



A quarter century after the 1997 Asian crisis: Looking back, where are we now?

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ABSTRACT

This study examines the evolution of systemic risk and contagion among Asian currencies and assesses whether vulnerabilities comparable to the 1997 Asian Crisis have re-emerged. Using daily exchange-rate returns for ten Asian currencies from 1994 to 2025, we combine component expected shortfall, an entropy-based systemic-risk concentration index, and the multilayer information spillover network framework. The findings show a transition from a highly concentrated crisis-period risk structure to a more diversified but still strongly interconnected regional currency system. The multilayer evidence identifies the South Korean won and Indonesian rupiah as persistent receivers of contagion, while the Chinese renminbi and Malaysian ringgit become more important receivers in the recent period. The Japanese yen emerges as a dominant transmitter of regional contagion, suggesting that yen-related policy and capital-flow developments may signal regional stress. The results support continuous surveillance, macroprudential coordination, and regional swap arrangements.

1. Introduction

Asian economies have become a central pillar of the global economic and financial system, undergoing profound structural and developmental transformations over the past two decades. Their rapid expansion—driven by industrialization, technological advancement, demographic shifts, and deep integration into global production networks—has reshaped global economic power balances. The region's economic importance is evident: according to the [International Monetary Fund \(2026\)](#), Asia and Pacific region's share of global GDP (PPP) is expected to rise from 45.67% in 2024 to 46.89% in 2026, while OECD projections ([Richter, 2025](#)) indicate that emerging Asia will account for 60% of global economic growth in 2025, up from 57% and 56% in 2023 and 2024. Its position as the world's "production factory," highlighted by [Koh et al. \(2005\)](#) and [Dumrongritikul et al. \(2019\)](#), further underscores its pivotal role in the global manufacturing landscape.

Yet Asia's remarkable rise has been accompanied by heightened exposure to both domestic and external shocks—an outcome closely tied to the same openness and integration that fuel its growth. Despite significant development, the region continues to exhibit structural vulnerabilities. [Chen et al. \(2016\)](#) and [Ye and Wei \(2012\)](#) highlight that economic fluctuations in Asian economies tend to be more severe and

persistent than in advanced economies, reflecting rigidities, uneven development, and the need for more robust institutional frameworks. These weaknesses have been amplified by rapid financial liberalization, which has deepened Asia's integration into global capital markets but also increased its sensitivity to shifts in investor sentiment, commodity price cycles, and geopolitical tensions. Currency markets have emerged as central conduits through which such shocks propagate. Exchange rate movements shape capital flows, external competitiveness, import costs, inflation dynamics, and the policy discretion of central banks. Episodes of heightened volatility, therefore, place authorities in challenging policy positions, forcing trade-offs between exchange-rate stabilization, monetary autonomy, and growth support. Given Asia's central role in global trade and production networks, currency instability can have consequences far beyond national borders, influencing global risk sentiment, supply chains, and financial market behavior. As Asia's economic weight expands, understanding the persistence of these vulnerabilities—and the mechanisms through which shocks transmit across its increasingly interconnected financial landscape—remains essential.

These vulnerabilities were revealed dramatically during the 1997 Asian Financial Crisis, a defining episode in the region's financial history. As [Barro \(2001\)](#) and [Radelet and Sachs \(1998\)](#) emphasize, before the crisis, East and Southeast Asian economies—particularly Thailand,

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Indonesia, Malaysia, South Korea, and the Philippines—were widely regarded as economic success stories, benefiting from export-driven growth, robust capital inflows, and rising international competitiveness. However, dependence on fixed or tightly managed exchange-rate regimes pegged to the U.S. dollar masked mounting structural pressures. Corsetti et al. (1999) argue that misaligned exchange rates, rising short-term external liabilities, and deteriorating asset quality contributed to mounting fragilities. The crisis erupted in July 1997 (Jin, 2015; Zhao et al., 2015) when Thailand abandoned its currency peg, triggering sharp onshore and offshore devaluations. The resulting shock rapidly spread across Indonesia, South Korea, Malaysia, the Philippines, Singapore, Hong Kong, and Japan (Radelet and Sachs, 1998; Tan et al., 2014), producing a regional contagion cycle marked by severe currency collapses, stock market crashes, capital flight, and abrupt reversals in private investment. The magnitude of the disruptions was substantial: equity markets fell by 30–80%, and several currencies experienced double-digit devaluations (Jang and Sul, 2002; Zurawicki and Braidot, 2005; Deesomsak et al., 2004), with Indonesia facing the most acute disruptions. The crisis provided an enduring lesson about the inherent fragility of Asian financial structures and the ease with which shocks can propagate across seemingly unrelated markets. Although Asia has since implemented substantial reforms—strengthening banking systems, enhancing prudential regulation, and gradually adopting more flexible exchange-rate regimes—many of the structural vulnerabilities exposed in 1997 remain relevant. A future shock of similar magnitude would likely produce repercussions far beyond financial losses, affecting trade flows, global supply chains, social stability, and policy coordination across the region. Consequently, a modern assessment of Asia's risk architecture must examine both the lessons of past crises and the complexities introduced by contemporary financial integration.

In recent decades, Asia's financial landscape has evolved significantly, yet the risks associated with currency markets and cross-market spillovers have become more multifaceted. Regional integration has deepened, cross-border capital flows have expanded, and global financial linkages have intensified. Li et al. (2020) state that Asia's rapidly developing digital economy, new trade structures, and accelerated technological adoption have further increased the speed and magnitude of financial interactions. Episodes such as the 2008 Global Financial Crisis, the 2015 Chinese stock market crash, and the COVID-19 pandemic have demonstrated that major global and regional shocks continue to exert powerful influence on Asian markets, often leading to sudden capital movements, liquidity pressures, and elevated volatility. At the same time, a substantial body of empirical evidence (Kodongo and Ojah, 2012; Boubakri and Guillaumin, 2015) indicates that currency risk remains significantly priced and becomes especially prominent during periods of heightened uncertainty. Peng et al. (2021) highlight that exchange rate volatility—particularly involving dominant regional currencies such as the Japanese yen—carries important implications for asset allocation, risk management, and the design of hedging strategies. Persistent intra-regional spillovers, asymmetric responses to shocks, and time-varying interactions suggest that Asian markets remain tightly interconnected despite having stronger financial systems today than during the 1997 crisis, as Kinkyo (2020, 2021) showed. These developments highlight the need for analytical frameworks capable of capturing extreme-risk behavior, complex interdependencies, and evolving channels of contagion in Asia's currency markets.

Against this backdrop, the objective of this study is to examine the evolution of systemic risk and contagion dynamics among major East and Southeast Asian foreign exchange markets most closely linked to the 1997 Asian Financial Crisis—specifically those of China, Hong Kong, Indonesia, Japan, Malaysia, the Philippines, Singapore, South Korea, Thailand, and Taiwan—from 1994 to 2025. These currencies are selected because they represent the core regional currency system surrounding the crisis (see Corsetti et al., 1999; Radelet and Sachs, 1998; Jang and Sul, 2002; Deesomsak et al., 2004; Kinkyo, 2020; Baig and Goldfajn, 1999; Barro, 2001; Gong et al., 2004), including directly

affected economies, such as Thailand, Indonesia, Malaysia, the Philippines, and South Korea, as well as regional financial centers and anchor economies, such as Hong Kong, Singapore, Japan, China, and Taiwan. Other regional currencies, such as the Indian rupee and Vietnamese dong, are excluded because, as argued by Dua and Sinha (2007), and previously documented by Radelet and Sachs (1998), and Corsetti et al. (1999), they were less directly integrated into the 1997 crisis transmission mechanism, and their inclusion would reduce cross-country comparability. This composition captures currencies that may transmit, receive, or amplify regional stress through trade, financial, and exchange-rate linkages, while also ensuring a consistent daily sample from the pre-crisis buildup to the recent period. Accordingly, the selected currency set provides an appropriate regional framework for assessing whether systemic-risk and contagion patterns resembling those observed during the 1997 Asian Financial Crisis have re-emerged.

Among alternative risk measures, focusing on systemic risk enables the identification of cascade-like transmission effects, revealing how distress originating in one currency market may propagate through the wider regional network. To address this, the study combines three complementary frameworks. First, it employs the Component Expected Shortfall (CES) framework of Banulescu and Dumitrescu (2015), which quantifies each market's contribution to regional losses under extreme conditions and captures asymmetries in tail behavior. Second, it constructs an entropy-based systemic-risk concentration index (EBI) (Billio et al., 2016) to evaluate whether regional risk is concentrated in a few dominant currencies or distributed more evenly across the currency system. This allows the analysis to distinguish between concentrated crisis-style fragility and more diversified forms of systemic vulnerability. Third, the study applies the multilayer information spillover network (MISN) framework of Wang et al. (2021), which builds on the Hong et al. (2001) and Hong et al. (2009) cross-correlation function causality approach and summarizes directional spillovers in a compact network structure. This framework decomposes risk transmission into three layers: mean spillovers, volatility spillovers, and extreme-risk spillovers. By estimating directed spillover networks across these layers, the analysis identifies persistent risk transmitters and receivers and shows whether contagion operates mainly through return interactions, volatility propagation, or extreme downside-risk channels. The study further considers both short- and longer-horizon spillover dependence by using alternative lag-bandwidth parameters, ($M = 5$) and ($M = 30$). In addition, rolling-window multilayer networks are estimated to capture the time-varying evolution of spillover connectedness across the Asian crisis period and the recent equal-length comparison period. This design enables the study to distinguish immediate contagion effects from more persistent, structurally embedded linkages and to assess whether recent Asian currency markets remain vulnerable despite lower and more diversified systemic risk contributions.

The contribution of this study is threefold. First, by examining systemic risk over a three-decade span, the analysis provides a long-horizon perspective on how structural vulnerabilities in Asian currency markets have evolved. Existing literature is largely concentrated on specific crisis episodes, shorter sample periods, single-method spillover approaches, or static connectedness frameworks (Yilmaz, 2010; Kinkyo, 2020, 2021; Yang et al., 2021; Kang et al., 2019; Tran and Vo, 2023; Alqaralleh et al. (2019); He and Hamori, 2021; Jebran et al., 2017; Chiranjivi and Sensarma, 2023), whereas this study offers broader evidence across multiple phases of regional and global financial stress. Second, the study contributes by offering an integrated framework that connects systemic-risk contribution, concentration, and transmission. CES identifies which currencies contribute most to regional tail-risk conditions, while the EBI shows whether these contributions are concentrated in a few dominant currencies or more evenly distributed across the system. The MISN framework of Wang et al. (2021) then traces how shocks travel across currencies and through which channels they are transmitted by separating spillovers into mean, volatility, and extreme-risk layers. This combined design provides a coherent mapping of Asian

currency-market fragility. Third, the study links this integrated evidence to policy-relevant surveillance. By jointly identifying systemically important contributors, concentration patterns, persistent receiver currencies, and dominant transmitters across different spillover layers, the framework provides a more comprehensive basis for monitoring systemic vulnerabilities than contribution, concentration, or spillover measures considered in isolation. This distinction is especially relevant because vulnerability is not limited to currencies that transmit shocks; currencies that consistently receive contagion effects also represent important nodes for investors, risk managers, and policymakers.

In the sections that follow, we first review the relevant literature. Section 3 presents the conceptual and mathematical foundations of the models employed, Section 4 reports and interprets the empirical findings, and Section 5 summarizes the main conclusions and discusses their broader implications.

2. Literature review

The study of Asian financial markets has generated a substantial and diverse literature, reflecting the region's growing economic importance and its susceptibility to systemic shocks. Researchers have examined Asia's structural transformation, the mechanisms underlying the 1997 crisis, and the evolving role of currency markets in transmitting volatility. A large body of work also explores spillovers, contagion dynamics, and the implications of deeper financial integration (see Wu and Wang, 2025; Yang et al., 2021; Tanaka and Fukuda, 2019; Ali et al., 2025), yet much less is known about how these interdependencies behave under extreme market conditions. This review synthesizes these strands to provide the conceptual foundation for analyzing systemic risk in Asian foreign exchange markets.

