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Assessing Financial Stress in China and ASEAN-4 Economies

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Abstract
The significant economic effects of multiple financial crises have necessitated the development of tools for measuring financial stress. This study constructed financial stress indices for four sub-markets — banking, bonds, stocks, and foreign exchange —and for China and the ASEAN-4 economies (Malaysia, Singapore, the Philippines, and Indonesia) from November 2006 to February 2024. The methodology primarily employed a dynamic CRITIC weighting method to analyze and integrate eight indicators across four sub-markets and compare it with the traditional static methods. This proposed model can consistently capture the correlation among submarkets. This feature is particularly important during a crisis, as banks and foreign-exchange risks often become more closely intertwined, making the index more suitable for emerging markets. In addition, it conducted a comparative analysis of financial stress dynamics between China and the four ASEAN countries over 18 years, revealing distinct risk characteristics: the evolution of stress in China is relatively smooth, whereas that in ASEAN economies is more sensitive to global capital flows and liquidity shocks. The empirical results demonstrate that dynamic weighting is an alternative tool for tracking financial stress during periods of heightened market turbulence.
Keywords: Financial Stress Index, Dynamic Critic Weighting Method, Systemic Financial Risk, China, ASEAN

Introduction

Measuring financial stress is a fundamental tool for assessing the robustness and systemic risk of a financial system. The output of this measurement quantifies the stress state and the intensity of risk contagion in financial markets under extreme conditions using a combination of indicators. This research interest emerged from multiple global financial crises, including the 1997 Asian financial crisis, the 2008 global financial crisis, and the 2020 COVID-19 pandemic, highlighting the urgent need for monitoring financial stress.

The China-ASEAN region has witnessed rapid economic and financial integration: bilateral trade reached $983.9 billion in 2024, and ASEAN has been China's largest trading partner from 2008 to 2023, while China's direct investment in ASEAN has increased more than

15 times between 2005 and 2023. China's outward direct investment in ASEAN has increased from USD 1577.1 million in 2005 to USD 251235.1 million in 2023, with an average annual growth rate of 41.99%. China's direct investment flows to ASEAN have increased from USD 410.3 million in 2008 to USD 5,826.1 million in 2023, with an average annual growth rate of 69.84% (Wind Economic Database, 2024).

While close economic and financial ties have deepened cooperation, they have also increased the risk of spillover, particularly under the influence of external policies and events, such as Sino–US trade frictions, the entry into force of the Regional Comprehensive Economic Partnership, and the deepening of the Belt and Road Initiative. Therefore, developing financial stress measurement tools that can accurately capture dynamic characteristics and regional features is crucial for preventing regional financial turmoil and providing a basis for decision-making in macroprudential policies.

First developed by Canadian bank economists Illing and Liu (2006), the financial stress index (FSI) has strong timeliness and intuitive appeal. The FSI measures stress on a country's financial system, providing information to detect financial risks and prevent crises. The FSI is also an important intermediary indicator for measuring the spread of financial risk in a macroeconomy. Moreover, FSI has been used in academia to study the impact and mechanisms of financial stress on the macroeconomy, to analyze the effectiveness of macroeconomic policies under different financial stress states, and to provide valuable references for regulators and policymakers in formulating effective policies under such conditions.

