights counterparties whose removal substantially reduces tail risk, suggesting exposures that are highly concentrated, strongly correlated with systemic factors, or poorly diversified. Yet removing a counterparty that contributes to portfolio diversification can instead increase tail risk. The DIP reflects systemic importance under current conditions by isolating the effect of an idiosyncratic shock that raises a counterparty's probability of default. The ICSR, in contrast, measures systemic risk in crisis episodes, capturing how elevated default risk in one counterparty spills over to others. This measure is especially useful for macroprudential stress testing, as it identifies borrowers whose deterioration could disproportionately amplify system-wide losses even if they are not top contributors under normal conditions.

In our framework, stress is modeled by assigning high-percentile probabilities of default. It should be noted, however, that during periods of severe turmoil, prevailing conditions may exceed these stressed percentiles, potentially yielding negative risk contributions.

3.3 Loss distribution model

The computation of the expected shortfall-based systemic risk measures requires the loss distribution of both the baseline and stressed portfolios. We generate these loss distributions using the Gaussian one-factor credit portfolio model, which provides an analytically tractable framework and forms the basis of the the Basel Internal Ratings Based (IRB) approach. Implementing the model requires two key inputs beyond the baseline and unconditional PDs, the exposures (EAD), and loss given default (LGD): the asset correlation parameter, which governs the sensitivity of counterparties to a common systematic factor, and the specification of PD spillovers, which capture the contagion effects underlying the incremental contribution to systemic risk (ICSR). Accordingly, this section is structured in three parts: first, we describe the one-factor Gaussian credit portfolio model; second, we discuss the estimation of asset correlations; and third, we explain how PD spillovers are incorporated into the model.

3.3.1 The one-factor Gaussian credit portfolio model

We employ the one-factor Gaussian credit portfolio model, which serves as the analytical foundation of the IRB approach and remains the benchmark model in both regulatory and academic work (Vasicek 2002; Gordy 2003). Compared with alternatives such as CreditMetrics (J.P. Morgan 1997) and CreditRisk+ (Credit Suisse Financial Products 1997), the Vasicek model combines analytical tractability with sufficient flexibility to capture heterogeneous probabilities of default and portfolio characteristics.[2] In particular, unlike CreditRisk+, which is well-suited only for very low default probabilities, the one-factor Gaussian model performs robustly across a broader range of credit risk environments (Bluhm, Overbeck, and Wagner 2016).

The model assumes that the default event of each counterparty is driven by a latent variable representing its asset value. For counterparty i, the asset value process is given by

$$A_i = \sqrt{\rho}\,Y + \sqrt{1-\rho}\,\epsilon_i, \tag{1}$$

where $Y \sim \mathcal{N}(0,1)$ is a common systematic risk factor, $\epsilon_i \sim \mathcal{N}(0,1)$ is an idiosyncratic shock independent across counterparties and from Y, and $\rho \in [0,1]$ denotes the asset correlation parameter. Both Y and ϵ_i are standard normal random variables.

Counterparty i defaults if its asset value falls below a threshold c_i, which is chosen to match the unconditional probability of default PD_i, i.e.,

$$PD(i) = \mathbb{P}(A_i \le c_i) = \Phi(c_i), \tag{2}$$

where $\Phi(\cdot)$ denotes the standard normal cumulative distribution function.

Conditional on the realization of the systematic factor $Y = y$, the probability of default of counterparty i is

$$PD(i \mid Y = y) = \mathbb{P}(A_i \le c_i \mid Y = y) = \Phi\left(\frac{c_i - \sqrt{\rho}\,y}{\sqrt{1-\rho}}\right). \tag{3}$$

For a finite, potentially heterogeneous portfolio, the law of large numbers does not apply, and the portfolio loss distribution must be obtained by aggregating individual counterparties' default events. Conditional on the realization of the systematic factor $Y = y$, the default indicator for counterparty i is a Bernoulli random variable with probability $PD(i \mid Y = y)$. The corresponding loss is $L_i(y) =$

2. CreditRisk+ was originally published by Credit Suisse First Boston, though it is widely attributed to Thomas C. Wilson. Similarly, CreditMetrics was published by J.P. Morgan, with the principal authors being Gregory Gupton, Christopher Finger, and Mickey Bhatia.

$EAD_i \times LGD_i \times \mathbf{1}_{\{\text{default of } i\}}$, and the portfolio loss is the sum

$$L(y) = \sum_{i \in N} EAD_i \times LGD_i \times \mathbf{1}_{\{A_i \leq c_i | Y = y\}}. \tag{4}$$

The conditional distribution of $L(y)$ is therefore binomially compounded across counterparties, and the unconditional loss distribution is obtained by integrating over the distribution of the systematic factor Y.

In practice, the unconditional loss distribution can be obtained in closed form only under the assumption of an asymptotic, homogeneous portfolio (Vasicek 2002; Gordy 2003). For finite and heterogeneous portfolios, as in our application, the loss distribution must be generated numerically, typically by Monte Carlo simulation. These loss distributions provide the basis for computing tail risk measures, in particular the Value-at-Risk and the Expected Shortfall, which we now define formally.

Value-at-Risk. Let α denote the target confidence level (e.g., 99.9% under Basel II). In the Vasicek asymptotic model, the portfolio Value-at-Risk at level α is

$$VaR_\alpha = LGD \times \Phi\left(\frac{c - \sqrt{\rho}\,\Phi^{-1}(\alpha)}{\sqrt{1-\rho}}\right), \tag{5}$$

where $c = \Phi^{-1}(PD)$ is the default threshold implied by the unconditional probability of default. In the heterogeneous case, VaR_α is instead obtained from the simulated loss distribution.

Expected Shortfall. Under Basel III, Expected Shortfall (ES) is used as a more coherent tail-risk measure. At confidence level α, ES is defined as

$$ES_\alpha = \frac{1}{1-\alpha} \int_\alpha^1 VaR_u \, du. \tag{6}$$

For the one-factor Gaussian benchmark, this integral admits a closed form that can be evaluated numerically. Let $z_\alpha = \Phi^{-1}(\alpha)$. Then

$$ES_\alpha = LGD \times \frac{1}{1-\alpha} \int_{z_\alpha}^{\infty} \Phi\left(\frac{c - \sqrt{\rho}\, z}{\sqrt{1-\rho}}\right) \phi(z)\, dz, \tag{7}$$

where $\phi(\cdot)$ denotes the standard normal density. In finite and heterogeneous portfolios, ES_α is obtained directly from the simulated loss distribution.