Early research highlights Asia's transformation into a major global economic powerhouse. Rathnayaka et al. (2022) document Asia's rapid rise in global output, with the region accounting for nearly 40% of world GDP (PPP) and more than half of global economic expansion. Dowling and Cheang (2000) and Koh et al. (2005) emphasize Asia's increasing integration into global value chains, particularly in electronics, textiles, and automotive production. Hirata and Otsu (2016) likewise show that deepening intra-Asian and global trade links have strengthened the region's economic and financial influence. Nasreen and Anwar (2014) report rising per capita incomes in Japan, South Korea, China, and India, reflecting long-term convergence toward advanced economies. Dumrongritikul et al. (2019) connect part of Asia's economic ascent to productivity gains, while Cunado et al. (2015) highlight the region's expanding role in energy and commodity markets. Nevertheless, Chen et al. (2016) and Ye and Wei (2012) emphasize structural challenges associated with inequality, supply-side constraints, and institutional rigidities. Altogether, this literature portrays Asia as a region whose economic complexity and structural transformation render the study of systemic risk both timely and essential.

The 1997 Asian Financial Crisis remains a central reference point for examining Asia's financial vulnerabilities. Barro (2001) and Radelet and Sachs (1998) highlight the roles of rigid currency pegs, excessive capital inflows, and macro-financial deterioration as key precursors to the crisis. Jin (2015) and Zhao et al. (2015) show how the collapse of the Thai baht sparked regional contagion through speculative pressures and quickly eroded investor confidence. Jang and Sul (2002) document severe equity declines and currency depreciations in Indonesia, South Korea, Malaysia, and Thailand, while Deesomsak et al. (2004) report extensive capital flight and abrupt reversals in private investment. Competing interpretations of the crisis include the financial-panic view (Corsetti et al., 1999; Dickinson and Mullineux, 2001), which emphasizes herd behavior and self-fulfilling expectations, and the fundamentalist perspective (Aggarwal, 1999; Aminian, 2005), which focuses on overleveraged financial systems, weak regulatory oversight, and fragile exchange-rate regimes. Although the crisis occurred decades ago, these mechanisms remain relevant for understanding how modern Asian

markets respond to shocks and transmit risks across borders.

A substantial body of research examines the role of currency risk in Asian financial markets. Kodongo and Ojah (2012) and Boubakri and Guillaumin (2015) show that currency risk commands a significant premium and is priced at both firm and market levels across emerging Asian economies. Grandmont-Gariboldi and Soenen (2000) and Barry and Rodriguez (2004) demonstrate that exchange-rate volatility significantly affects stock returns, particularly during periods of market stress. Peng et al. (2021) highlight the importance of the USD/JPY exchange rate in shaping risk management strategies, given the yen's regional influence. Phylaktis and Ravazzolo (2004) find considerable heterogeneity in real exchange-rate deviations from PPP across Asian economies, suggesting structural differences in inflation dynamics, financial integration, and exposure to external shocks. Studies by Nishikawa and Sato (2025) and Kinkyo (2021) emphasize policy dimensions including capital-flow regulation, foreign-exchange liberalization, and prospects for coordinated regional exchange-rate frameworks. Taken together, this literature positions currency markets as active transmitters of volatility, rather than passive indicators of fundamentals.

As Asia's financial systems have become more integrated both regionally and globally, research on spillovers and contagion dynamics has expanded accordingly. Chan-Lau and Ivashchenko (2003) find that U. S. markets historically influenced Asian financial behavior, though more recent studies (Wang and Xiao, 2023) suggest strengthening intra-Asian spillovers. Tran and Vo (2023) and Alqaralleh et al. (2019) show that spillover intensity increases sharply during global and regional crises such as the 2008 financial crisis, the 2015 Chinese market crash, and the COVID-19 pandemic. He and Hamori (2021), Kang et al. (2019), and Yilmaz (2010) report stronger co-movement and higher interconnectedness during turbulent periods, consistent with crisis-driven contagion. Shang and Hamori (2025) document that geopolitical tensions, economic policy uncertainty, and crude oil shocks exert powerful cross-market spillovers. Using wavelet and high-frequency approaches, Chiranjivi and Sensarma (2023) and Jebran et al. (2017) reveal time-varying and asymmetric volatility transmission, especially during negative shocks. Pham et al. (2024) show that smaller but highly interconnected financial institutions become key sources of systemic risk during tail events. Collectively, these studies highlight a regional financial network in which shocks can propagate rapidly across markets through both financial and currency channels.

Finally, a growing strand of literature indicates that many vulnerabilities exposed during the 1997 crisis persist today in more complex forms. Yilmaz (2010) demonstrates that increased financial and trade integration has strengthened cross-border volatility transmission. Hirata and Otsu (2016) reaffirm that deeper linkages continue to heighten sensitivity to global shocks. Cunado et al. (2015) highlight the region's exposure to commodity-market fluctuations, while Chen et al. (2016) identify structural rigidities that continue to challenge financial resilience. Rathnayaka et al. (2022) emphasize environmental and social pressures associated with rapid economic expansion. Together, these studies illustrate that Asia—despite significant reforms—remains exposed to structural vulnerabilities, exchange-rate fragilities, and increasingly complex financial interdependencies.

Regarding the models used in the literature for the estimation of systemic risk, we observe considerable interest especially in market-based measures such as CoVaR, marginal expected shortfall and component expected shortfall (Acharya et al., 2017; Caporin and Santucci de Magistris, 2012; Cai et al., 2015; Adrian and Brunnermeier, 2016), as well as in network-based connectedness indices in the work of Diebold & Yilmaz (2009, 2012). Following their papers, many research publications relied on their methodology to assess return and volatility spillovers across equities, commodities, and exchange-rate markets. However, the nuance of systemic risk, particularly its tail-focused, crisis-driven behavior, appears to be examined only to a limited extent in this literature. Moreover, variance-decomposition models remain less suited for uncovering the asymmetric and nonlinear

dynamics characteristic of systemic distress. In this respect, the systemic-risk literature increasingly relies on market-based tail-risk measures to evaluate how distress is transmitted across institutions, asset classes, and national markets. For instance, studies on banking and financial institutions use CoVaR, MES, expected shortfall, and related measures to identify systemically important entities and distress contributors (Adrian and Brunnermeier, 2016; Acharya et al., 2017; Brownlees and Engle, 2017; Banulescu and Dumitrescu, 2015; Wang et al., 2017; Corsi et al., 2018; Armanious, 2024; Caliskan et al., 2021). Similar evidence is generated in equity markets, where tail-risk measures are used to assess downside exposure, crisis vulnerability, and market-wide loss contribution (Allen et al., 2012; Kelly and Jiang, 2014; Eckernkemper, 2018; Cevik et al., 2024; Mazzarisi et al., 2020). Further applications are also observed in commodity, energy, and cryptocurrency markets, where systemic-risk measures help identify whether shocks remain market-specific or become transmitted across broader financial systems (Reboredo, 2015; Morelli, 2023; Syuhada et al., 2024; Fang et al., 2023; Gong et al., 2019; Zhang et al., 2022; Jiang et al., 2022; Manguzvane and Ngobese, 2023). However, applications to currency markets, particularly Asian currency systems, remain comparatively limited, leaving room for a more direct assessment of systemic-risk contribution in regional foreign-exchange markets.

We also observe that tail-risk-based systemic models have been applied only selectively to Asian markets when referring specifically to the core of systemic-risk investigation. For instance, the CES model of Banulescu and Dumitrescu (2015) has become a benchmark for decomposing system-wide losses into institution-specific contributions and identifying systemically important financial institutions. Subsequent studies extended this framework to link systemic risk with severe real-economy downturns, such as Caporin et al. (2022), or to identify systemically important stock markets in global equity networks and domestic financial sectors, as in Cevik et al. (2024) and Manguzvane and Ngobese (2023). Beyond these applications, CES-type approaches have also been used to evaluate systemic contributions in banking sectors, equity markets, commodity-linked markets, and broader financial networks (Banulescu and Dumitrescu, 2015; Günay et al., 2024; Cevik et al., 2024; Armanious, 2024; Manguzvane and Ngobese, 2023; Caporin et al., 2022). Some studies focus on institution-level contributions to aggregate financial distress (Banulescu and Dumitrescu, 2015; Pham et al., 2021; Acharya et al., 2017; Adrian and Brunnermeier, 2016; Armanious, 2024), while others extend the logic to country-level or market-level systemic-risk ranking across international financial systems (Liu et al., 2020; Cevik et al., 2024; Manguzvane and Ngobese, 2023). In currency-market research, however, CES-based evidence is still relatively scarce, especially for studies that treat exchange rates as direct contributors to regional systemic stress rather than as control variables or transmission channels. Yet its application to Asian currency markets is still limited. This gap offers an opportunity to extend CES-based systemic-risk analysis to a geographic region that is both highly integrated and historically crisis-sensitive. In the present study, CES is therefore used to quantify the magnitude of systemic contribution across Asian currencies, allowing us to identify which exchange-rate markets contribute more strongly to system-wide currency stress during crisis-sensitive periods.

At the same time, the level of systemic contribution alone does not fully reveal whether currency-market stress is concentrated in one or a few dominant currencies or distributed more evenly across the regional system. For this reason, the revised study complements CES with entropy-based measures that summarize the concentration structure of systemic risk weights. Entropy-based measures have been widely used in financial and economic research to describe uncertainty, concentration, diversification, information distribution across systems and the cross-sectional distribution of risk (Gong et al., 2019; Bekiros et al., 2017; Philippatos and Wilson, 1972; Usta and Kantar, 2011; Zhou et al., 2013; Billio et al., 2016). In equity markets, entropy indicators are used to

capture market disorder, portfolio diversification, information complexity, and the distribution of risk across assets (Philippatos and Wilson, 1972; Usta and Kantar, 2011; Bera and Park, 2008; Ormos and Zibriczy, 2014; Zhou et al., 2013). Similar entropy-based evidence is found in banking, commodity, energy, and cryptocurrency markets, where entropy measures help evaluate whether stress is concentrated in a small set of dominant units or dispersed across a broader system (Billio et al., 2016; Gradojevic and Caric, 2017; Dimpfl and Peter, 2013; Gkillas et al., 2021; Gong et al., 2019). In exchange-rate and international finance applications, entropy-based approaches also provide useful information about currency-market uncertainty, regime shifts, and cross-market dependence patterns among currencies and foreign-exchange dealers (Janczewski et al., 2024; Billio et al., 2016; Kinkyo, 2020, 2021). This additional layer is particularly useful for distinguishing between concentrated stress episodes, in which systemic pressure is driven by a limited number of currencies, and more diversified stress configurations, in which risk is more equally distributed across the regional currency system.

The multilayer spillover-network framework of Wang et al. (2021) provides a useful methodological structure for examining directional dependence across different channels of financial transmission. Its roots can be linked to the broader causality-testing literature developed by Hong et al. (2001), which examines directional dependence in mean and variance through cross-correlation-based testing, and Hong et al. (2009), which extends this logic to causality in risk by focusing on directional spillovers in the extreme tails. Recent studies increasingly show that multilayer network perspectives can reveal richer dependence structures than single-layer spillover models. For instance, studies in equity markets provide evidence on multilayer spillovers across return, volatility, and tail-risk channels (Wang et al., 2021, 2017; Dai et al., 2023). Similar applications are also found in cryptocurrency markets, where multilayer frameworks are used to examine shock transmission across digital assets and broader financial systems (Jiang et al., 2022). Additional evidence is generated for currency markets, showing that exchange-rate spillovers may operate through different information channels, market conditions, and time horizons (Janczewski et al., 2024; Kinkyo, 2020, 2021; Greenwood-Nimmo et al., 2025). However, despite these developments, limited evidence exists on how multilayer dependence structures can be used to evaluate systemic risk and contagion effects in Asian currency markets, especially across mean, volatility, and extreme-risk transmission layers. Building on these strands, this study uses the multilayer framework to capture the directional transmission of stress across these channels in Asian currency markets.

3. Methodology

To evaluate systemic vulnerability and extreme-risk transmission across Asian currency markets, we employ an integrated framework combining CES, EBI, and the MISN framework. The following subsections introduce the methodological background of each approach.