The problem that this paper aims to solve is to reveal the dynamic characteristics of financial stress in China and ASEAN-4 countries, namely Malaysia, Singapore, the Philippines, and Indonesia, which will affect the economic performance and living quality of these countries' citizens. The advantages of using the dynamic FSI have been argued by Qin et al. (2022) and Zhu & Jiang (2024), who demonstrated that the dynamic weighting method is more effective in capturing financial market fluctuations and interconnections between sub-markets in China. While existing research on financial stress in the ASEAN region typically focuses on static methods (e.g., PCA or static weighting), this study adopts the dynamic CRITIC weighting method, providing a more flexible and adaptive tool for capturing market risks and enhancing understanding of financial stress dynamics in the region. Moreover, this paper compares dynamic FSI across countries, as the transmission effects of financial stress vary significantly, particularly amid global economic fluctuations, with ASEAN countries exhibiting greater sensitivity to financial stress (Poonpatpibul et al., 2018; Tan et al., 2023). The computation of dynamic FSI addresses whether it differs significantly across the examined countries. Additionally, the previous papers have not only provided the overall dynamic FSI; they have also not shown the FSI in the stock market, bond market, banking market, and exchange rate market, nor have they compared the overall dynamic and overall static FSI, so they do not show how they differ. Lastly, this paper also reveals the main contributor to the financial stress, which has not been explained before.

In other words, this study advances the use of financial stress measures in regional risk management through methodological innovation and empirical analysis. The study aims to construct an FSI using the dynamic CRITIC weighting method to adapt to changes in market structure and more sensitively reflect the evolution of overall financial stress, in addition to financial stress in the banking, bond, stock, and foreign exchange markets in China and ASEAN-4 countries. Moreover, this paper compares FSI measured in the static and dynamic frameworks to illustrate differences between them during some crises. Lastly, the contribution of each market segment in explaining the dynamic FSI in the examined countries is also discussed.

This study addresses gaps in the literature by developing a dynamic FSI that complements traditional static financial stress measurement methods. Although the static method is widely used in the study of financial stress (e.g., Tng, 2012; Illing, 2006), it assumes that correlations among sub-markets remain constant over time, whereas the dynamic CRITIC method overcomes this limitation. In other words, the dynamic CRITIC weighting method is more effective at capturing extreme financial risks than traditional static methods. The results also offer policymakers a more adaptable tool for identifying and managing financial stress in real time, particularly in China and ASEAN-4. The results will be significant for policymakers, helping them understand the sensitivity of financial stress across different financial markets and design appropriate preemptive policies to reduce it in the examined markets. Reduction in financial stress is critical for more sustainable economic growth. Academically, the findings also address debates about how financial stress evolves in China and ASEAN-4 over time, in aggregate or across different financial markets.

The study reveals that the financial stress index (FSI) for China and the ASEAN-4 countries varies significantly, with ASEAN countries generally exhibiting higher volatility. Specifically, the banking sector contributes the most to financial stress in China, Malaysia, and Singapore. The Philippines is more affected by foreign-exchange stress, while in Indonesia, stocks and bonds play a bigger role. This paper is structured as follows. After the introduction, Section 2 presents the related literature, followed by the discussion of data and methodology in Section 3. The results and discussion are presented in Section 4. Section 5 concludes.

Literature Review

The financial stress index (FSI) is widely used to study financial risk. Early research typically aggregated multiple market indicators into a composite index. Common methods included factor analysis or weighting based on variance and contrast strength. For instance, Illing and Liu (2006) measured Canada’s FSI using methods such as factor analysis and credit weighting. There is also a comprehensive framework for constructing a stress index for policy monitoring. Then, Hakkio and Keeton (2009) constructed the Kansas City Financial Stress Index to analyze the period from 1999 to 2009 during the financial crisis. The study showed that the index's peak could correspond to extreme financial events during the period, empirically demonstrating that the FSI can capture the extreme values of financial risk. Balakrishnan (2011) measured the FSI of emerging economies and studied the transmission of financial stress from developed to emerging economies. Furthermore, Ozcelebi (2020) studied the impact of FSIs in developed countries on other countries and found that developed countries leverage their economic superiority to impose stress on emerging economies.