The implementation of the model requires specifying stressed probabilities of default and asset correlations, which we discuss in the following subsections.

3.3.2 Conditional stressed probabilities of default

To estimate conditional stressed PDs, we model the joint distribution between each counterparty J and every other counterparty of the jurisdiction under analysis. We stress counterparty J by setting its PD to a high percentile (e.g., the 90th or 95th) of its unconditional distribution, and then evaluate the corresponding percentile of the conditional PD distribution for the affected counterparty. The resulting PD is the stressed PD of the affected counterparty represents the spillover effect from J. Formally, stressed PDs are obtained by:

1. Selecting a counterparty $J \in \{N^I\}$ to be stressed and fitting bivariate distributions between J and each other counterparty $K \in \{N^I_{-J}\}$.
2. Setting the PD of counterparty J to a high quantile of its unconditional distribution,
$$PD^S(J) = F_J^{-1}(q_J)$$
3. For each counterparty $K \in \{N^I_{-J}\}$, evaluating its conditional PD distribution given $PD^S(J)$, $F_{K|PD^S(J)}(K)$, setting a quantile $q_{K|J}$, and finding the corresponding PD,
$$PD^S\left(K \mid PD^S(J)\right) = F^{-1}_{K|PD^S(J)}\left(q_{K|J} \mid PD^S(J)\right).$$

This procedure is repeated for each $J \in \{N^I\}$ in turn, yielding the full set of stressed PDs and conditional stressed PDs required for the construction of the ICSR systemic risk portfolios.

The estimation requires constructing the bivariate distribution of the PDs between each pair of counterparties in order to derive conditional stressed PDs. Since the marginal distributions of PDs can be estimated separately, what remains is to capture their dependence structure in a flexible way. Copulas provide this functionality: by Sklar's theorem, any multivariate distribution can be decomposed into its marginal distributions and a copula that represents the dependence between variables (Sklar 1959). Thus, by combining separately estimated marginals with an appropriate copula, it is possible construct the full bivariate distribution of PDs.

To estimate the copula, we adopt a nonparametric approach since parametric copulas may impose restrictive functional forms that fail to capture tail dependence or complex nonlinear relationships. To overcome these limitations, we rely on the probit-transformation local likelihood estimator introduced by Geenens, Charpentier, and Paindaveine (2017). The probit transformation maps copula data from the unit square to the real line, thereby eliminating boundary effects. The joint density in the transformed domain is then estimated by local likelihood methods, which provide smooth and consistent estimates, including in the tails. Back-transformation yields valid copula density estimates with natural handling of unbounded densities near the corners of the unit square.

3.3.3 Asset correlation estimation

We estimate asset correlation following Proposition 1 in Gordy (2000). The key assumptions in the proposition are that default risk is driven by a single systematic factor, while idiosyncratic shocks are independent across counterparties and independent of the factor. The original formulation assumes that there is large pool of obligors belonging to the same counterparty class. For obligor i in a specific class, its creditworthiness is represented by a latent variable

$$y_i = w\,x + \sqrt{1-w^2}\,\epsilon_i,$$

where $x \sim \mathcal{N}(0,1)$ is the systematic factor, $\epsilon_i \sim \mathcal{N}(0,1)$ is an idiosyncratic shock, and w is the factor loading. Default occurs when y_i falls below a threshold $C = \Phi^{-1}(\bar{p})$, with $\bar{p}$ denoting the unconditional probability of default. Conditional on x, defaults are independent across obligors.

In our context, we only have a single counterparty and such a pool does not exist. But because we observe a time series of PDs for a single counterparty, we interpret these observations as independent realizations from a pool of identical obligors with the same unconditional PD $\bar{p}$. Under these assumptions, Proposition 1 shows that the variance of the conditional default probability realizations of counterparty i satisfies

$$\mathrm{Var}[p] \;=\; \mathbf{\Phi}_2\big(C, C; w^2\big) \;-\; \bar{p}^2, \tag{8}$$

where $\mathrm{Var}[p]$ is the empirical variance estimated from the counterparty's PD time series, and $\mathbf{\Phi}_2(\cdot,\cdot;\rho)$ denotes the bivariate standard normal distribution with correlation ρ.[3] This relationship allows us to recover the factor loading w from the time-series variance of PDs, and the corresponding asset correlation is given by $\rho_i = w^2$, which we then use in the one-factor Gaussian credit portfolio model introduced earlier.

4 Systemic risk ranking implementation

4.1 Data

4.1.1 BIS locational banking statistics

The cross-country bank exposure is sourced from the BIS Locational Banking Statistics (LBS)[4], which are collected under the auspices of the Committee on the Global Financial System. The quarterly statistics track international banking activity on a residence or host basis: banks' cross-border claims and liabilities are reported by the location of the banking office, so foreign branches and subsidiaries are attributed to the host jurisdiction rather than the jurisdiction of the parent banking group,

3. In practice, the empirical variance of PD time series may be affected by finite-sample variability and by non-stationarities in the estimated PDs. The calibration therefore implicitly assumes that the PD series is stationary and that observed fluctuations reflect variation due to the common factor rather than structural breaks or changes in model inputs.

4. For detailed informatin about the dataset, see https://data.bis.org/topics/LBS

or home jurisdiction. The data are reported on an unconsolidated basis, including intragroup and inter-office business, with detailed breakdowns by instrument, currency, sector, and counterparty economy.

The LBS are compiled from 48 reporting jurisdictions while counterparties reside in more than 200 countries and jurisdictions. The dataset captures around 95 percent of global cross-border banking activity but there are some gaps as a number of important financial centers and emerging markets either do not report or do not make their data publicly available. Also, quality and granularity of the data vary by jurisdiction, partly because local implementation of the BIS reporting guidelines can differ across jurisdictions. Data are aggregated at the jurisdiction level (i.e. showing total exposures of all banks in each reporting economy), rather than for individual banking institutions so it reflects aggregate positions, not bank-level exposures.

The rankings for each of the four Asian economies with publicly available BIS data—Hong Kong China, Japan, Korea, and the Philippines—are constructed using 2025 Q1 cross-border banking claims data. Since these claims are not directly reported, the claims vis-à-vis a counterparty jurisdiction are calculated by subtracting claims on the domestic non-banking sector from the total claims on that jurisdiction. The resulting values are set equal to the economy's EAD to the jurisdiction.

Table 2: Cross-border claims, in billion USD (2025Q1).