3.1. Component expected shortfall (CES)

According to the CES model of Banulescu and Dumitrescu (2015), CES quantifies the contribution of each variable to the system's tail risk. Let the aggregate system, or regional currency portfolio, return be defined as:

$$r_{mt} = \sum_{i=1}^n w_{it} r_{it} \quad (1)$$

where w_{it} denotes the portfolio weight of currency i at time t , constructed from value-adjusted exchange-rate series, and r_{it} denotes the corresponding log return. For the system-level expected shortfall, we define a distress threshold C , typically the system VaR. The conditional expected shortfall is:

$$ES_{m,t-1}(C) = -E_{t-1}(r_{mt}|r_{mt} < C) \quad (2)$$

This measures the expected system loss conditional on entering the left tail. The marginal expected shortfall of currency i is defined as:

$$MES_{i,t-1}(C) = -E_{t-1}(r_{it}|r_{mt} < C) \quad (3)$$

MES captures the sensitivity of currency i to system-wide tail events. A high MES indicates strong co-movement with the system during distress periods. CES then incorporates both the currency's tail sensitivity and its portfolio weight,

$$CES_{i,t-1}(C) = -w_{it}E_{t-1}(r_{it}|r_{mt} < C) \quad (4)$$

A key property of CES is additivity. The system-wide expected shortfall can be decomposed into currency-level contributions.

$$ES_{m,t-1}(C) = \sum_{i=1}^n CES_{i,t}(C) \quad (5)$$

Consequently, CES can also be expressed as a percentage of total system expected shortfall:

$$CES\%_{0i,t}(C) = \frac{CES_{i,t}(C)}{ES_{m,t}(C)} \times 100 \quad (6)$$

This percentage form allows direct comparison of each currency's relative contribution to regional systemic risk. A high MES indicates strong tail co-movement with the system, while a high w_{it} reflects the currency's relative importance in the regional portfolio. A high CES% therefore identifies currencies that contribute more substantially to system-wide tail losses. This additive and weight-adjusted structure makes CES suitable for comparing systemic risk contributions across the Asian crisis episode and the recent equal-length period.

3.2. Entropy-based index of systemic-risk concentration

To complement the CES analysis, we construct an EBI to assess whether systemic-risk contributions are concentrated in a few currencies or more evenly distributed across the regional currency system. The index is inspired by the entropy-based early-warning framework of Billio et al. (2016), who apply entropy to the cross-sectional distribution of systemic-risk measures, including MES, Δ -CoVaR, and network connectedness, to detect structural changes in financial fragility. Following their Shannon entropy formulation, we use a plug-in estimator based on the observed cross-sectional distribution of CES% values rather than the Bayesian entropy estimation procedure used in their full framework.

Let $CES\%_{0i,t}$ denote the percentage contribution of currency i to total regional systemic risk at time t , where $i = 1, \dots, N$. We convert the cross-sectional CES% values into normalized systemic-risk weights:

$$p_{i,t} = \frac{|CES\%_{0i,t}|}{\sum_{i=1}^N |CES\%_{0i,t}|} \quad (7)$$

where $p_{i,t}$ represents the relative systemic-risk weight of currency i . The absolute value is used to focus on the magnitude of systemic-risk contributions, and N is fixed at 10, corresponding to the ten currencies in the sample. A small numerical offset is applied only to avoid instability from zero entries and does not alter the interpretation of the index. Shannon entropy is then computed as:

$$H_t = -\sum_{i=1}^N p_{i,t} \ln(p_{i,t}) \quad (8)$$

The maximum entropy occurs when systemic-risk contributions are equally distributed across all currencies and is given by:

$$H_{\max} = \ln(N) \quad (9)$$

We then transform normalized entropy into an entropy-based

concentration index:

$$EBI_t = 1 - \frac{H_t}{H_{\max}} \quad (10)$$

The EBI ranges between 0 and 1. Values close to 0 indicate that systemic-risk contributions are more evenly distributed across currencies, while values close to 1 indicate that systemic risk is concentrated in a smaller number of dominant currencies. Therefore, a higher EBI reflects stronger systemic-risk concentration and greater contagion potential, whereas a lower EBI indicates a more diversified or muted stress profile. For visualization, we use 0.2 and 0.5 as reference thresholds to distinguish low, moderate, and elevated concentration regimes. These thresholds are not treated as formally estimated crisis cutoffs, but as visual guides for interpreting changes in systemic-risk concentration over time.

3.3. Multilayer information spillover network (MISN)

To examine directional risk transmission across Asian currency markets, we employ the MISN framework of Wang et al. (2021). This approach builds on the Hong-type cross-correlation function (CCF) causality framework and summarizes pairwise spillover effects in a compact network form. The model separates information transmission into three layers: mean spillovers, volatility spillovers, and extreme-risk spillovers. The mean layer captures return-based information transmission, the volatility layer captures second-moment dependence, and the extreme-risk layer captures downside tail-risk spillovers through VaR-exceedance indicators.

Let $r_{i,t}$ denote the log return of currency i at time t . In the first step, each return series is filtered using an ARMA-GARCH-type specification to obtain the estimated residuals $\hat{\varepsilon}_{i,t}$, the conditional mean $\hat{\mu}_{i,t}$, and the conditional variance $\hat{h}_{i,t}$. The mean spillover layer is constructed from standardized residuals:

$$\hat{u}_{i,t} = \frac{\hat{\varepsilon}_{i,t}}{\sqrt{\hat{h}_{i,t}}} \quad (11)$$

The volatility spillover layer is constructed from centered squared standardized residuals:

$$\hat{v}_{i,t} = \frac{\hat{\varepsilon}_{i,t}^2}{\hat{h}_{i,t}} - 1 \quad (12)$$

For the extreme-risk layer, we first estimate the downside VaR loss:

$$\hat{V}_{i,t} = -\hat{\mu}_{i,t} - z_{\alpha} \sqrt{\hat{h}_{i,t}} \quad (13)$$

where z_{α} is the left-tail quantile of the standardized residuals. Since $\hat{V}_{i,t}$ is expressed as a positive downside VaR loss, the VaR-exceedance indicator is defined as:

$$\hat{Z}_{i,t} = 1(r_{i,t} < -\hat{V}_{i,t}) \quad (14)$$

Thus, the three layer-specific variables are $\hat{u}_{i,t}$, $\hat{v}_{i,t}$, and $\hat{Z}_{i,t}$, corresponding to mean, volatility, and extreme-risk spillovers, respectively.

In the second step, we apply the Hong-type CCF test to each ordered currency pair. A directed spillover from currency i to currency j is identified when lagged values of currency i 's layer-specific variable help predict the current value of currency j 's corresponding layer-specific variable. Let $\hat{\rho}_{ij}(k)$ denote the sample cross-correlation between the current target variable and the k -period lagged source variable. The test statistic is constructed as:

$$Q(M) = \frac{T \sum_{k=1}^{T-1} K^2(k/M) \hat{\rho}_{ij}^2(k) - C_T(M)}{(2D_T(M))^{1/2}} \quad (15)$$

where M is the lag-bandwidth parameter and $K(\cdot)$ is the kernel function.

The centering and standardization constants are defined as:

$$C_T(M) = \sum_{k=1}^{T-1} (1 - k/T) K^2(k/M) \quad (16)$$

$$D_T(M) = \sum_{k=1}^{T-1} (1 - k/T) \{1 - (k+1)/T\} K^4(k/M) \quad (17)$$

Following Hong et al. (2009) and Wang et al. (2021), we use the Daniell kernel:

$$K(x) = \frac{\sin(\pi x)}{\pi x} \quad (18)$$

A directed edge is assigned when the test statistic exceeds the right-tail critical value. Because the network construction involves $N(N-1)$ directed pairwise tests within each layer, we apply a Bonferroni-adjusted significance level when determining statistically significant spillover edges:

$$\beta^* = \frac{\beta}{N(N-1)} \quad (19)$$

where β is the baseline significance level and β^* is the adjusted significance level used for edge selection. Accordingly, the right-tail critical value is computed using the Bonferroni-adjusted level. For each layer α , the adjacency matrix is defined as:

$$a_{ij}^{[\alpha]} = \begin{cases} 1, & \text{if currency } i \text{ has a significant spillover effect on currency } j, \\ 0, & \text{otherwise} \end{cases} \quad (20)$$

The resulting multilayer system consists of three directed adjacency matrices corresponding to the mean, volatility, and extreme-risk layers. To summarize the density of each layer, we calculate the layer-specific degree:

$$a^{[\alpha]} = \sum_{i,j=1, i \neq j}^N a_{ij}^{[\alpha]}, \quad \alpha = 1, 2, \dots, L \quad (21)$$

where $a_{ij}^{[\alpha]}$ represents the directed spillover edge from currency i to currency j on layer α . A larger value of $a^{[\alpha]}$ indicates a greater number of significant directed spillover links on that layer and therefore stronger layer-specific interconnectedness. We report networks for $M = 5$ and $M = 30$, where $M = 5$ captures short-horizon spillover dependence and $M = 30$ captures longer-horizon or more persistent transmission. To examine the time-varying dimension of spillover connectedness, we also estimate rolling-window multilayer networks using a 240-day window and a 20-day step, following Wang et al. (2021). This allows us to trace the dynamic degree of mean, volatility, and extreme-risk spillovers across the Asian crisis period and the recent equal-length comparison period.

4. Empirical analysis

Systemic risk analysis and the identification of contagion patterns become particularly important when economic and financial linkages among currency markets are strong and dependencies are complex. Identifying systemically risky currencies or currency-market nodes within such a network provides both time and strategic advantage for developing and implementing appropriate policy responses during periods of turbulence. Given that the 1997 Asian crisis originated from speculative attacks on the Thai baht, this study examines its onset and subsequent evolution through exchange rate dynamics. Building on this motivation, the empirical analysis investigates systemic-risk contributions, concentration patterns, and directional spillover dynamics among major Asian currencies using the CES framework of Banulescu and Dumitrescu (2015), the EBI early-warning logic of Billio et al. (2016),

and the MISN approach of Wang et al. (2021), respectively. The sample period spans from January 4, 1994, to October 27, 2025, thereby encompassing various market developments and allowing for comparison with the Asian crisis episode and the recent equal-length period. This approach enables meaningful cross-period comparisons and offers valuable insights for both policymakers and market participants. The empirical investigation focuses on ten Asian currencies: the Chinese Renminbi (CR), Hong Kong Dollar (HKD), Indonesian Rupiah (IR), Japanese Yen (JY), Malaysian Ringgit (MR), Philippine Peso (PP), Singapore Dollar (SD), South Korean Won (SKW), Thai Baht (TB), and Taiwan Dollar (TD). The data are obtained from LSEG Eikon, with all exchange rates quoted as units of local currency per U.S. dollar; accordingly, a positive return indicates depreciation of the respective Asian currency against the U.S. dollar, while a negative return indicates appreciation. All analyses are conducted using daily logarithmic returns multiplied by 100 to express them in percentage terms.

Table 1 displays the descriptive statistics of the variables. The mean returns of all currencies are close to zero, although some cross-country differences are notable. IR exhibits significantly higher positive means, reflecting post-crisis adjustments and appreciation tendencies in response to regional recovery and monetary stabilization. In contrast, CR presents a slightly negative mean, consistent with its managed exchange rate regime during much of the sample period. Volatility, as measured by standard deviation, varies considerably across currencies. IR, TB, and SKW show the highest volatility, emphasizing their greater exposure to speculative pressures and vulnerability during crisis episodes. Conversely, HKD and TD display lower volatility, consistent with their policy frameworks and stronger financial linkages to stable markets. Skewness coefficients indicate modest asymmetries in the return distributions of most variables. HKD, IR, and TB are positively skewed, implying the presence of occasional large appreciations, while other currencies mostly exhibit mild negative skewness, reflecting downward pressure during turbulent phases. Kurtosis values are strikingly high, especially for HKD, SKW, PP, and IR, signaling heavy tails and the likelihood of extreme market movements. The Jarque–Bera test confirms significant deviations from normality across all currencies, reinforcing the presence of fat-tailed and non-linear behaviors typical of crisis-driven markets. Finally, both the Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) tests reject the null hypothesis of a unit root, confirming stationarity in all log-return series.