Another mainstream research stream concerns dimension reduction methods, the most common of which is Principal Component Analysis (PCA), for extracting a small set of potential "stress factors" from indicators of sub-markets such as banks, bonds, stocks, and foreign exchange. Poonpatpibul et al. (2018) used PCA to investigate the stock, sovereign, and corporate debt markets, banking markets, and FX markets in China, Hong Kong (China), Indonesia, Japan, Korea, Malaysia, the Philippines, Singapore, and Thailand. Their results suggest that the FSI of each economy can identify stress originating from global, regional, and domestic events. While the PCA framework is intuitive and easy to implement, it assumes that correlations among sub-markets are constant within the sample and do not change over time, which is questionable in practice (Jolliffe, 2005).

In recent years, research has gradually shifted towards dynamic weighting and non-linear region identification methods to depict the features of market linkages over time and handle "indicator conflicts". In Chinese research, a representative direction is to replace the static dependence structure in the CRITIC class of methods with a rolling or time-varying dependence structure, thereby enabling sub-market linkages to evolve. For instance, some studies have adopted dynamic Spearman-critic weighting to construct systemic risk indices for sub-markets and have combined generalized variance decomposition to describe directional spillover and spillover relationships among domestic sub-markets (Zhang et al., 2023). Similarly, studies construct China's financial stress indices using dynamic CRITIC weighting and identify high- and low-risk states, employing Markov regime-switching models, BN-class decomposition, and other methods (Zhu & Jiang, 2024). In addition to index construction, recent Chinese literature has expanded further to high-frequency measurement and early warning applications. For example, Tan et al. (2023) present a systemic financial risk framework based on daily data, combining (i) dynamic, time-varying correlated empowerment mechanisms with (ii) Markov regime identification, and further introducing machine learning models (such as XGBoost and SHAP interpretation) for early warning and interpretability analysis. The related work also evaluated and extended state-transition models for monitoring systemic risk in China (Wang & Xi, 2025).

On the other hand, the literature in the research of ASEAN economies since 2023 has gradually shifted from static aggregation-based to (i) higher-frequency stress monitoring, (ii) region-based stress identification, and (iii) cross-border connectivity/spillover perspectives. Previous research has commonly used equal-variance weights or Principal Component Analysis (PCA) to construct FSI indicators. For example, Tng et al. (2012) utilized PCA to construct FSIs for ASEAN-5 countries, highlighting the significant role of stock markets in transmitting financial stress during crises. Similarly, Dahalan et al. (2016) applied PCA to measure Malaysia's FSI and found that the selected variables explained around 53% of the total variation. Besides, Chan-Lau et al. (2024) examine high-frequency financial stress measures across ASEAN+3 economies and apply a univariate regime-switching framework to identify low-, medium-, and high-stress regimes, thereby identifying risk regimes and providing predictive insights into financial stability.

Sadia et al. (2022) further contribute to the field by analyzing the determinants of financial stress using panel data methods and PCA, though their study focuses more broadly on emerging markets than on ASEAN countries. At the regional level, the risk spillover network study reveals the time-varying propagation characteristics of financial stress among Asian economies, suggesting that stress may spread through cross-market and cross-national channels (Li et al., 2023). In addition, the ASEAN literature has begun to link FSI to structural risk drivers, such as the construction of the ASEAN-5 Financial Stress Index and the examination of the relationship between climate risk exposure and financial system stress (Izzuddin & Nainggolan, 2025).

Despite the abundance of research on FSI, there is still a lack of systematic evidence to construct comparable, sub-market (bank, bond, equity, foreign exchange) FSI for China and ASEAN-4 simultaneously under a unified indicator system over a longer time window, especially covering the post-pandemic period, and to explicitly incorporate time-varying characteristics of cross-market dependency structures during the weighting phase. This paper uses a dynamic CRITIC dynamic weighting framework to construct FSI for China and ASEAN-4, respectively, under a consistent sub-market indicator system, and conducts a comparative analysis of stress evolution and differences among the economies, thereby compensating for the above deficiencies.