	Hong Kong China	Japan	Korea	The Philippines
ASEAN, of which:	157.7	125.7	13.8	4.0
Singapore	121.5	86.0	6.8	2.7
Plus 3, of which:	413.0	104.1	44.4	4.9
China	250.0	38.2	27.0	0.6
Advanced economies, of which:	703.0	962.6	74.6	16.1
United States	98.8	372.4	29.8	6.8
European Union	80.3	151.5	10.9	1.0
Emerging markets	363.9	97.0	41.9	2.8
Others	48.2	10.1	4.2	0.1

Note: See footnote 5 for economy groups' composition.
Source: BIS and the Authors.

Table 2 shows the aggregate cross-border claims of the four reporting Asian economies on different economies and economy groups, based on jurisdictions covered in the 2025Q1 banking statistics.[5]

5. ASEAN: Indonesia, Malaysia, the Philippines, Singapore, Thailand, and Vietnam; Plus 3: China, Hong Kong China, Japan, and Korea; Advanced economies: Australia, Austria, Belgium, Canada, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hong Kong, China; Iceland, Ireland, Israel, Italy, Japan, Korea, Latvia, Lithuania, Malta, Netherlands, New Zealand, Norway, Portugal, Singapore, Slovenia, Spain, Sweden, Switzerland, and United Kingdom, United States; European Union: Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Malta, the Netherlands, Poland, Portugal, Romania, Slovenia, Spain, and Sweden; Emerging markets: Argentina, Brazil, Chile, China, Colombia, Egypt, Hungary, India, Indonesia, Kuwait, Malaysia, Mexico, Peru, the Philippines, Poland, Qatar, Saudi Arabia, South Africa, Thailand,

Table 3 provides additional detail by showing the top fifteen counterparties. Claims are mostly concentrated in the United States, the United Kingdom, China, and Japan. Among ASEAN countries, Singapore and Hong Kong China are the most important counterparties.

Table 3: Asian economies: top counterparties by EAD, in billions USD (2025Q1).

Hong Kong, China		Japan		Korea		The Philippines	
Counterparty	EAD	Counterparty	EAD	Counterparty	EAD	Counterparty	EAD
China	250.0	United States	372.4	United States	29.8	United States	6.8
Singapore	121.5	United Kingdom	230.4	China	27.0	Singapore	2.7
United Kingdom	118.3	Singapore	86.0	Japan	9.4	Japan	2.5
Japan	113.7	France	64.2	Hong Kong, China	8.1	Hong Kong, China	1.2
United States	98.8	Luxembourg	49.6	United Kingdom	7.0	United Kingdom	1.2
Australia	73.6	Hong Kong, China	48.5	Singapore	6.8	Indonesia	0.9
Korea	49.3	China	38.2	France	5.4	India	0.6
France	43.8	Australia	31.6	Indonesia	3.1	China	0.6
Taiwan POC	37.1	Germany	29.0	India	2.9	Korea	0.5
Switzerland	30.9	Belgium	23.0	Taiwan POC	2.7	Germany	0.4
United Arab Emirates	27.9	Canada	18.9	Australia	2.3	Netherlands	0.3
Qatar	20.1	Korea	17.4	Vietnam	2.3	Thailand	0.2
Macao China	19.8	Thailand	16.2	Germany	2.1	Australia	0.2
India	17.6	Netherlands	15.1	Poland	1.6	Luxembourg	0.2
Germany	15.6	India	13.7	United Arab Emirates	1.4	Malaysia	0.1

Note: EAD represent cross-border claims on the banking sector.
Source: BIS.

4.1.2 CRI probability of default (PD)

Implementing the one-factor Gaussian credit portfolio model, including the calculation of the asset correlations, requires estimates of the PD of the counterparty banking jurisdiction (see section 3). We approximate the PD of the aggregate jurisdiction as the arithmetic average of the 1-year PDs of its publicly-listed individual banks.[6] The banks' monthly PD time series data are sourced from the National University of Singapore, Credit Research Initiative database (CRI 2023). The aggregation is necessary as data on cross-border banking exposure to individual banks are not available though it might overstate or understate the default risk if exposures are concentrated on low risk or high risk banks. The data, accessed on July 2025, covers the period October 1996 to July 2025. The PDs, generated by a reduced form hazard model based on Duan, Sun, and Wang (2012), are real-world probabilities, so no risk adjustments are necessary to estimate potential real-world losses. The last 10 years of data, covering January 2015 to July 2025 are used in the calculation of the unconditional stressed PDs, the conditional stressed PDs, and the asset correlations; and PD observations as of

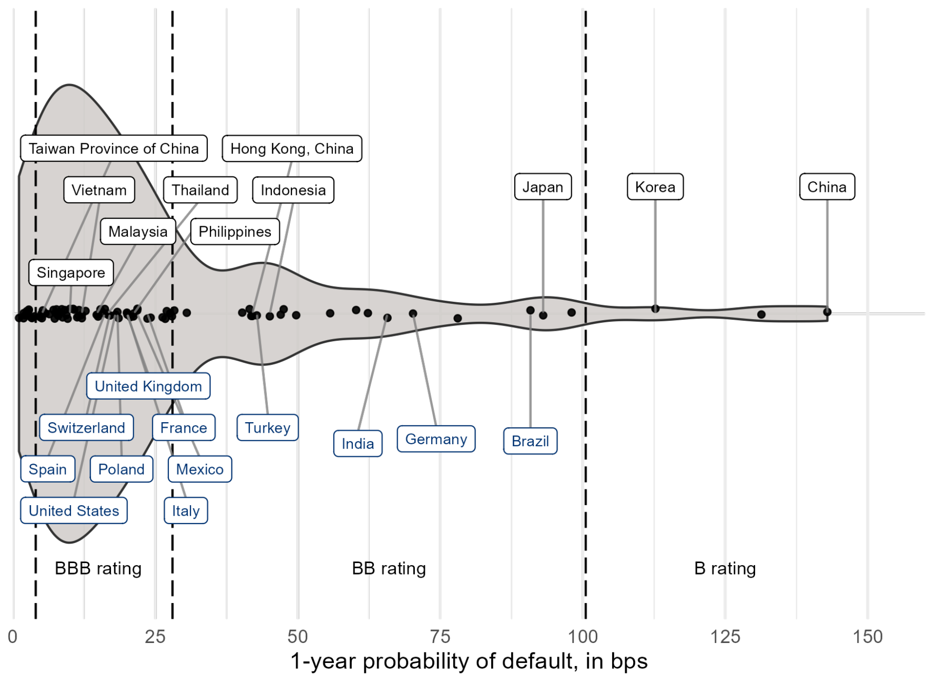
Turkey, and United Arab Emirates; Others: Bangladesh, Bahrain, Georgia, Ghana, Jamaica, Jordan, Kazakhstan, Kenya, Liechtenstein, Oman, Pakistan, Papua New Guinea, Malawi, Mauritius, Moroccco, Nigeria, North Macedonia, Panama, Rwanda, Sri Lanka, Taiwan Province of China, Tanzania, Togo, Tunisia, Uganda, and Venezuela.