In Fig. 1, we exhibit the return series of the variables. According to the patterns illustrated, HKD, SD, and TD display limited fluctuations throughout the sample period, reflecting these economies' tightly managed or partially controlled exchange rate regimes during the late 1990s and early 2000s. TD remains one of the most stable currencies in the sample, with contained movements and limited crisis contagion, supported by strong reserves and conservative monetary management. Similarly, SD shows relatively low volatility throughout, highlighting the Monetary Authority of Singapore's managed float framework and the economy's solid fundamentals that shielded it from extreme contagion. Volatility remains subdued until gradual financial liberalization in the mid-2010s, after which mild variations become more visible, particularly around global shocks such as the U.S.–China trade tensions and the COVID-19 pandemic. This behavior confirms the managed nature of these currencies and their relative insulation from speculative pressures during most of the period. The CR shows limited volatility before 2005, consistent with China's fixed exchange rate regime. A visible increase in fluctuations appears after the 2005 reform, when China introduced a managed float system. The pronounced spikes around 2008–2010 reflect global financial stress, while the later period displays renewed stability, indicating continued management of the currency and effective intervention policies that constrained excessive market volatility. IR shows pronounced volatility during the 1997–1998 Asian crisis, when it depreciated sharply following massive speculative attacks. Though calmer afterward, volatility reemerges during the 2008 GFC and again in 2020 during pandemic-related turbulence, reflecting

Table 1
Descriptive statistics.

	CR	HKD	IR	JY	MR
Mean	−0.0067	0.0001	0.0246	0.0033	0.0070
Median	−0.0017	0.0000	0.0000	0.0105	0.0000
Std. Dev.	0.6397	0.0583	1.3003	0.6660	0.4836
Skewness	−0.2428	1.0402	2.0583	−0.4190	−0.3373
Kurtosis	13.5119	118.2845	107.9483	8.6718	43.2789
Jarque-Bera	36,787	4416,661	3664,622	10,920	539,122
ADF	−17.5527	−55.4087	−19.5912	−90.5519	−18.0111
PP	−137.3310	−129.8069	−89.1685	−90.5502	−82.7237
	PP	SD	SKW	TB	TD
Mean	0.0095	−0.0029	0.0046	0.0008	0.0037
Median	0.0000	0.0000	−0.0052	0.0013	0.0000
Std. Dev.	0.4756	0.3563	0.8291	0.8470	0.2899
Skewness	−1.2414	−0.3833	−2.5223	0.7920	−0.2719
Kurtosis	87.3409	12.8756	172.3688	27.6374	19.4013
Jarque-Bera	2365,176 ^a	32,595 ^a	9538,113 ^a	202,485 ^a	89,463 ^a
ADF	−21.4001 ^a	−94.2384 ^a	−16.6332 ^a	−60.9797 ^a	−83.8006 ^a
PP	−86.1187 ^a	−94.2585 ^a	−85.5155 ^a	−120.8137 ^a	−85.4900 ^a

^a indicates the significance 1% level. ADF: Augmented Dickey-Fuller test; PP: Phillips-Perron test. CR (Chinese Renminbi), HKD (Hong Kong Dollar), IR (Indonesian Rupiah), JY (Japanese Yen), MR (Malaysian Ringgit), PP (Philippine Peso), SD (Singapore Dollar), SKW (South Korean Won), TB (Thai Baht), TD (Taiwan Dollar).

sensitivity to capital flow reversals, but none of these episodes were as severe as the impact of the Asian crisis. JY exhibits moderate fluctuations with notable appreciation episodes during global risk-off periods, particularly in 1998, 2008, and 2020, consistent with its safe-haven status. MR experiences strong disturbances during the crisis, followed by stabilization after the adoption of capital controls in 1998. Post-2005, mild fluctuations indicate progressive liberalization and adaptation to global market conditions. PP presents high volatility during the crisis period, with subsequent moderate stability. SKW experiences heavy turbulence during the 1997–1998 crisis but demonstrates clear stabilization afterward, despite short-lived volatility around 2008 and 2020—reflecting improved macro-financial resilience. TB, as the origin of the 1997 crisis, records extreme volatility during the crisis onset. After the adoption of a floating regime, fluctuations subside considerably, with only moderate responses to later global shocks.

Following the descriptive statistics, we proceed to the main empirical analysis, beginning with CES, to identify the currencies that are most systemically risky, namely those contributing the most to regional financial distress. CES builds on the Marginal Expected Shortfall (MES) framework of [Acharya et al. \(2010\)](#) and allows the decomposition of the overall portfolio's expected shortfall into the percentage contributions of each asset—here, individual Asian currencies—conditional on the system being in distress. This feature is vital in capturing the extent to which each currency amplifies or transmits systemic stress when extreme events occur. To generate CES%, the authors first construct a systemic portfolio and estimate each currency's conditional tail dependence through volatility modeling. This combination enables the dynamic estimation of tail risk contributions through time. The resulting CES% values provide a clear and time-varying ranking of currencies according to their systemic importance. A higher CES% identifies currencies that contribute more strongly to regional systemic losses, while lower values indicate more limited contributions to system-wide distress. In constructing the econometric framework, we follow [Caporin and Santucci de Magistris \(2012\)](#) and [Cai et al. \(2015\)](#) and use a value-weighted regional currency portfolio. Unlike firm- or institution-level applications of CES, currencies do not have a directly observable market-capitalization measure that can be used as a comparable weighting basis. We therefore normalize each exchange-rate series to one at the beginning of the relevant sample period and allow it to evolve according to its cumulative value changes. At each point in time, the weight of each currency is calculated as its normalized value relative to the total normalized value of all currencies in the system. This procedure provides time-varying portfolio weights while avoiding distortions arising from differences in currency quotation scales. In line

with the original methodology of [Banulescu and Dumitrescu \(2015\)](#), the test is performed on a quarterly basis. Since our reference point is the 1997 Asian Financial Crisis, we center the first analysis window around this event by incorporating three years before and three years after its occurrence. Accordingly, the benchmark period spans from the beginning of January 1994 to December 2000, covering the pre-crisis buildup, the peak of the turmoil, and the initial recovery phase. In the second stage, the same analytical framework is applied to the most recent seven-year period, from October 2018 to September 2025, allowing us to explore whether systemic risk patterns observed during the crisis years have reemerged or evolved under current market conditions. The results of the CES% analysis are presented in [Tables 2 and 3](#) for the first and second phases, respectively.

According to the results in [Table 2](#), during the pre-crisis period from 1994 to the first half of 1997, JY dominates systemic risk, with CES% values frequently ranging between 25% and 59%. This strong contribution might be attributed to Japan's central role in regional funding and carry-trade activities. JY's leading role indicates that shocks originating in Japan could easily transmit across Asian markets through cross-border financial linkages. Meanwhile, TB exhibits an upward trend in CES% from 1995 onward, fluctuating around 20% while reaching 40% in 1995Q1, signaling early fragility as speculative pressures intensified and foreign reserves weakened under the fixed exchange rate regime. Other ASEAN currencies contribute only modestly to systemic risk within the regional market portfolio. Taken together, our findings highlight the systemic importance of JY and TB during the pre-crisis period—the former due to its economic influence and regional linkages, and the latter because of its growing vulnerability to speculative attacks. The onset of the 1997 crisis is clearly reflected in the CES findings. TB's CES% rises sharply to around 72% in 1997Q2, consistent with the timing of speculative attacks that began in May 1997 and culminated on July 2, 1997, when Thailand was forced to abandon its fixed exchange rate. This identifies TB as the single dominant source of systemic risk precisely at the time of the devaluation and the collapse of the currency peg. This dramatic spike represents the center of contagion, where losses in TB explain the majority of the region's extreme tail losses. Simultaneously, JY's systemic contribution declines, reflecting the transition of the crisis epicenter from Japan's funding environment to the ASEAN currency systems. After the devaluation, from 1998 onward, IR becomes the leading source of systemic risk. Its CES% remains consistently high, between 17% and 60% through 2000, corresponding to Indonesia's severe economic contraction, political instability, and repeated financial volatility during IMF program implementation. These results imply that during regional stress, losses in IR dominate the

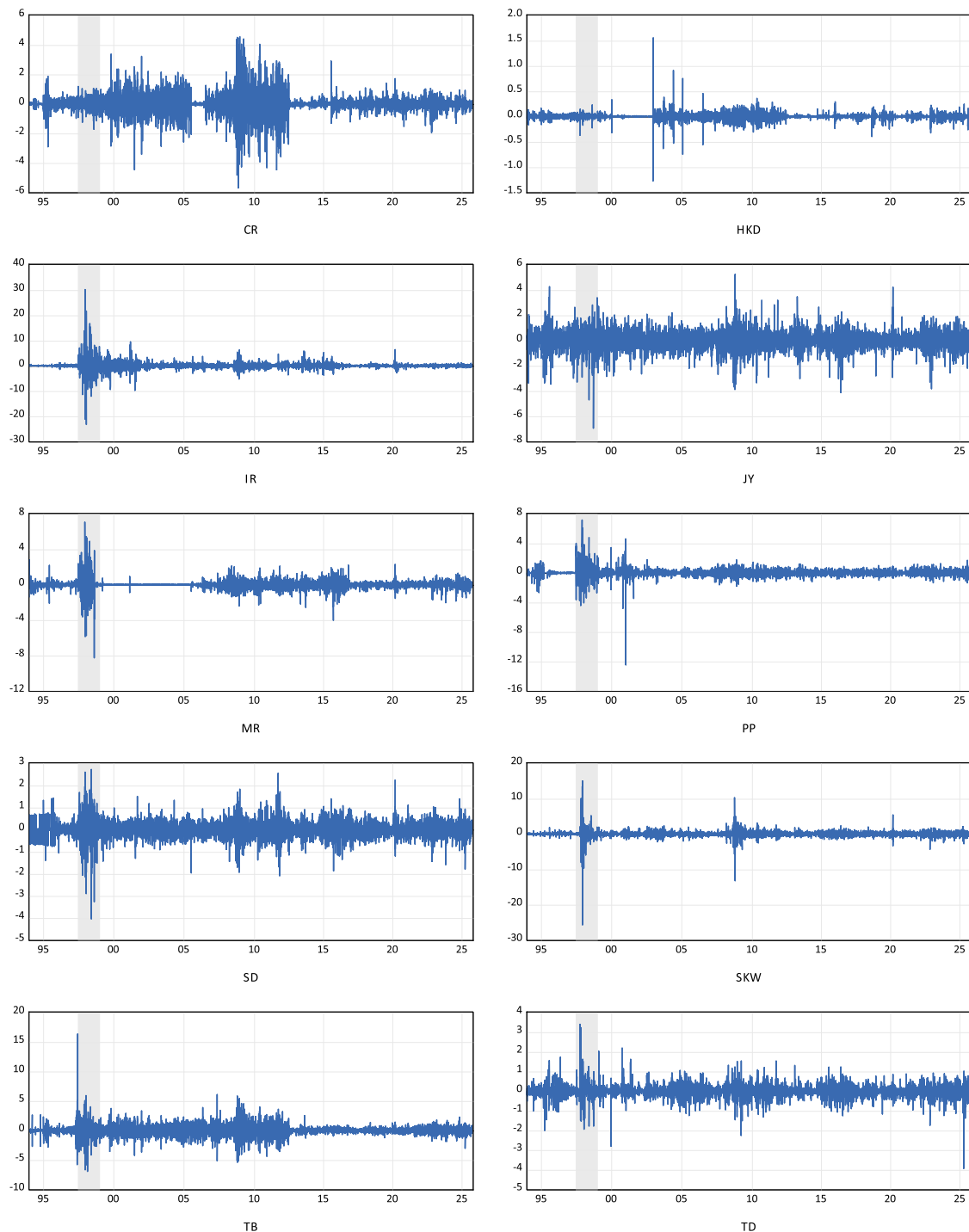


Fig. 1. Return Series of the Variables.