Data and Methodology

Data

This study examined risks in the banking, stock, bond, and foreign exchange markets as primary variables. Specifically, eight indicators were selected to construct an FSI for China and the ASEAN-4 (Malaysia, Singapore, the Philippines, and Indonesia) to measure systemic financial risk. Table 1 presents these indicators and the formulas used to calculate them. Owing to data availability, the sample spans November 2006 to February 2024. Data on the stock market, banking sector, and foreign exchange market were primarily sourced from the iFind database, whereas bond market data were obtained from online Asian bond databases, particularly for yields and monthly changes. The higher the FSI, the greater the financial stress; values above 0.5 indicate a high-risk range (Illing & Liu, 2006; Hakkio & Keeton, 2009).

The stock market index contains two variables: year-on-year returns and stock market volatility indexes. Year-on-year returns are multiplied by -1 so that lower returns reflect greater stress. Stock market volatility is proxied by the conditional variance, estimated using a GARCH(1,1) model. The GARCH (1,1) model accounts for time-varying volatility by incorporating lagged returns and past variances. Previously, Tng et al. (2012) used these two indicators to calculate the stock market risk in Indonesia, Malaysia, the Philippines, Singapore, and Thailand. Moreover, Cardarelli, Elekdag, and Lall (2010) used market returns (year-on-year change) and stock market volatility (GARCH) to represent the stock market and the FSI.

The bond market stress index includes two indicators: the interest rate spread, defined as the difference between 2- and 10-year government bonds, and the volatility of 10-year government bond yields. The bonds are denoted in the local currency. The magnitude of the interest rate spread reflects the slope of the local currency benchmark bond yield curve. The higher the absolute number of spreads, the steeper the yield curve. A positive spread indicates a normal yield curve, whereas a negative spread indicates an inverted yield curve. The spread is determined by the last bid on the previous trading day for government benchmark bond yields. Spreads are expressed in basis points, where a 1% yield corresponds to 100 basis points. A similar indicator was used by Hakkio and Keeton (2009), who employed the Aaa/10-year Treasury spread and the Consumer ABS/5-year Treasury spread to calculate the FSI.

The 10-year local-currency bond yield volatility is defined as the standard deviation of daily yield changes over the preceding 21 trading days, which serves as a proxy for the calendar month. Subsequently, the daily data were aggregated into monthly data. Daily yield changes are calculated from the prior closing bid yields of the local-currency benchmark 10-year government bonds. This approach is consistent with existing studies, such as that of Paddy (2025), who measured bond yield volatility using daily yield changes aggregated over a monthly horizon to analyze risk factors across emerging and developed economies. Similarly, Chan-Lau et al. (2024) compute bond yield volatility based on daily yield changes, with particular emphasis on ASEAN+3 economies.

The banking sector provides liquidity to the entire market. Financial stress in the banking sector is critical to the stability and development of the overall financial system. This study selected two indicators to reflect risk pressure in the banking sector. The first variable is the TED spread, which is the difference between the 3-month interbank lending rate and the 3-month Treasury yield. The TED spread represents counterparty and market liquidity risks in interbank transactions. A higher TED spread indicates a higher risk premium that banks require for interbank lending, thereby increasing borrowing costs and financial risk. Tytell et al. (2009) used the TED spread (three-month Libor minus three-month Treasury yield) to represent the bank market and examined how financial stress is transmitted from advanced to emerging economies, employing a new FSI for emerging economies. The second variable is the actual volatility of the interbank lending rate, represented by the GARCH volatility of the 1-month interbank lending rate. This indicator reflects fluctuations in interbank market sentiment. Li and Zhang (2021) used these two indicators to calculate bank market risk in China and the US.