6. This assumption carries two caveats. First, the aggregate PD might underestimate or overestimate the default risk derived if individual bank exposure data were available, a data limitation problem which would not be addressed using the median or weighted PDs. Using the mean PD as a proxy, however, aligns with the use of the portfolio-level approach. Second, PDs are only available for listed banks, which may understate or overlook default risk in jurisdictions where non-listed banks, such as Korea, play an important role.

March 2025 are used to estimate the loss distributions used in the systemic risk calculations. PDs range from a minimum, negligible value (Panama) to a maximum of 330 bps (Togo), with a median of 16 bps and a mean of 32 bps, with first and third quantiles of 8 and 40 bps respectively.

Figure 1 shows the March 2025 mean 1-year PD distribution of the banking jurisdictions in the data sample, highlighting those corresponding to advanced economies, Asian economies, and large emerging markets. The figure also shows the PD-implied Standard and Poor's credit rating bands based on CRI (2021). Advanced economies exhibit PDs consistent with Standard and Poor's investment grade rating of BBB, with the exception of Germany, which has a B sub-investment rating. Among Asian economies, the dispersion in 1-year PDs is reflected in the rating dispersion. The most advanced jurisdictions in the region display sub-investment grade ratings similar to those of several large emerging markets. In particular, China and Korea's PDs, at 143 bps and 113 bps, are the third and fifth highest in the sample, placing them in the B rating band.

Figure 1: Banking jurisdictions, mean 1-year probability of default distribution



Note: PD-implied Standard and Poor's credit rating bands based on CRI (2021).
Source: CRI and the Authors.

High PDs associated with large exposures could increase systemic risk. But contrary to intuition, a high PD value for a counterparty does not necessarily translate into higher risk contributions. Under the MCSR approach, this counterintuitive result occurs when the counterparty exhibits low or negative asset correlation with the portfolio, providing diversification benefits that offset the elevated default risk. For the DIP measure, a counterparty with an already high PD may show limited sensitivity to additional stress scenarios, resulting in a relatively small change in expected shortfall when conditions deteriorate further. Similarly, under the ICSR approach, if a counterparty's high PD reflects system-wide stress conditions affecting all institutions simultaneously, its individual contribution to systemic risk may appear modest since other counterparties are experiencing comparable distress levels.

4.1.3 Loss given default (LGD)

Loss given default (LGD) in banking-sector defaults is shaped by several structural factors. Seniority of claims is a major recovery determinant: senior secured exposures generally recover substantially more than subordinated or junior debt. Collateral quality and enforceability also play a role, as secured interbank loans may be recovered in full while unsecured claims often result in near-total losses. The length of the resolution process is another key determinant, since protracted workouts diminish recoverable value through administrative, legal, and market costs. Finally, macroeconomic conditions amplify these effects, with downturns eroding collateral values and extending recovery times.

Empirical studies illustrate the range of outcomes. Using German supervisory data, Upper (2011) finds a mean LGD of about 45 percent on interbank exposures, with a U-shaped distribution concentrated near full recovery and near total loss. For failed U.S. banks, James (1991) documents average asset losses of roughly 30 percent, plus 10 percent resolution costs. Long-run recovery data for financial institutions' senior unsecured bonds show recoveries of around 37 percent, implying LGDs near 63 percent (Moody's Ultimate Recovery Database, summarized in Altman et al. 2005; BIS (2009)).

Case studies confirm the severity under systemic stress: senior bond recovery for Lehman Brothers fell from early estimates near 30 percent to CDS auction settlements closer to 9 percent Moody's Investors Service (2008), while Icelandic bank defaults in 2008 yielded average senior unsecured recoveries of about 29 percent, with some claims worth only 1–7 cents on the dollar BIS (2009). Time to recovery is also substantial: Global Credit Data Global Credit Data (2020) reports an average "time to resolution" of about two years, while Fiori and Mistrulli (2024)) finds median resolution times of 1.7 years and time-to-recovery between 0.8 and 1.4 years.

In our modeling, we adopt a conservative assumption of 100 percent LGD, which likely overstates realized losses. Nonetheless, given that loan recovery from failed banks is typically protracted and highly uncertain, this assumption is appropriate for systemic risk assessments. Importantly, the relative rankings are unaffected, as the same LGD value is applied uniformly across all counterparties. This would not be the case when the LGD differs across counterparties.

4.2 Portfolio construction

As outlined above, for each Asian economy the credit portfolio is defined as its cross-border banking claims on the banking sector of individual jurisdictions, which are treated as obligors. Within each jurisdiction, individual banks are aggregated into a single representative entity whose exposure at default (EAD) is given by the sum of total claims on that jurisdiction's banking sector. The LGD is set equal to 100 percent, and the asset correlations are calculated from the representative PD time series using Equation (8).

The one-year representative probability of default (PD) is computed as the arithmetic average of the one-year PDs of the constituent banks with the unconditional stressed PD is defined as the empirical 95$^{\text{th}}$ percentile of the distribution of the representative one-year PD. The same percentile is employed to derive conditional stressed PDs: if counterparty j is designated as stressed, with its PD fixed at the empirical 95$^{\text{th}}$ percentile, then the conditional stressed PD of counterparty k is defined as the 95$^{\text{th}}$ percentile of the conditional distribution obtained under the stress scenario for j.

Finally, for each counterparty, the MCSR, DIP,and ICSR portfolios are constructed according to the rules presented in Table 1.