Note: CR (Chinese Renminbi), HKD (Hong Kong Dollar), IR (Indonesian Rupiah), JY (Japanese Yen), MR (Malaysian Ringgit), PP (Philippine Peso), SD (Singapore Dollar), SKW (South Korean Won), TB (Thai Baht), TD (Taiwan Dollar).

systemic risk of the currency network, confirming that contagion shifted toward Indonesia's fragile macroeconomic structure. Despite global shocks such as the Russian default and the LTCM collapse in 1998, the regional systemic leadership remains with IR, indicating that domestic structural fragility, rather than external shocks, determined systemic risk within Asia. By 2000, both IR and TB maintain notable CES% shares, pointing to post-crisis aftershocks, whereas JY's influence moderates compared to its pre-crisis levels.

The CES% results for the second period, presented in Table 3, spanning from late 2018 to the third quarter of 2025, illustrate a

markedly different structure of systemic risk across Asian currencies compared to the 1990s crisis era. The results show that systemic risk is now more diversified, with several currencies sharing moderate to high CES% values rather than a single dominant source as observed during the 1997–1998 crisis. This shift indicates a more balanced but still interconnected regional structure, where systemic influence is distributed among multiple markets rather than concentrated in one currency. Early in the sample (2018–2021), IR, SKW, MR, and PP stand out as the leading contributors to systemic risk. IR frequently records CES% values between 10% and 30%, making it the most systemically important

Table 2

Component Expected Shortfall (CES) analysis during the 1997 Asia financial crisis.

	CR	HKD	IR	JY	MR	PP	SD	SKW	TD	TB
94-Q1	-0.51	0.25	2.03	51.79	18.08	2.12	22.04	-3.94	-1.45	9.59
94-Q2	0.55	0.27	1.25	49.4	-0.88	6.45	29.76	-2.42	11.18	4.44
94-Q3	-0.54	0.14	0.79	38.54	9.84	35	12.87	-2.49	0.24	5.62
94-Q4	-0.66	0.29	0.64	29.01	7.25	47.18	5.24	-0.78	4.18	7.64
95-Q1	22.71	0.27	0.00	25.61	4.27	4.13	3.68	0.46	-2.03	40.89
95-Q2	6.37	0.62	0.14	46.93	8.28	6.55	8.34	1.84	3.47	17.45
95-Q3	1.96	0.32	0.45	58.82	12.21	-0.14	10.15	4.25	3.02	8.96
95-Q4	7.61	0.46	2.39	43.65	8.11	3.85	7.71	7.29	3.12	15.8
96-Q1	5.66	0.48	4.16	36.36	12.00	1.46	9.46	5.84	5.28	19.31
96-Q2	9.41	0.48	0.94	41.37	7.60	0.06	5.64	6.58	6.46	21.45
96-Q3	13.94	0.47	3.19	43.35	4.88	0.03	2.88	3.88	5.10	22.27
96-Q4	6.71	0.43	3.19	45.61	5.46	0.09	4.30	7.71	4.49	22.01
97-Q1	12.36	0.39	3.08	41.62	7.08	0.29	5.8	4.12	3.72	21.54
97-Q2	0.60	0.13	0.09	20.98	2.42	-0.03	2.03	0.65	0.98	72.14
97-Q3	0.43	0.06	26.45	5.17	22.48	11.17	4.59	0.22	0.40	29.02
97-Q4	0.02	0.02	21.75	1.09	3.39	5.63	2.60	56.8	0.36	8.34
98-Q1	0.25	0.03	37.81	3.55	17.59	6.87	6.6	8.80	1.69	16.81
98-Q2	-0.15	0.04	36.01	6.35	17.99	8.62	12.88	3.99	2.44	11.83
98-Q3	-1.37	0.04	17.71	12.13	26.68	8.53	13.38	4.41	1.85	16.63
98-Q4	0.79	0.06	41.19	11.03	2.74	6.67	6.5	6.58	2.59	21.85
99-Q1	2.00	0.13	42.76	14.35	4.95	4.39	7.34	4.83	4.12	15.13
99-Q2	0.74	0.04	60.82	8.99	1.81	3.81	5.46	4.18	3.42	10.74
99-Q3	2.80	0.03	47.05	8.04	0.56	4.28	5.37	3.52	1.44	26.91
99-Q4	6.95	0.06	43.74	7.03	0.35	4.09	5.96	4.58	3.78	23.45
00-Q1	5.20	0.05	40.91	14.86	0.71	4.47	7.99	4.98	4.56	16.27
00-Q2	5.84	0.05	46.85	10.46	0.11	6.99	6.57	4.27	3.55	15.31
00-Q3	3.65	0.05	36.56	11.79	0.22	7.31	5.85	8.61	2.90	23.07
00-Q4	3.82	0.04	35.55	5.58	0.08	7.02	4.83	10.02	2.33	30.73

Note: CR (Chinese Renminbi), HKD (Hong Kong Dollar), IR (Indonesian Rupiah), JY (Japanese Yen), MR (Malaysian Ringgit), PP (Philippine Peso), SD (Singapore Dollar), SKW (South Korean Won), TB (Thai Baht), TD (Taiwan Dollar). The dates in each column represent the specific days on which the impact of commodities on portfolio systemic risk is calculated. The quarter labels indicate the periods for which the CES contributions of each currency to total regional systemic risk are reported.

Table 3

Component Expected Shortfall (CES) analysis over recent years.

	CR	HKD	IR	JY	MR	PP	SD	SKW	TD	TB
18-Q4	6.88	0.57	20.56	6.6	10.98	13.77	5.41	17.51	9.24	8.48
19-Q1	6.62	0.50	13.92	9.84	9.66	16.58	5.65	14.02	7.30	15.92
19-Q2	7.53	0.78	10.41	8.55	11.79	12.3	5.05	15.64	13.5	14.45
19-Q3	11.09	0.74	15.47	5.32	13.05	15.39	5.09	16.40	9.57	7.87
19-Q4	9.27	1.30	10.48	4.99	19.24	11.68	3.83	19.10	10.09	10.02
20-Q1	5.31	0.14	29.66	6.60	17.06	2.98	5.26	24.63	3.67	4.69
20-Q2	5.88	0.33	25.52	4.84	13.71	8.44	6.63	18.57	8.45	7.63
20-Q3	8.33	0.35	16.31	9.87	13.73	6.75	5.8	15.47	12.51	10.89
20-Q4	7.41	0.40	14.98	8.90	14.43	4.99	5.28	19.80	6.59	17.23
21-Q1	8.56	0.51	13.36	10.91	13.27	6.11	7.38	16.2	7.64	16.05
21-Q2	7.81	0.41	13.17	6.34	11.93	13.73	5.23	18.31	8.59	14.46
21-Q3	7.04	0.57	9.90	6.30	9.99	17.74	5.54	17.79	7.59	17.56
21-Q4	4.93	0.62	9.91	8.75	14.39	18.31	5.21	14.41	7.81	15.67
22-Q1	5.03	0.51	6.34	16.25	9.41	8.88	4.30	20.23	13.32	15.73
22-Q2	6.73	0.44	9.45	16.58	7.95	12.57	5.83	20.45	8.88	11.11
22-Q3	15.13	0.29	9.56	11.00	9.67	10.58	4.99	17.98	9.03	11.77
22-Q4	6.23	0.52	7.60	21.16	13.62	12.14	4.46	17.46	5.95	10.84
23-Q1	7.86	0.24	7.53	14.75	17.32	7.58	3.62	21.29	7.17	12.62
23-Q2	11.12	0.47	6.19	12.05	14.48	6.17	5.22	22.17	7.88	14.25
23-Q3	5.84	0.85	11.64	11.96	10.81	8.75	5.49	18.36	7.79	18.51
23-Q4	6.51	0.24	12.37	12.09	14.45	8.40	3.73	14.54	13.11	14.56
24-Q1	7.27	0.29	12.43	11.48	17.05	8.33	3.77	19.08	9.90	10.40
24-Q2	4.58	0.40	17.86	17.42	9.94	8.47	4.74	13.69	9.33	13.58
24-Q3	4.77	0.63	11.10	17.17	21.38	7.39	3.11	9.98	12.59	11.89
24-Q4	3.82	0.42	14.3	17.89	16.00	11.07	5.30	11.58	6.52	13.10
25-Q1	5.6	0.44	14.66	17.12	13.82	10.93	5.94	11.14	5.99	14.36
25-Q2	3.10	0.28	12.72	11.15	15.98	12.89	3.46	17.31	13.90	9.20
25-Q3	5.52	0.51	13.27	13.08	10.84	16.68	3.85	16.81	8.89	10.55

Note: CR (Chinese Renminbi), HKD (Hong Kong Dollar), IR (Indonesian Rupiah), JY (Japanese Yen), MR (Malaysian Ringgit), PP (Philippine Peso), SD (Singapore Dollar), SKW (South Korean Won), TB (Thai Baht), TD (Taiwan Dollar). The dates in each column represent the specific days on which the impact of commodities on portfolio systemic risk is calculated. The quarter labels indicate the periods for which the CES contributions of each currency to total regional systemic risk are reported.

currency in several quarters, consistent with Indonesia's continuing sensitivity to global capital flow cycles and commodity price volatility. MR also exhibits elevated and persistent CES% levels, often exceeding 10%, reflecting its exposure to fluctuations in energy and commodity markets as well as strong trade linkages with China and other regional partners. SKW shows relatively high CES% values, around 14–25%, reflecting Korea's strong financial openness and its dual role as both a regional funding and investment currency. PP similarly exhibits CES% in the 5–18% range, driven by external financing dependence and domestic fiscal pressures that amplify its co-movement with broader regional shocks. When we look at the second phase of this period, from 2022 to 2025, as markets adapt to post-pandemic normalization, energy price volatility, and renewed geopolitical uncertainty, CES% levels moderate yet remain relatively higher for JY, IR, SKW, MR, and TB compared to others, implying that regional risk remains concentrated among these currencies. Interpreting these findings, currencies with higher CES%—notably IR, JY, SKW, TB, and MR—represent the core transmitters of regional tail risk in recent years. Their dominance indicates that when extreme losses occur in the regional currency portfolio, shocks originating in these markets account for a disproportionate share of systemic distress.

To better summarize our results and enhance the readability of CES% patterns, we construct an EBI to visually capture the evolution of systemic-risk concentration presented in Tables 2 and 3. The index is inspired by the entropy-based early-warning framework of Billio et al. (2016) and quantifies changes in the cross-sectional distribution of CES% contributions across currencies. Specifically, the EBI shows whether systemic-risk contributions are concentrated in a few currencies

or more evenly distributed across the regional currency system. Higher values indicate stronger systemic-risk concentration and greater contagion potential, while lower values reflect a more balanced or relatively muted stress profile across the currency set. Results presented in Fig. 2 show clear differences between the Asian crisis period and the recent post-COVID period. In the upper panel, covering 1994–2000, the index displays pronounced fluctuations with a sharp peak around 1997, coinciding with the Asian financial crisis triggered by speculative pressure on the Thai baht. This indicates a surge in systemic-risk concentration, where stress became dominated by a limited number of currencies. The surrounding periods exhibit moderate concentration levels, reflecting partial stabilization but persistent vulnerability. In contrast, the lower panel, covering the recent period, presents a more stable and subdued trajectory, with only a mild increase around the COVID-19 shock. The subsequent flattening suggests that currency stress was less concentrated than during the Asian crisis episode, pointing to a more balanced distribution of currency-market pressure across the region. These results indicate that systemic-risk concentration was substantially higher during the Asian crisis period, when stress was dominated by a small number of currencies. In contrast, the recent period exhibits a flatter and lower EBI profile, suggesting a more balanced distribution of currency-market pressure across the region. This implies that Asian currency markets have become less concentrated in terms of systemic-risk contributions, although dispersed vulnerabilities remain and require monitoring through complementary spillover-based evidence.