Finally, the foreign exchange market stress index includes an exchange market pressure (EMP) index and implied exchange rate volatility. The latter refers to the volatility implied by the market's expectations of future exchange rate movements, typically derived from exchange rate options or other financial instruments. The EMP followed Kaminsky et al. (1997) and Balakrishnan et al. (2011) as follows:

$$EMP = e - (\sigma_e/\sigma_r) \cdot r \quad (1)$$

where e and r represent month-on-month changes in the nominal exchange rate and foreign reserves.The terms $\sigma_e$and $\sigma_r$represent the standard deviations of e and r, computed over the full sample period, respectively. They are used to scale the two components to ensure comparability. Accordingly, the stress on foreign exchange rates is reflected in depreciation of the exchange rate and depletion of foreign reserves. Changes in exchange rates cause fluctuations in asset prices, which manifest as market risk. Ozcelebi (2020) used the EMP to investigate the effects of changes in financial stress in developed countries on emerging economies. Lastly, the implied exchange rate volatility is measured as the conditional volatility from a GARCH(1,1) model estimated on monthly log returns of the nominal exchange rate. Table 1 summarizes the data symbols, definitions, and formulas for each selected indicator.

Table 1
Selection and Calculation Methods for FSI Components

Market	Indicator name	Symbol	Definition	Formula
Stock market	Stock Market Returns	X_{11}	Negative year-on-year returns indicate higher stress (Tng et al., 2012)	$\mathrm{R_t} = -(\mathrm{P_t} - \mathrm{P_{t-1}})/\mathrm{P_{t-1}}$ $\mathrm{P_t}$ represents the stock price at the current period, and $\mathrm{P_{t-1}}$ represents the stock price in the previous period, with $\mathrm{R_t}$ being the return rate calculated based on the price change.
	Stock Volatility Index	X_{12}	GARCH (1,1) volatility of monthly stock returns (Engle, 1982)	Fit GARCH (1,1) to monthly log returns to obtain conditional variance
Bond market	Interest Rate Spread 2- and 10-year – LCY Government Bond	X_{21}	2- and 10-year LCY government bond yield spread (Hakkio & Keeton, 2009)	$\mathrm{Spread_t} = \mathrm{Yield_{2y,t}} - \mathrm{Yield_{10y,t}}$
	Yield Volatility 10 yr LCY Government Bonds	X_{22}	Measures the bond market interest rate risk via daily yield changes (Hakkio & Keeton, 2009)	$\sqrt{\frac{1}{n-1}\sum_{d=1}^{n}(\Delta Y_d)^2}$ n=21-day rolling, monthly aggregation. $\Delta \mathrm{Y_d}$ represents the daily change in bond yields.
Banking market	TED spread	X_{31}	3-month interbank rate minus 3-month treasury yield; proxy for liquidity/counterparty risk (Tytell et al., 2009)	$\mathrm{TED_t} = \mathrm{i_{interbank,t}} - \mathrm{i_{treasury,t}}$
	Interbank lending rate volatility	X_{32}	GARCH (1,1) volatility of the 1-month interbank lending rate; indicates banking sector sentiment (Li & Zhang, 2021)	Fit GARCH (1,1) to monthly interbank rate changes
Exchange rate market	Exchange Market Pressure (EMP)	X_{41}	Captures currency stress via Δe_t and Δr_t (Kaminsky et al, 1997; Ozcelebi, 2020)	$EMP = \Delta e_t - (\sigma_e/\sigma_r) \cdot \Delta r_t$
	Implied Volatility	X_{42}	Reflects uncertainty in FX markets; GARCH (1,1) conditional volatility of monthly exchange rate returns	GARCH (1,1) on the monthly natural logarithm of the exchange rate

Methodology

Standardization, Transformation, and Weights Determination

This subsection starts by illustrating the extreme value method for standardising financial indicators to reduce the impact of variables of different magnitudes on the FSI. The formula is shown below.

$$x_i' = \frac{x_i - x_{min}}{x_{max} - x_{min}} \quad (2)$$

where x_i' represents the i-th sample data of the basic indicator variable, X. x_{min} and x_{max} are the minimum and maximum values of the variable X in the sample interval, respectively. After standardization, the data fall within the [0, 1] range, thereby improving the effectiveness of the synthetic FSI.