4.3 Loss distribution and systemic risk contribution calculations

Monte Carlo simulation is used to generate the loss distribution since the one-factor Gaussian credit portfolio model does not have a closed form distribution specification. The simulation consists of $N = 1$ million replications. Each replication involves:

1. Drawing a realization of the systematic risk factor from the standard normal distribution $\mathcal{N}(0, 1)$;
2. Drawing a realization of the idiosyncratic shock from the standard normal distribution $\mathcal{N}(0, 1)$ for each of the counterparties;
3. Computing the counterparty-specific asset return, A_i, from equation (1);
4. Determining if a counterparty defaults by comparing the asset return to thresholds implied by PDs, c_i, obtained by inverting equation (2); i.e. if $A_i < c_i$ the portfolio experiences a loss equal to $EAD_i \times LGD_i$.
5. Calculating portfolio loss as $\sum_i EAD_i \times LGD_i$.

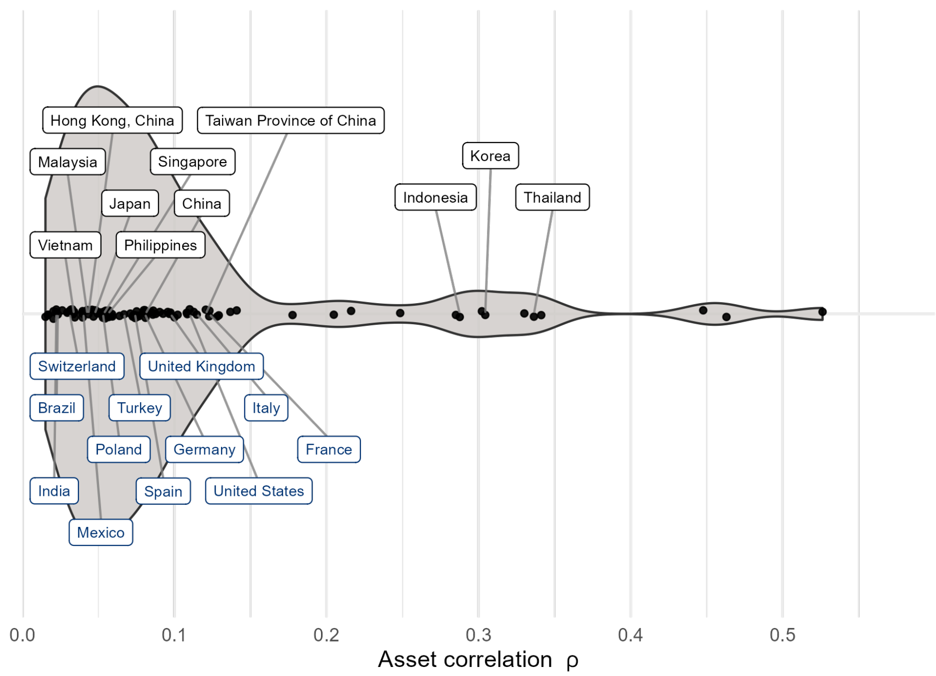
For each systemic risk approach (MCSR, DIP, and ICSR), Monte Carlo simulation is used to estimate the expected shortfall of the stressed and baseline portfolios for a given counterparty, with the difference between the two serving as that counterparty's risk contribution. The contributions are esimated for four different confidence levels, $\alpha \in \{0.90, 0.95, 0.99, 0.999\}$.

5 Results

5.1 Asset correlation

In the one-factor Gaussian credit portfolio model, asset correlation is the key parameter that determines how much of a jurisdiction's credit risk is driven by the common systemic factor, and hence how much it contributes to and is exposed to systemic risk. A jurisdiction with a high correlation value would contribute disproportionally to overall portfolio risk, offsetting a small exposure while providing little diversification benefits. Figure 2 shows that this does not seem to be the case for most of the banking jurisdictions that are counterparties to Hong Kong China, Japan, Korea, and the Philippines. Correlations range from a low of 0.015 (Qatar) to a high 0.83 (Rwanda), with a median of 0.07 and a mean of 0.11, with the first and third quantiles at 0.04 and 0.11 respectively. Jurisdictions in Africa and the Middle East display the lowest values, while higher correlations are observed across all other regions. While asset correlations are somewhat higher in western advanced economies, three Asian economies (Indonesia, Korea, and Thailand) are among those in the top percentiles of the distribution, suggesting high vulnerability to global shocks regardless of their counterparty exposures.

Figure 2: Asset correlation distribution



Source: CRI and the Authors.

5.2 Systemic risk contributions

Tables 4 to 7 report the systemic risk contributions and associated rankings for Hong Kong China, Japan, Korea, and the Philippines, derived from the three methodological approaches, MCSR, DIP, and ICSR, at confidence levels of 90, 95, and 99 percent. For each jurisdiction, the set of counterparties considered accounts for at least 90 percent of its total EAD. Counterparties are ranked in descending order according to their contributions at the 99th percentile, the most extreme tail risk event, and serves as the baseline for the discussion of the results below.

Across all jurisdictions, the systemic risk rankings, regardless of the approach used, are not fully aligned with a ranking based on the counterparties' EAD (Table 3). This EAD-based ranking essentially represents a too-big-to-fail ranking. Instead, the MCSR ranking represents a diversification ranking, the DIP represents an idiosyncratic shock ranking, and the ICSR represents a spillover or contagion ranking. These three rankings capture interconnectedness through different mechanisms: the MCSR and DIP model dependence on a common risk factor using a Gaussian copula, while the ICSR additionally uses conditional stressed PDs.

Moreover, we should not expect high concordance (or similarity) among the three systemic risk methodologies themselves, as each captures fundamentally different dimensions of risk. The MCSR focuses on diversification benefits under normal market conditions, the DIP emphasizes institution-specific vulnerabilities during idiosyncratic stress, and the ICSR measures contagion effects during system-wide crises. Across all four jurisdictions analyzed (Tables 8 to 11), we observe that concordance among the MCSR, DIP, and ICSR rankings is indeed limited, reflecting this methodological diversity by design. This pattern confirms that comprehensive systemic risk assessment requires understanding these distinct but complementary risk channels rather than relying on any single measure.

These methodological differences become evident when examining individual economy results, which reveal distinct patterns of systemic risk concentration for each reporting jurisdiction. The MCSR rankings show that China represents the primary source of systemic risk to Hong Kong China across all confidence levels, followed by Japan in second position and Korea in third (Table 4). These top three rankings remain consistent under the DIP measure, which captures conditions when counterparties experience idiosyncratic shocks. This concentration of systemic risk among Asian economies reflects the regional economic integration and banking system interconnectedness within the Asia-Pacific region from Hong Kong China's perspective

The ICSR rankings present a markedly different pattern, as under extreme scenarios, the primary systemic counterparties shift to Switzerland, France, and the United States. Differences across counterparties are small, however, suggesting these rankings are consistent with a global distress event. Notably, some jurisdictions display negative MCSR contributions, indicating that these jurisdictions, scattered worldwide (Taiwan POC, United States, Qatar, UAE, and Singapore), provide diversification benefits that reduce overall systemic risk under normal market conditions. However, the DIP measure reveals how diversification benefits might not persist in the event of idiosyncratic shocks, especially to China.