After completing the CES% analysis and the entropy-based evidence on systemic-risk concentration, we proceed with the MISN framework

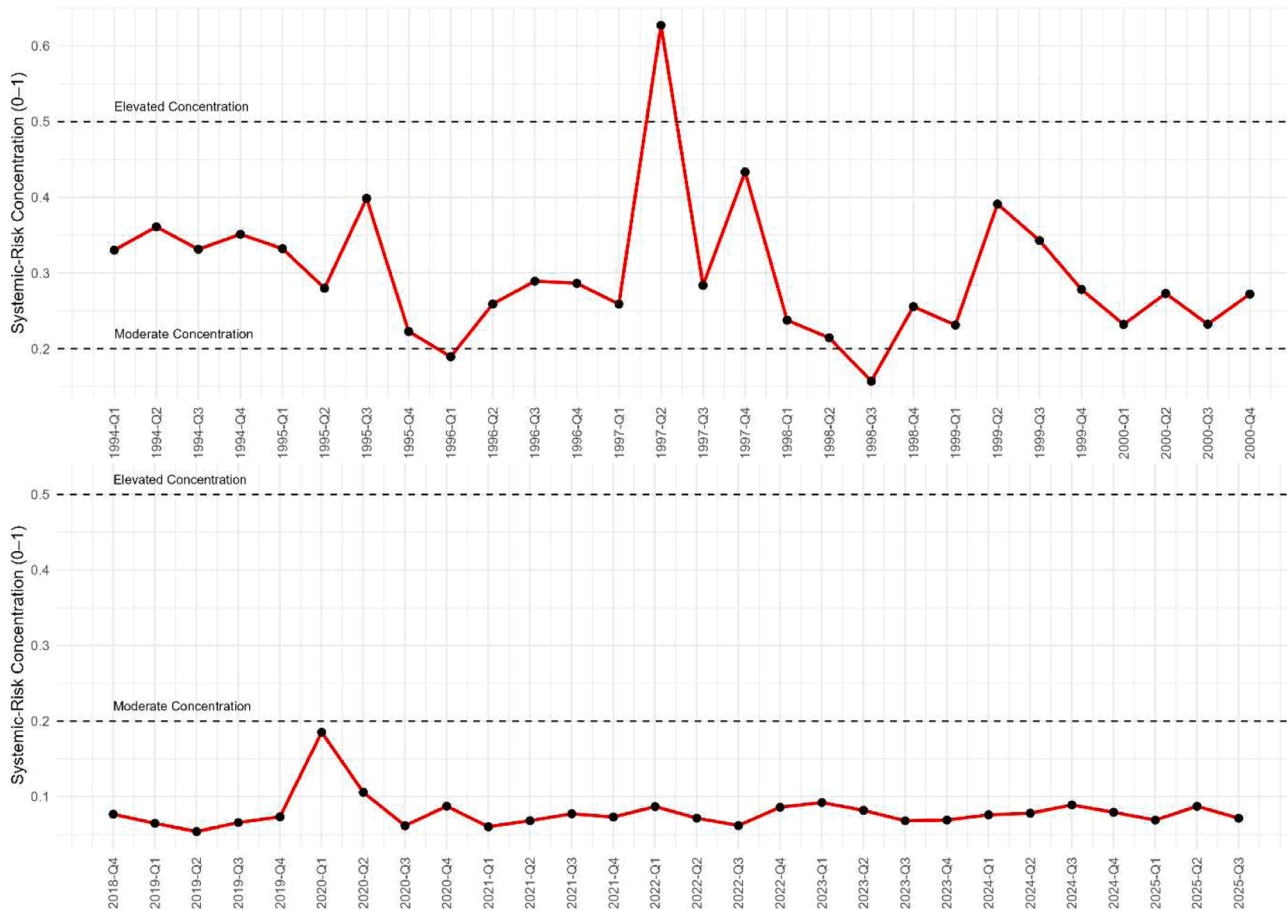


Fig. 2. Entropy-based index of systemic-risk concentration in Asian currency markets.

Note: The horizontal lines at 0.2 and 0.5 are used as visual reference thresholds to distinguish low, moderate, and elevated concentration regimes; they are not treated as formally estimated crisis thresholds.

following Wang et al. (2021). While the CES% results identify the currencies that contribute most to regional systemic losses, and the entropy-based index shows whether these contributions are concentrated or more evenly distributed across the currency system, the multilayer network analysis allows us to examine how risk-related information is transmitted between individual currencies and through which channels this transmission occurs. In this sense, the analysis moves beyond portfolio-level contribution and concentration perspectives and provides a compact visual representation of directional spillover interactions among Asian currencies. Rather than relying only on pairwise causal interactions, the network approach of Wang et al. (2021) enables us to identify the main risk-transmitting and risk-receiving currencies and compare how these roles differ between the Asian crisis episode and the recent equal-length period. As lag-bandwidth choices, we employ $M = 5$ to capture short-horizon spillover dependence and $M = 30$ to capture longer-horizon or more persistent transmission across the mean, volatility, and extreme-risk layers.¹ Following Wang et al. (2021), we further estimate rolling-window multilayer networks using a 240-day window and a 20-day step to trace the time-varying evolution of these spillover channels. By examining network density, direction, and layer-specific composition, the analysis shows whether regional risk transmission is driven mainly by return interactions, volatility propagation, or extreme downside-risk spillovers, thereby supporting clearer policy implications for surveillance, liquidity preparedness, and macroprudential coordination. Fig. 3 presents the degree of each spillover layer across alternative values of the lag-bandwidth parameter M .

Fig. 3 reports the layer-specific degree of the multilayer spillover networks across alternative lag orders M for the Asian crisis period and the recent equal-length comparison period. The mean layer (black) captures return-based information transmission, the volatility layer (red) captures the propagation of uncertainty and conditional second-moment shocks, and the extreme-risk layer (blue) captures VaR-exceedance spillovers that correspond most closely to downside tail-risk contagion. The results show that mean spillovers dominate in both periods, indicating that return-based information transmission is the most widespread channel of regional currency-market interaction. However, the recent period displays a denser network than the Asian crisis period, especially in the mean and extreme-risk layers. In the crisis period, the maximum degree occurs in the mean layer at $M = 5$, suggesting stronger short-horizon transmission. In the recent period, the mean layer peaks around $M = 10$, while extreme-risk spillovers remain relatively high at shorter horizons and decline gradually as M increases. This suggests that recent Asian currency markets are more broadly interconnected, with both return-based and downside-risk channels playing important roles.

Fig. 4 presents static multilayer spillover networks across episodes, layers, and lag bandwidths. The patterns show that there are clear differences between the Asian crisis period and the recent equal-length period. During the crisis period, the network is mainly driven by the mean spillover layer, with 33 edges at $M = 5$ and 29 edges at $M = 30$. This suggests that return-based information transmission was the most active channel of contagion during the 1994–2000 window. By contrast,

the volatility and extreme-risk layers are much more selective. At $M = 5$, the volatility layer contains only 9 edges, while the extreme-risk layer contains 17 edges. At $M = 30$, the volatility layer remains limited with 10 edges, and the extreme-risk layer declines to 9 edges. This indicates that crisis-period spillovers were not equally distributed across all risk channels; rather, they were concentrated in specific directional linkages and currencies. In the recent period, the structure changes substantially. The networks become much denser across all three layers. At $M = 5$, the mean and extreme-risk layers both contain 39 edges, while the volatility layer has 35 edges. This shows that short-horizon spillovers are now widespread not only through return interactions but also through downside-risk and volatility channels. At $M = 30$, the networks remain highly connected, with 39 mean edges and 33 edges in both volatility and extreme-risk layers. This persistence suggests that recent spillovers are not merely short-lived reactions but reflect more durable interconnections across Asian currency markets. Taken together, results in Fig. 4 suggest that the 1997 crisis period was characterized by more concentrated and channel-specific contagion, whereas the recent period displays a broader, more multilayered spillover structure. This supports the CES% evidence that systemic risk is now distributed across a broader set of currencies, while also reinforcing the entropy-based finding of a less concentrated but still highly interconnected regional risk structure.

Fig. 5 shows that the time-varying degree of spillover connections changes substantially across periods, layers, and lag bandwidths. In the Asian crisis period, the $M = 5$ plot indicates that short-horizon spillovers were relatively moderate before 1997, but the mean layer rises sharply during 1997–1998, reaching the highest degree around the crisis peak. Extreme-risk spillovers also increase during this period, while volatility spillovers remain comparatively lower and less persistent. This suggests that the immediate crisis transmission was driven mainly by return-based interactions, with downside-risk linkages intensifying around the crisis. For $M = 30$, the crisis-period dynamics appear more persistent but less intense than in the short-horizon case. While the $M = 5$ mean layer reaches its highest point around 1998, close to 40 significant directed edges, the corresponding $M = 30$ peak is lower, at around 30 edges. Volatility spillovers are more active before and during the crisis buildup, while the mean layer still rises around the crisis peak. Extreme-risk spillovers remain present but generally below the mean and volatility layers. This suggests that longer-horizon crisis transmission was more gradual and less explosive than short-horizon transmission, involving both volatility and mean channels rather than only tail-risk contagion. In the recent period, the structure is broader and more persistent. At $M = 5$, mean and volatility spillovers are strong around 2019–2020, weaken during 2021, and then rise again from 2022 onward. Extreme-risk spillovers become especially important after 2022 and remain elevated into 2024–2025, showing stronger downside-risk interactions in the recent period. At $M = 30$, recent spillovers become even more persistent across all layers. Volatility peaks strongly around 2022–2023, while mean and extreme-risk spillovers also remain high. This indicates that recent Asian currency-market interconnections are not only short-lived but also structurally persistent. These findings support the CES% and EBI results by showing that systemic risk is now more broadly distributed across currencies, while remaining deeply embedded in the regional spillover network.

To better compare the MISN results with the earlier CES% evidence, we revisit the CES results by dividing each episode into two subperiods and reporting the average CES% values in Table 4. For the Asian crisis episode, we distinguish between the pre-crisis/buildup phase and the crisis/post-crisis phase, namely 1994Q1–1997Q1 and 1997Q2–2000Q4. For the recent equal-length episode, we use 2018Q4–2021Q4 and 2022Q1–2025Q3, with 2022 marking the beginning of a sharp post-pandemic shift in global monetary conditions. Table 4 shows that the systemic-risk structure differs substantially across the two episodes. During the Asian crisis episode, systemic risk shifted toward the currencies directly exposed to regional financial turmoil. In particular, IR's average CES% contribution increased from 1.71 in 1994Q1–1997Q1 to

¹ Following Wang et al. (2021), each return series is filtered using a variable-specific ARMA(p,q)-GARCH(1,1) model with standardized Student's t innovations. The ARMA orders are selected separately for each currency by minimizing the Schwarz information criterion. For the Asian crisis period, the selected specifications are CR: ARMA(1,2), HKD: ARMA(1,1), IR: ARMA(0,1), JY: ARMA(0,0), MR: ARMA(1,1), PP: ARMA(0,0), SD: ARMA(0,1), SKW: ARMA(0,0), TD: ARMA(1,0), and TB: ARMA(0,1). For the recent period, they are CR: ARMA(0,1), HKD: ARMA(0,0), IR: ARMA(1,0), JY: ARMA(0,0), MR: ARMA(1,0), PP: ARMA(0,0), SD: ARMA(0,0), SKW: ARMA(0,0), TD: ARMA(0,1), and TB: ARMA(0,0). For the extreme-risk layer, we estimate downside VaR at the 5% left-tail level ($\alpha=0.05$).

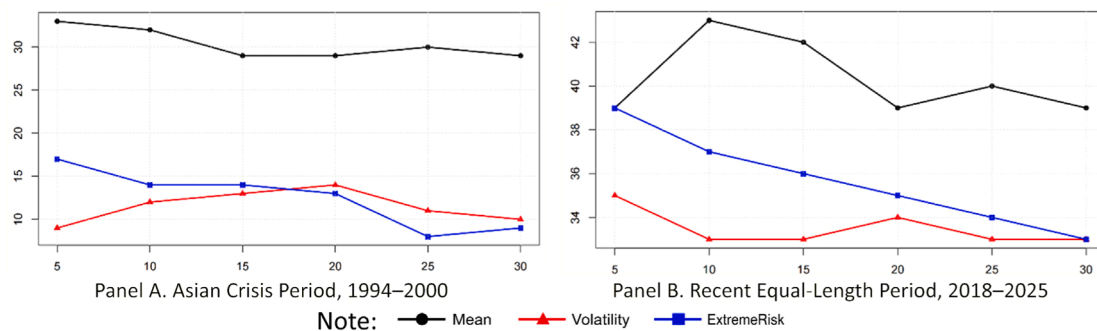


Fig. 3. Layer-specific degree of multilayer spillover networks across lag order M .