To synthesize the local market stress index, indicator weights can be determined using equal-variance weights, expert scoring, or the analytic hierarchy process. However, these methods have limitations. The use of equal-variance weights to synthesise the basic indicators of the FSI in local markets often ignores individual differences in each indicator's contribution to financial stress, thereby substituting an average impact for the indicators' differential impacts. Double-counting can occur when synthesizing local-market financial stress arising from volatility spillovers across indicators within the same market. Expert scoring and the analytic hierarchy process also have their limitations. The expert scoring method relies on subjective assessments, which may yield unstable results due to evaluator bias; the analytic hierarchy process, although it mitigates some biases, is complex and requires extensive expert judgment.

In this paper, the weights of the two indicators for individual financial market sectors were calculated using the inverse-standard-deviation method.

$$\omega_i = \frac{1/\sigma_i}{\sum_i^n 1/\sigma_i} \quad (3)$$

In formula (3), the standard deviation corresponds to the indicator. Specifically, σ_i denotes the indicator's standard deviation over the sample period. Indicators with lower variability are assigned relatively larger weights, reflecting their higher stability, while indicators exhibiting excessive fluctuations receive smaller weights to avoid disproportionate influence on the composite index.

Using the standardized indicator values x_i' and the corresponding weights ω_i, the financial stress index (FSI) for a given sub-market can be expressed as:

$$FSI = \sum_{i=1}^{n} \omega_i x_i' \quad (4)$$

Equation (4) represents the general aggregation form of a sub-market FSI. The FSIs for the stock market, bond market, foreign exchange market, and banking sector are derived by utilizing the formulas below, namely:

$$FSI_{STOCK} = \frac{1}{1/\sigma_{X_{11}} + 1/\sigma_{X_{12}}} \times \left[\frac{1}{\sigma_{X_{11}}} \times \frac{X_{11} - min(X_{11})}{max(X_{11}) - min(X_{11})} + \frac{1}{\sigma_{X_{12}}} \times \frac{X_{12} - min(X_{12})}{max(X_{12}) - min(X_{12})}\right] \quad (5)$$

$$FSI_{BOND} = \frac{1}{1/\sigma_{X_{21}} + 1/\sigma_{X_{22}}} \times \left[\frac{1}{\sigma_{X_{21}}} \times \frac{X_{21} - min(X_{21})}{max(X_{21}) - min(X_{21})} + \frac{1}{\sigma_{X_{22}}} \times \frac{X_{22} - min(X_{22})}{max(X_{22}) - min(X_{22})}\right] \quad (6)$$

$$FSI_{BANK} = \frac{1}{1/\sigma_{X_{31}} + 1/\sigma_{X_{32}}} \times \left[\frac{1}{\sigma_{X_{31}}} \times \frac{X_{31} - min(X_{31})}{max(X_{31}) - min(X_{31})} + \frac{1}{\sigma_{X_{32}}} \times \frac{X_{32} - min(X_{32})}{max(X_{32}) - min(X_{32})}\right] \quad (7)$$

$$FSI_{EXCHANG} = \frac{1}{{}^{1}/_{\sigma_{X_{41}}} + {}^{1}/_{\sigma_{X_{42}}}} \times \left[\frac{1}{\sigma_{X_{41}}} \times \frac{X_{41} - min(X_{41})}{max(X_{41}) - min(X_{41})} + \frac{1}{\sigma_{X_{42}}} \times \frac{X_{42} - min(X_{42})}{max(X_{42}) - min(X_{42})}\right] \quad (8)$$

where σ is the standard deviation. X_{11} and X_{12} are the first and second indicators of the stock market, X_{21} and X_{22} are the first and second indicators of the bond market, X_{31} and X_{32} are the first and second indicators of the banking market, and X_{41} and X_{42} are the first and second indicators of the exchange rate market, respectively.