Japan is a notable example that exposures alone are not all that matters when ranking counterparties. The MCSR and DIP rankings show that the top three counterparties are the United States, the United Kingdom, and Hong Kong China, despite Japan's exposure to the latter being one order of magnitude below its exposures to the US and UK (Table 5). Under current conditions, the MCSR shows that the economy benefits from the diversification provided by its claims on European economies (France, Germany), and others in the region (China, Korea, and Singapore). As in the case of Hong Kong China, the ICSR rankings placed Western advanced economies as the top three risk contributors.

Unlike Japan, Korea's top two risk contributors in the MCSR and DIP rankings are China and the United States, the two countries to which Korea has the largest exposures (Table 6). The MCSR ranking suggests diversification benefits are limited for Korea. In a global distress event, the ICSR ranking indicates that the economy is affected by spillovers from both European jurisdictions (Germany and the United Kingdom) and Asian jurisdictions (China and Hong Kong, China), in sharp contrast to Japan and Hong Kong, China, where global distress risk is more unbalanced. Notably, Korea shows greater concentration in its ICSR rankings compared to other economies analyzed, with Germany's contribution being distinctly larger than other jurisdictions' contributions.

For the Philippines, similarly to Korea, the systemic risk rankings align with two of the economy's largest exposures: the United States and Japan. Moreover, in contrast to other countries, these two jurisdictions consistently rank among the top contributors regardless of the ranking approach used (Table 7). The economy, as others, gains very little in terms of diversification as the MCSR ranking shows. Regional risk exposures are mainly confined to Japan, with risk contributions from other jurisdictions in the region being order of magnitudes lower (MCSR and DIP rankings).

Among counterparties it is notable that Singapore is not among the top ranked risk contributors to any of the economies analyzed. Based on the size of the exposures, Singapore, as a counterparty, ranks second for Hong Kong China, third for Japan, sixth for Korea, and second for the Philippines. Two factors might contribute to its relatively small risk contributions. First, the PD of its banking sector is small (Figure 1), and second, its asset correlation lies in the lower percentiles of the sample distribution (Figure 2).

Table 4: Hong Kong, China: systemic risk rankings, in million USD (2025Q1)

Banking Jurisdiction	ES90	R90	ES95	R95	ES99	R99
MCSR Measure						
China	3577.203	1	123566.208	1	135847.334	1
Japan	1083.358	2	121072.363	2	1047.057	2
Korea	542.068	3	120531.072	3	498.825	3
United Kingdom	360.871	4	13676.125	4	351.801	4
Australia	360.348	5	9629.311	7	320.384	5
Switzerland	56.755	10	9817.199	5	203.071	6
India	109.794	8	-1057.076	11	47.784	7
France	104.459	9	9706.762	6	-21.575	8
United Arab Emirates	36.439	11	-1461.857	12	-37.769	9
Singapore	118.866	7	1717.322	8	-42.342	10
Qatar	18.493	13	-917.703	10	-57.679	11
United States	185.173	6	202.069	9	-80.295	12
Taiwan Province of China	36.212	12	-2123.833	13	-556.387	13
DIP Measure						
China	3577.850	1	70149.799	1	249954.602	1
Japan	1077.402	2	21124.290	2	1087.979	2
Korea	542.080	3	10628.385	3	629.914	3
United Kingdom	349.216	5	6846.967	5	487.440	4
Australia	370.251	4	7259.405	4	323.908	5
Singapore	112.041	7	2196.744	7	144.322	6
India	107.425	9	109.460	12	105.478	7
United States	181.671	6	3561.970	6	103.522	8
Switzerland	56.432	10	1106.444	9	77.598	9
France	108.534	8	2127.991	8	76.497	10
Taiwan Province of China	37.453	11	734.331	10	51.864	11
United Arab Emirates	36.294	12	711.601	11	36.973	12
Qatar	17.753	13	21.657	13	28.061	13
ICSR Measure						
Switzerland	138130.618	8	133477.212	1	6948.096	1
France	137336.763	10	133277.485	2	6748.368	2
United States	138232.659	7	133225.378	3	6696.261	3
Taiwan Province of China	138233.029	6	133035.531	4	6506.415	4
Singapore	138309.427	5	133008.057	5	6478.940	5
Australia	137859.853	9	132963.997	6	6434.880	6
United Kingdom	138625.916	3	132892.712	7	6363.596	7
China	137137.207	11	132880.232	8	6351.116	8
Korea	138568.133	4	132873.600	9	6344.483	9
Japan	138974.444	1	132686.120	10	6157.003	10
India	138887.821	2	132569.248	11	6040.131	11
United Arab Emirates	106582.050	12	28332.276	12	4990.685	12
Qatar	2093.302	13	9827.559	13	1698.205	13

Note: ESXX and RXX denote expected shortfall and ranking at the XX percent confidence level, with XX taking the values of 90, 95, and 99 percent.
Source: BIS, CRI, and the Authors.

Table 5: Japan: systemic risk rankings, in million USD (2025Q1)