35.68 in 1997Q2–2000Q4, while TB's contribution increased from 16.69 to 22.55. By contrast, JY's average CES% contribution declined sharply from 42.47 in the first subperiod to 9.43 in the second subperiod. This indicates that the Asian crisis period was characterized by a rotation of systemic risk away from JY and toward the currencies most directly affected by the crisis.

In the recent episode, the most notable change is the renewed systemic contribution of the Japanese yen. Its average CES% rises from 7.52 in 2018Q4–2021Q4 to 14.74 in 2022Q1–2025Q3, representing an increase of approximately 96%. This post-2022 rise is consistent with the sharp increase in dynamic spillover degrees shown in Panel B of Fig. 5 and motivates closer examination of the underlying macro-financial conditions. Accordingly, even before turning to the multilayer spillover evidence of Wang et al. (2021), the CES% subperiod analysis indicates that the Japanese yen regained systemic importance in the recent period, although under a macro-financial mechanism distinct from that observed during the Asian crisis.

The 2022–2025 period was characterized by prolonged unconventional monetary policy, delayed policy normalization, and persistent structural weaknesses in the Japanese economy. Nishigaki (2025) attributes the recent depreciation of the yen to portfolio-balance effects, income disparities, and interest-rate differentials between Japan and the United States, while Ito (2025) emphasizes Japan's weak long-term growth, declining productivity, and deteriorating international purchasing power. Hasui and Teranishi (2026) further show that, consistent with its inflation-overshooting commitment, the Bank of Japan did not respond to positive cost-push shocks and maintained the zero interest-rate policy until March 2024. At the same time, Japanese monetary authorities conducted yen-buying interventions while the Bank of Japan maintained monetary accommodation, creating a tension between exchange-rate stabilization and the domestic monetary-policy stance. Esaka and Fujii (2026) find that the September 2022 intervention had only a short-lived effect, whereas the October interventions produced more persistent effects. These developments provide a plausible macro-financial explanation for the renewed systemic importance of JY in the recent period and indicate that Japanese policy developments do not remain confined to the domestic market. The CES results show a marked increase in the systemic contribution of JY after 2022, while the multilayer analysis records higher spillover degrees under both $M = 5$ and $M = 30$, with the most pronounced increase occurring in the volatility layer. These developments provide a plausible macro-financial context for the stronger regional spillover and contagion dynamics observed after 2022.

5. Conclusion

This study examines systemic risk and contagion dynamics across major Asian foreign exchange markets from 1994 to 2025, focusing on the transmission mechanisms shaping regional financial stability. Using daily exchange-rate data for ten Asian currencies—covering both advanced and emerging economies—the analysis combines three

complementary frameworks: CES to assess each currency's contribution to regional systemic risk, an EBI to evaluate the concentration and dispersion of systemic-risk contributions, and the MISN framework to examine how risk-related information is transmitted across mean, volatility, and extreme-risk channels. The study aims to trace the systemic risk and contagion patterns that characterized the 1997 Asian financial crisis and evaluate whether similar dynamics have reemerged in recent years. The empirical investigation focuses on the ten Asian currencies: CR (Chinese Renminbi), HKD (Hong Kong Dollar), IR (Indonesian Rupiah), JY (Japanese Yen), MR (Malaysian Ringgit), PP (Philippine Peso), SD (Singapore Dollar), SKW (South Korean Won), TB (Thai Baht), TD (Taiwan Dollar).

5.1. Empirical findings

The CES analysis investigates systemic risk over two equal-length subsamples, 1994–2000 and 2018–2025. The CES% results show the evolution of systemic risk in Asian currency markets, shifting from single-source contagion in the 1990s to a more diversified, multi-nodal structure in recent years. Before the Asian Financial Crisis (1994–1997), JY was the dominant risk contributor, reflecting Japan's regional funding influence. TB showed rising CES% before the crisis, indicating vulnerability. During the crisis, TB's CES% surged to 72%, while post-crisis contagion shifted to IR, which remained a significant risk source until 2000. Post-2018, systemic risk became more dispersed, with IR, MR, SKW, and PP contributing significantly. Between 2022 and 2025, systemic risk leadership expanded to include JY, IR, SKW, MR, and TB, reflecting continued interdependence. Notably, JY's rise after 2022 marks its renewed role as a systemic risk carrier within the regional currency network, reflecting the effects of yen depreciation, monetary-policy divergence, and changing capital-flow conditions.

We further investigate systemic risk using an EBI that captures whether systemic risk weights are distributed homogeneously or concentrated heterogeneously across the variables. The index provides a visual representation of regional risk-concentration patterns and helps summarize changes in market-stress structure over time. The results show that entropy-based risk concentration in the second sample period (2018–2025) is substantially lower than in the 1994–2000 interval, suggesting lessened concentration of systemic pressure in one or a few dominant currencies, a more diversified and evenly distributed entropy profile across Asian currency markets, improved macro-financial resilience, and stronger crisis-management capacity in Asian markets. However, lower concentration does not imply the disappearance of systemic risk; rather, it suggests that risk has become more dispersed across the regional currency system, making it necessary to examine the directional channels through which spillovers are transmitted.

The multilayer information spillover results provide a compact representation of directional contagion across currencies by separating transmission into mean, volatility, and extreme-risk layers. These layers are based on standardized residuals, centered squared standardized residuals, and VaR-exceedance indicators, respectively. We report $M = 5$

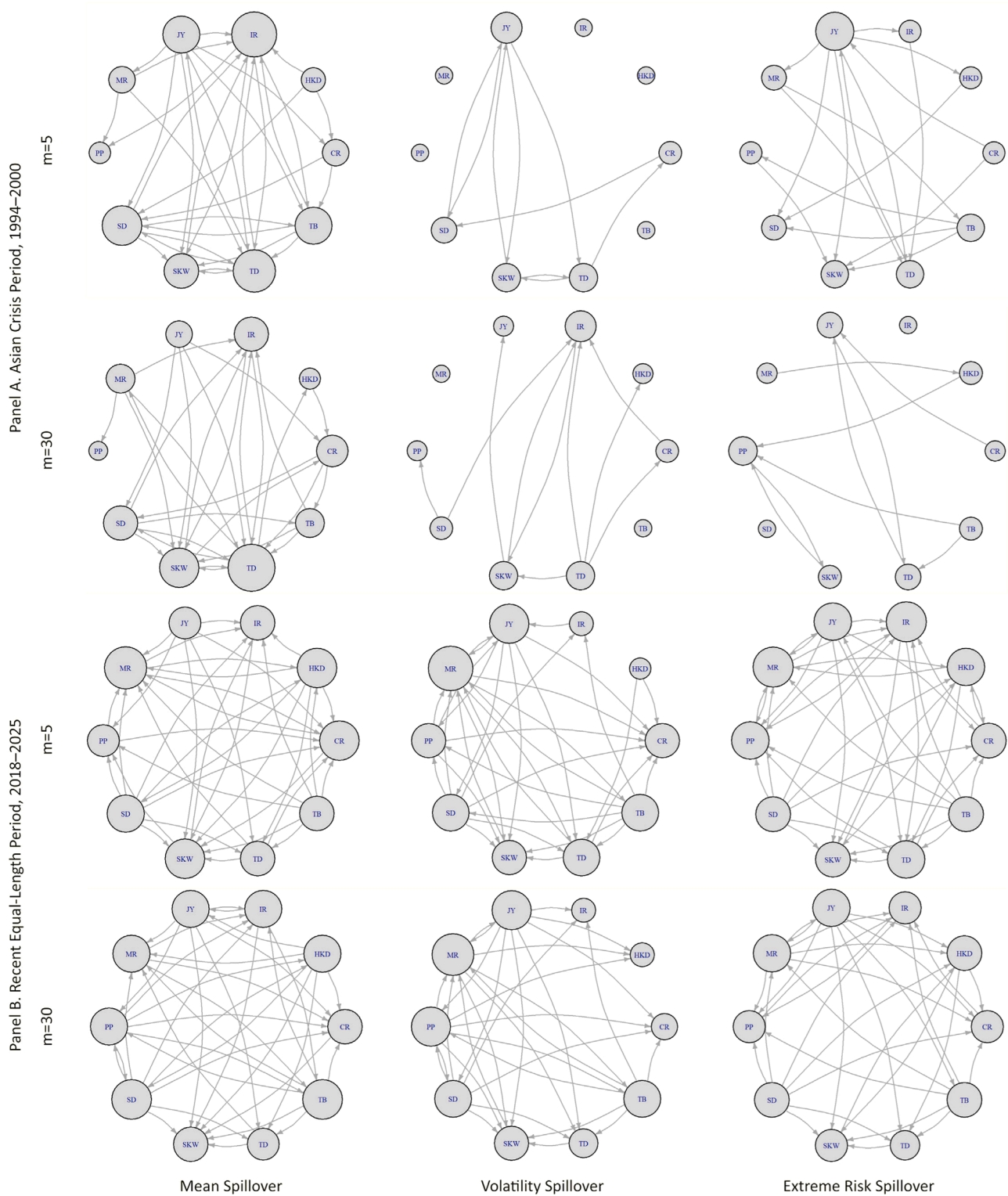


Fig. 4. Static Multilayer Spillover Networks across Episodes, Layers, and Lag Bandwidths.

Note: CR (Chinese Renminbi), HKD (Hong Kong Dollar), IR (Indonesian Rupiah), JY (Japanese Yen), MR (Malaysian Ringgit), PP (Philippine Peso), SD (Singapore Dollar), SKW (South Korean Won), TB (Thai Baht), TD (Taiwan Dollar). Nodes represent currencies, arrows indicate significant directed spillovers, and node size reflects network degree. Panel A reports the Asian crisis period, 1994–2000, while Panel B reports the recent equal-length period, 2018–2025. The parameter M denotes the lag-bandwidth used in the Hong-type causality test, with lower values capturing shorter-horizon spillovers and higher values capturing more persistent lagged transmission. Networks are shown for $M = 5$ and $M = 30$ across mean, volatility, and extreme-risk layers.

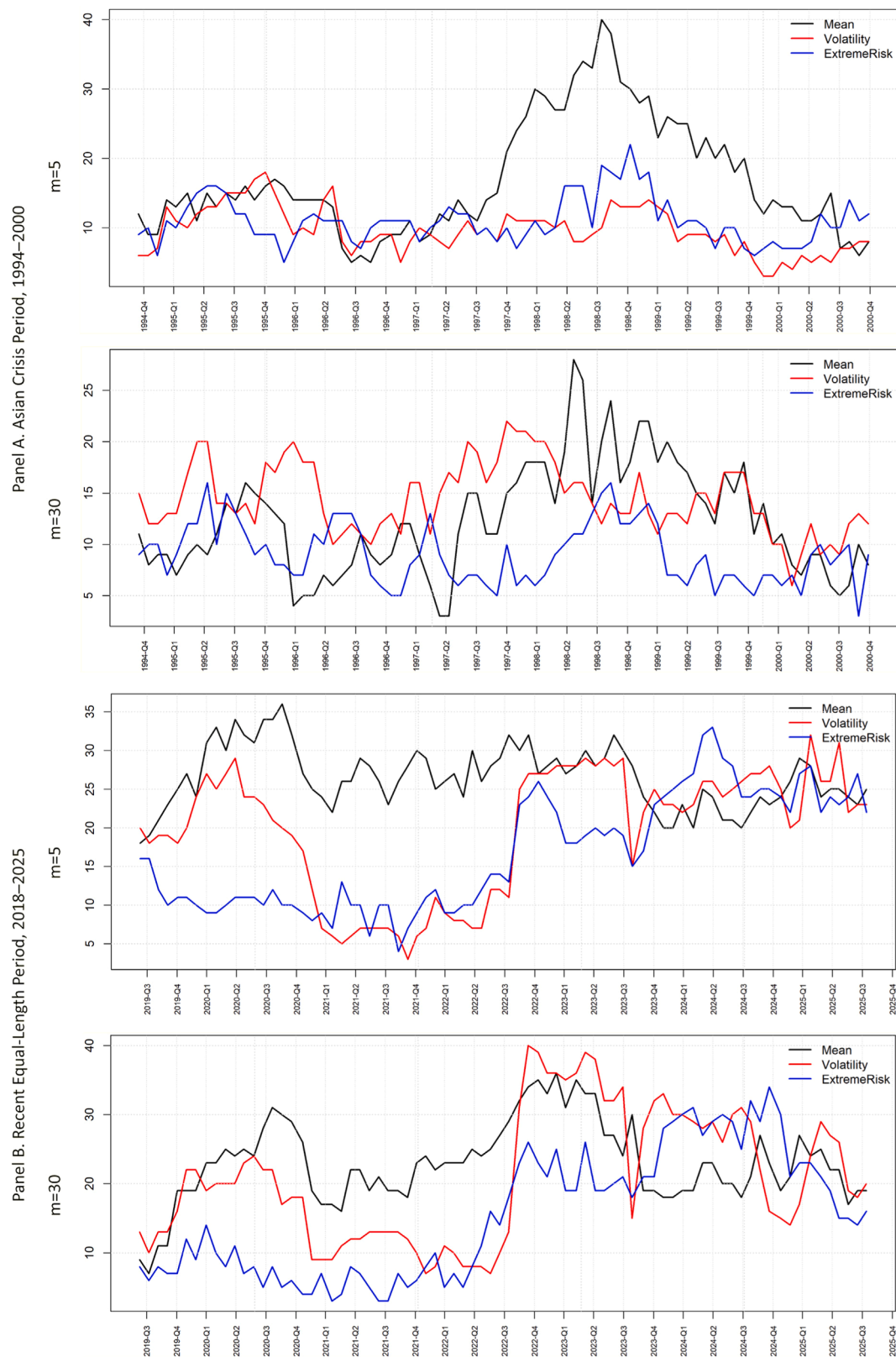


Fig. 5. Dynamic degree of multilayer spillover networks.

Note: The figure reports the time-varying degree of multilayer spillover networks for two equal-length periods: Panel A covers the Asian crisis period, 1994–2000, and Panel B covers the recent comparison period, 2018–2025. The networks are estimated using rolling windows of 240 trading days with a 20-day step. $M = 5$ captures short-horizon spillover dependence, while $M = 30$ captures longer-horizon or more persistent transmission. The degree measures the number of significant directed spillover edges in each rolling window. Black, red, and blue lines represent mean, volatility, and extreme-risk spillover layers, respectively.

Table 4

Average CES contributions across the two event-based subperiods of each episode.

		CR	HKD	IR	JY	MR	PP	SD	SKW	TD	TB
A	P1	6.58	0.37	1.71	42.47	8.01	8.24	9.84	2.49	3.60	16.69
	P2	2.10	0.06	35.68	9.43	6.81	5.99	6.53	8.43	2.43	22.55
B	P1	7.44	0.56	15.67	7.52	13.33	11.44	5.49	17.53	8.66	12.38
	P2	6.61	0.44	11.13	14.74	13.51	10.06	4.52	16.80	9.35	12.83

Note: CR (Chinese Renminbi), HKD (Hong Kong Dollar), IR (Indonesian Rupiah), JY (Japanese Yen), MR (Malaysian Ringgit), PP (Philippine Peso), SD (Singapore Dollar), SKW (South Korean Won), TB (Thai Baht), TD (Taiwan Dollar). P1 and P2 denote the two event-based subperiods of each episode, respectively. For A (1994–2000), P1 covers 1994Q1–1997Q1 and P2 covers 1997Q2–2000Q4. For B (2018–2025), P1 covers 2018Q4–2021Q4 and P2 covers 2022Q1–2025Q3.

and $M = 30$ networks to capture short- and longer-horizon spillovers, and complement the static results with rolling-window estimates using a 240-day window and a 20-day step. The results show that mean spillovers dominate in both episodes, indicating that return-based information transmission is the most widespread layer of interaction. In the Asian crisis period, the static networks contain 33 mean-layer edges at $M = 5$ and 29 at $M = 30$, while volatility spillovers remain limited with 9 and 10 edges, respectively. Extreme-risk spillovers also decline from 17 edges at $M = 5$ to 9 edges at $M = 30$, suggesting that crisis-period transmission is mainly short-horizon and concentrated in the mean layer. In contrast, the recent period exhibits a much denser multilayer structure. At $M = 5$, the mean and extreme-risk layers both contain 39 edges, while the volatility layer contains 35 edges. At $M = 30$, the networks remain highly connected, with 39 mean-layer edges and 33 edges in both the volatility and extreme-risk layers. The dynamic degree plots reinforce this pattern: the crisis period shows a sharp short-horizon mean-layer peak around 1998, whereas the recent period displays a marked post-2022 increase across mean, volatility, and extreme-risk layers. This confirms that recent spillover dependence is broader, more persistent, and more evenly distributed across layers than during the 1997 crisis episode.

5.2. Policy implications

Our results provide valuable information for policymakers, investors, and risk managers concerned with systemic-risk monitoring in Asian currency markets. The evidence suggests that policy measures introduced after the 1997–1998 Asian financial crisis may have contributed to lower systemic-risk concentration in the region. However, the persistence of systemic risk and contagion pressure indicates that vulnerability does not necessarily remain attached to the original crisis epicenter. Although the Thai baht was the dominant CES contributor at the onset of the 1997 crisis, its importance was not persistent throughout the full crisis episode and appears more limited in the recent sample. This illustrates why surveillance should distinguish short-lived concentration spikes from persistent transmitter or receiver roles. By contrast, the Indonesian rupiah shows a stronger profile in terms of absorbing market stress. The multilayer analysis further shows that IR and SKW persistently receive tail-risk-related contagion effects in both periods, while CR and MR join this vulnerable receiver group in the recent period. These findings indicate that historical contagion patterns are dynamic and that monitoring models should be updated regularly. Scenario analyses should therefore consider alternative origins of stress, changing receiver-transmitter roles, and multiple contagion channels to improve the robustness and timing of policy responses.

The second observation relates to the dominant currency within the regional network. Regardless of whether the period is turbulent or relatively tranquil, the results show that the Japanese yen occupies a dominant role among Asian currencies. This role is not simply explained by macroeconomic size. Although China exceeds Japan in several macroeconomic scale indicators, such as GDP and the total value of exports and imports, our results indicate that the Japanese yen remains a key source of directional spillover effects in both periods analyzed. This suggests that yen-related shocks play a central role in shaping regional

contagion dynamics. Therefore, changes in Japanese monetary policy, yen depreciation pressures, and shifts in yen-related capital-flow dynamics may serve as important early indicators of stress propagation across Asian currency markets. Our statistical evidence further shows that the influence of the yen-centered transmission channel has gained momentum in the recent period, increasing its relevance for both systemic-risk contributions and contagion dynamics. This finding should be treated cautiously by more vulnerable economies in the region, as yen-driven shocks may generate broader stress across Asian currency markets. Accordingly, weaker or more exposed economies may benefit from strengthening policy buffers, improving liquidity preparedness, and developing precautionary measures against potential yen-related shocks.

Another useful insight concerns the distribution of systemic risk and contagion effects across currencies. Crisis periods tend to generate more concentrated, single-node or few-node risk structures, whereas more tranquil periods are associated with more distributed, multi-node patterns. This information is valuable for both policymakers and investors because it shows whether systemic vulnerability is concentrated in a few dominant currencies or dispersed across the regional currency system. To capture this pattern, we use the entropy-based index constructed from CES% values to measure the degree of systemic-risk concentration in the market. More advanced versions of this index could provide valuable early-warning information by detecting whether systemic risk is shifting toward a more concentrated structure. Statistical tools such as exponential moving averages or kernel-based smoothing can be used to track the evolving path of this index and identify persistent upward movements in systemic-risk concentration. Such monitoring may provide policymakers and investors with earlier signals of rising vulnerability and additional time to take precautionary measures.

Across alternative (M) values, we observe that Return-based transmission is the most consistently widespread channel across specifications, but volatility and extreme-risk spillovers are also substantial in the recent period and, at short horizons, extreme-risk connectedness is as dense as the mean layer. Given the interpretation of each layer, this finding is important because it implies that the first moment of exchange-rate series, namely return movements and conditional mean dynamics, contains substantial information about the regional currency network. This suggests that, in addition to volatility models from the GARCH family, return-based models from the ARMA family may also be useful for capturing early signs of systemic-risk transmission. Policymakers may therefore benefit from investigating which macroeconomic and microstructure indicators are most closely associated with exchange-rate return dynamics. Such indicators may provide earlier and more informative signals for monitoring exchange-rate contagion and systemic-risk networks in the region.

These recommendations can be implemented through the existing Chiang Mai Initiative Multilateralisation and ASEAN+3 Macroeconomic Research Office framework rather than by creating new institutions. AMRO's core surveillance tools rely mainly on country-level macro-financial indicators and external-vulnerability ratios, which are informative but generally lower-frequency and may not fully capture rapidly changing cross-currency contagion. Our market-based CES% and EBI measures could complement these assessments by providing periodic

market-based indicators of system-wide risk contribution and concentration, while MISN could identify the currencies and channels through which stress propagates. Sustained increases in EBI could therefore support earlier ASEAN+3 consultation, coordinated stress testing, and greater readiness to activate precautionary liquidity support. Because receiver and transmitter roles change over time, such monitoring should focus on regional risk concentration and network transmission rather than on any single currency.

Country-level measures should reflect currencies' heterogeneous network positions and the dominant transmission channel. Because contagion operates mainly through return rather than volatility or extreme-risk channels, surveillance frameworks focused primarily on volatility may overlook information contained in earlier exchange-rate return movements. Our findings therefore suggest that authorities may consider measures addressing directional foreign-exchange exposure, including net open-position limits, differentiated reserve requirements on foreign-currency liabilities, and targeted requirements on short-term inflows. The four currencies also require different responses. IR and SKW are persistent receivers across both periods, supporting structural measures such as standing foreign-currency liquidity requirements, stronger corporate hedging rules, and stress tests calibrated to exchange-rate return shocks. CR and MR enter the vulnerable group only in the recent period, indicating a change in their risk position rather than a persistent condition. Surveillance should therefore focus on the sources of this shift, including offshore renminbi positioning in China and short-term foreign-currency bank funding and non-resident bond exposures in Malaysia. These measures should remain transparent, proportionate, and subject to periodic reassessment.

5.3. Limitations

This study has several limitations that open avenues for future research. First, although the selected currencies represent major Asian foreign exchange markets, future studies could include a broader set of regional and global currencies to capture wider contagion channels. Second, while alternative lag-bandwidth parameters distinguish short- and longer-horizon spillovers, frequency-domain methods could provide a more direct decomposition across horizons. Third, daily data may miss very rapid stress transmission, particularly during the 1997 Asian crisis; higher-frequency intraday data could therefore improve the identification of network formation and contagion. Fourth, the EBI thresholds used here are descriptive reference bands rather than formally estimated crisis cutoffs. Future research could calibrate them against dated crisis episodes, alternative model specifications, and false-positive and false-negative rates, drawing more directly on the early-warning indicator literature. This would help determine appropriate monitoring frequencies, persistence criteria, and operational trigger levels. Finally, future studies could compare Asian currency networks with other crisis episodes, such as the 1992–1993 European Exchange Rate Mechanism crisis, to identify region-specific contagion features and support more tailored policy frameworks.

CRedit authorship contribution statement

Samet Gunay: Writing – original draft, Software, Formal analysis, Data curation, Conceptualization, Methodology. **Péter Juhász:** Writing – original draft, Visualization. **Helena Naffa:** Writing – original draft, Methodology.

Conflict of Interest

The authors declare that there is no conflict of interest, financial or otherwise that might influence the objectivity of our work.

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