Banking Jurisdiction	ES90	R90	ES95	R95	ES99	R99
MCSR Measure						
Hong Kong, China	218.201	5	-129.936	8	47467.454	1
United States	698.061	2	11310.480	4	38904.166	2
United Kingdom	703.001	1	10244.608	5	27615.101	3
Canada	43.773	11	-1341.091	9	1004.277	4
Belgium	104.161	9	-2003.433	10	496.675	5
Germany	226.596	4	53022.294	2	-297.602	6
Australia	154.636	7	-2265.126	11	-1840.328	7
Korea	191.452	6	52987.150	3	-1918.702	8
China	546.875	3	53342.572	1	-2617.882	9
Singapore	84.088	10	208.469	7	-5382.897	10
France	153.166	8	969.794	6	-15283.986	11
DIP Measure						
United Kingdom	727.527	1	13091.618	1	54969.959	1
United States	678.900	2	12216.580	2	51295.790	2
Hong Kong, China	212.297	5	3820.220	5	16040.594	3
France	152.977	8	2752.768	8	11558.504	4
Singapore	80.720	10	1452.534	10	6098.995	5
China	543.426	3	9778.777	3	1931.987	6
Australia	154.021	7	2771.549	7	620.405	7
Korea	190.639	6	3430.485	6	608.774	8
Germany	219.711	4	3953.631	4	575.838	9
Belgium	101.892	9	1833.510	9	273.027	10
Canada	45.460	11	818.035	11	128.271	11
ICSR Measure						
United Kingdom	99650.730	3	111618.855	2	237395.929	1
Germany	101745.157	2	117678.212	1	237352.476	2
United States	102084.670	1	102380.872	9	237124.029	3
Belgium	98338.352	5	99285.032	10	236724.784	4
Singapore	93848.683	11	103093.049	7	236701.751	5
Hong Kong, China	94411.792	9	103567.187	6	236610.863	6
Canada	98701.253	4	98912.620	11	236574.008	7
Australia	94720.283	8	102588.348	8	236549.873	8
France	94247.380	10	105768.077	5	236353.540	9
China	98184.033	6	111257.084	3	236001.084	10
Korea	96367.931	7	108910.108	4	235745.392	11

Note: ESXX and RXX denote expected shortfall and ranking at the XX percent confidence level, with XX taking the values of 90, 95, and 99 percent.
Source: BIS, CRI, and the Authors.

Table 6: Korea: systemic risk rankings, in million USD (2025Q1)

Banking Jurisdiction	ES90	R90	ES95	R95	ES99	R99
MCSR Measure						
China	385.975	1	12342.216	1	14894.988	1
United States	55.798	3	1013.801	4	408.611	2
Japan	89.233	2	1227.931	3	107.602	3
Indonesia	13.369	8	975.858	5	40.909	4
Germany	16.146	7	-49.073	11	40.743	5
India	18.447	6	658.688	7	38.191	6
Australia	11.389	10	731.263	6	36.593	7
France	12.808	9	-98.363	13	33.583	8
Hong Kong, China	36.303	4	1266.342	2	32.823	9
Singapore	6.607	11	-95.471	12	23.744	10
Vietnam	2.822	12	-30.243	10	17.108	11
United Kingdom	21.370	5	-5.075	8	14.404	12
Poland	2.490	14	-25.595	9	11.486	13
Taiwan Province of China	2.642	13	-184.572	14	6.299	14
DIP Measure						
China	384.016	1	7423.757	1	23915.806	1
United States	55.128	3	1065.738	3	3433.299	2
Japan	89.613	2	1732.394	2	96.796	3
Hong Kong, China	37.264	4	720.380	4	34.180	4
United Kingdom	20.813	5	402.353	5	29.657	5
India	18.266	6	353.124	6	19.291	6
Germany	16.146	7	20.280	12	18.776	7
France	12.888	9	249.149	8	18.394	8
Indonesia	13.339	8	257.869	7	16.458	9
Australia	11.677	10	225.729	9	13.182	10
Singapore	6.410	11	123.927	10	6.310	11
Taiwan Province of China	2.616	13	50.571	11	3.879	12
Vietnam	2.829	12	3.725	13	3.286	13
Poland	2.485	14	2.643	14	1.744	14
ICSR Measure						
Germany	20740.341	1	15979.785	2	6412.944	1
United Kingdom	18302.114	13	15969.605	3	4441.299	2
China	19271.444	3	15987.960	1	4411.656	3
Hong Kong, China	19026.605	8	15915.339	11	4405.297	4
Australia	18950.698	9	15924.316	9	4394.434	5
United States	18567.411	12	15945.368	8	4380.000	6
Indonesia	19182.346	5	15953.470	6	4363.558	7
France	19052.536	7	15862.418	13	4345.762	8
India	19164.608	6	15961.735	5	4339.816	9
Poland	19300.874	2	15969.519	4	4337.731	10
Singapore	18783.233	11	15910.247	12	4324.579	11
Japan	19186.590	4	15951.014	7	4321.040	12
Taiwan Province of China	18946.386	10	15917.056	10	4319.326	13
Vietnam	13228.986	14	9330.756	14	3305.646	14

Note: ESXX and RXX denote expected shortfall and ranking at the XX percent confidence level, with XX taking the values of 90, 95, and 99 percent.
Source: BIS, CRI, and the Authors.

Table 7: The Philippines: systemic risk rankings, in million USD (2025Q1)

Banking Jurisdiction	ES90	R90	ES95	R95	ES99	R99
MCSR Measure						
Japan	24.225	1	1253.383	1	849.463	1
United States	12.782	2	200.516	5	652.063	2
Indonesia	4.028	6	-3.519	8	23.321	3
India	3.715	7	1232.873	4	21.754	4
Korea	5.748	4	1234.907	3	20.825	5
Hong Kong, China	5.541	5	6.078	7	17.601	6
China	8.206	3	1237.364	2	17.107	7
United Kingdom	3.553	8	-8.158	9	-6.466	8
Singapore	2.593	9	23.589	6	-48.826	9
DIP Measure						
Japan	24.329	1	447.900	1	1951.824	1
United States	12.847	2	236.510	2	1030.645	2
Singapore	2.781	9	51.196	9	223.097	3
China	8.110	3	149.308	3	8.366	4
Korea	5.854	4	107.775	4	6.742	5
Hong Kong, China	5.556	5	102.291	5	6.029	6
India	3.732	7	68.707	7	5.242	7
Indonesia	3.964	6	72.969	6	5.019	8
United Kingdom	3.416	8	62.894	8	3.175	9
ICSR Measure						
India	1919.468	3	2044.254	2	3805.363	1
Japan	1925.563	1	2090.935	1	3804.169	2
United States	1911.994	5	1790.549	9	3803.221	3
United Kingdom	1906.084	7	1791.908	8	3802.761	4
Singapore	1908.238	6	1807.086	6	3800.808	5
Hong Kong, China	1902.789	8	1797.768	7	3800.527	6
Korea	1899.923	9	2042.639	3	3798.383	7
China	1916.722	4	2013.617	5	3797.191	8
Indonesia	1921.847	2	2027.205	4	3794.920	9

Note: ESXX and RXX denote expected shortfall and ranking at the XX percent confidence level, with XX taking the values of 90, 95, and 99 percent.
Source: BIS, CRI, and the Authors.

Lastly, Tables 8 to 11 show the concordance of the rankings for the same metric across different confidence levels, and between different metrics at the same confidence level. DIP rankings show high consistency across different confidence levels in Korea and Hong Kong, China, where the Kendall rank correlation coefficient τ typically exceeds 0.8. MCSR rankings are also concordant across confidence levels, with τ above 0.5 for most countries, though not as strong as the DIP rankings, with the exception of Japan. In contrast, ICSR rankings show the lowest concordance across all countries analyzed. Concordance across different rankings at the 90 percent confidence level is very strong between the MCSR and the DIP rankinges can be very strong in all countries ($\tau > 0.90$).

Table 8: Hong Kong, China: systemic risk rankings concordance, Kendall τ

	Risk metric		
	MCSR	DIP	ICSR
Panel A: same metric, different confidence levels concordance			
R90 and R95	0.67	0.92	-0.05
R90 and R99	0.67	0.87	-0.05
R95 and R99	0.74	0.79	1.00
Panel B: different metrics, same confidence level concordance			
90 percent confidence level			
MCSR	—	0.92	0.33
DIP	—	—	0.30
95 percent confidence level			
MCSR	—	0.62	0.03
DIP	—	—	0.00
99 percent confidence level			
MCSR	—	0.72	0.13
DIP	—	—	0.10

Note: RXX denote rankings at XX percent confidence levels, with XX taking the values of 90, 95, and 99 percent.
Source: BIS, CRI, and the Authors.

Table 9: Japan: systemic risk rankings concordance, Kendall τ

	Risk metric		
	MCSR	DIP	ICSR
Panel A: same metric, different confidence levels concordance			
R90 and R95	0.42	1.00	0.09
R90 and R99	0.20	0.49	0.35
R95 and R99	-0.09	0.49	-0.05
Panel B: different metrics, same confidence level concordance			
90 percent confidence level			
MCSR	—	1.00	0.38
DIP	—	—	0.38
95 percent confidence level			
MCSR	—	0.42	0.56
DIP	—	—	0.49
99 percent confidence level			
MCSR	—	-0.09	0.38
DIP	—	—	0.24

Note: RXX denote rankings at XX percent confidence levels, with XX taking the values of 90, 95, and 99 percent.
Source: BIS, CRI, and the Authors.

Table 10: Korea: systemic risk rankings concordance, Kendall τ

	Risk metric		
	MCSR	DIP	ICSR
Panel A: same metric, different confidence levels concordance			
R90 and R95	0.58	0.87	0.49
R90 and R99	0.60	0.93	0.85
R95 and R99	0.49	0.84	0.38
Panel B: different metrics, same confidence level concordance			
90 percent confidence level			
MCSR	—	1.00	0.19
DIP	—	—	0.19
95 percent confidence level			
MCSR	—	0.54	0.16
DIP	—	—	0.23
99 percent confidence level			
MCSR	—	0.58	0.27
DIP	—	—	0.38

Note: RXX denote rankings at XX percent confidence levels, with XX taking the values of 90, 95, and 99 percent.
Source: BIS, CRI, and the Authors.

Table 11: The Philippines: systemic risk rankings concordance, Kendall τ

	Risk metric		
	MCSR	DIP	ICSR
Panel A: same metric, different confidence levels concordance			
R90 and R95	0.56	0.50	0.28
R90 and R99	0.78	0.61	0.50
R95 and R99	0.56	0.33	0.22
Panel B: different metrics, same confidence level concordance			
90 percent confidence level			
MCSR	—	1.00	0.22
DIP	—	—	0.22
95 percent confidence level			
MCSR	—	0.56	0.44
DIP	—	—	0.33
99 percent confidence level			
MCSR	—	0.22	0.39
DIP	—	—	0.28

Note: RXX denote rankings at XX percent confidence levels, with XX taking the values of 90, 95, and 99 percent.
Source: BIS, CRI, and the Authors.

6 Conclusions

While it may be tempting to rank counterparties simply by the size of their exposures, such an approach ignores critical factors including default risk, interconnectedness, and co-dependence among financial institutions. We argue for the implementation of a systemic risk assessment method derived from the three portfolio-based approaches, the MCSR, DIP, and ICSR metrics, which integrates the risks arising from exposures, counterparty default risk, and dependence in the global banking system. Each of the approaches captures a different dimension of systemic risk: the MCSR provides a diversification-based ranking, the DIP captures idiosyncratic shock effects, and the ICSR measures spillover or contagion potential. Together with exposure data, it becomes possible to capture too-big-to-fail and too-connected-to-fail risk; two major concerns in financial stability analysis.

Nonetheless, two data limitations should be noted. First, indirect exposures beyond interbank linkages are not directly observed and are typically better captured by market-based models.[7] Second, exposures are measured only at the jurisdictional level, as bank-level bilateral data are generally unavailable to the public. Even so, the aggregate rankings remain informative, guiding surveillance toward the most relevant jurisdictions and helping prioritize limited supervisory resources.

7. Examples include CoVaR (Adrian and Brunnermeier 2016), variance decomposition rankings (Diebold and Yilmaz 2014; Chan-Lau 2017), the marginal expected shortfall (Acharya et al. 2017), and the systemic risk measure SRISK (Acharya, Engle, and Richardson 2012).

Even with these caveats, the multi-dimensional framework proves essential when examining our empirical application to four Asian banking systems, which demonstrates that systemic risk assessment benefits significantly from employing multiple complementary methodologies. The three approaches reveal distinct risk dimensions—diversification effects under normal conditions, vulnerabilities during institution-specific stress, and contagion potential during systemic crises. While Hong Kong China and Japan derive substantial benefits from their diversified international banking relationships, Korea and the Philippines exhibit more concentrated risk profiles that closely mirror their largest bilateral exposures. Notably, during global financial distress scenarios, systemic threats predominantly emanate from advanced Western economies rather than regional Asian counterparties.

The analysis further highlights heterogeneity in how interconnectedness manifests across jurisdictions and stress scenarios. Singapore illustrates how exposure size alone can be misleading: despite substantial regional banking linkages, it poses minimal systemic threat due to strong fundamentals and low correlation with global risk factors. Moreover, ranking stability varies considerably across methodologies, with DIP showing the greatest consistency across confidence intervals, while ICSR proves most volatile. For policymakers and supervisors, the key implication is clear: systemic risk surveillance must move beyond exposure size and adopt a multi-pronged framework that integrates diversification, idiosyncratic shocks, and contagion channels, ensuring that scarce supervisory resources are directed where systemic vulnerabilities are most likely to materialize.

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