Computation of Aggregated FSI

Combining various sub-market stress indices into a single financial market stress index facilitates a more comprehensive understanding of the overall risk conditions, particularly systemic financial risk. Note that the inverse-standard-deviation method is used solely as a baseline for calculating sub-market sector weights. Previous studies have primarily employed methods such as factor analysis, the entropy method, and the static CRITIC weighting method to calculate indicator weights in aggregated FSI. Among these approaches, the static CRITIC weighting method accounts for inter-indicator correlations across sub-markets, whereas entropy-based methods do not explicitly consider such correlations, and factor analysis focuses on extracting common components. However, these methods are inherently static and do not explicitly model dynamic risk spillover effects. The risk transmission between submarkets in the financial market is time-varying. When the risk is low, the risk spillover between sub-markets is not significant. However, once a high-risk shock occurs in the financial market, it quickly spreads across sub-markets. The risk correlation coefficient calculated using the static CRITIC weighting method is static and cannot effectively capture the time-varying nature of sub-market risk spillover (Diakoulaki et al., 1995). Moreover, the traditional CRITIC weighting method is typically based on the static correlation coefficient over the Full Sample period, making it difficult to capture the time-varying characteristics of the Risk spillover Relation among financial sub-markets. Numerous empirical studies have shown that risk transmission between financial markets intensifies during crises and weakens during stable periods, suggesting that market-related structures exhibit clear dynamics (Billio et al., 2012; Diebold & Yilmaz, 2014).

Therefore, in this study, we adopt a dynamic CRITIC weighting method that extends the standard CRITIC approach by allowing both indicator volatility and cross-market correlations to vary over time within a rolling-window framework. Unlike static CRITIC weights computed over the full sample, the dynamic CRITIC method updates indicator weights in response to changes in market volatility and interdependence, thereby enabling the aggregated financial stress index to adapt to shifting market conditions. While this approach does not explicitly model directional spillover effects, it provides a flexible and time-varying aggregation mechanism that better reflects the evolving co-movement structure among financial sub-markets. This dynamic weighting strategy has been shown to improve the measurement of financial stress in empirical applications (Zhang et al., 2023; Zhu & Jiang, 2024).

Specifically, assuming n samples to be evaluated, involving p financial market indicators or evaluation indicators. This forms an original indicator data matrix,

$$X = \begin{pmatrix} x_{11} & \cdots & x_{1p} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{np} \end{pmatrix} \quad (9)$$

where x_{ij} represents the value of the *j-th* evaluation indicator for the i-th sample. The following steps are used to compute the component weights in the aggregated FSI.
Step 1: To eliminate the impact of different dimensions on the index, each indicator must be processed in non-dimensional form using the formulas below.

Positive indicators : $x'_{ij} = \frac{x_j - x_{min}}{x_{max} - x_{min}}$ (10)

Negative indicators : $x'_{ij} = \frac{x_{max} - x_j}{x_{max} - x_{min}}$ (11)

Where x'_{ij} is the standardized value of the indicator for market i at time t. x_{min} and x_{max} are the indicator's minimum and maximum values for the sample period.

Step 2: Dynamic CRITIC components (36-month rolling window)
The CRITIC method assigns weights based on two dimensions: contrast intensity and indicator conflict. Specifically, this study used a 36-month rolling-window method to calculate weights for each time period. For each 36-month window, correlations between sub-markets and each indicator's volatility were calculated from historical data to determine the new weights. The reason for applying the 36-month rolling window is to account for the time-varying nature of the financial market linkage. A 36-month rolling window can also strike a good balance between stability and sensitivity: it can not only smooth short-term noise but also dynamically adjust the relevant structure in response to changes in market conditions (Billio et al., 2012; Zhang et al., 2023). Lastly, this approach ensures that the financial stress index can reflect market dynamics in real time, respond quickly to sudden economic events, and effectively capture fluctuations in market risk.

The contrast intensity of the indicator j at the time point t is measured by the standard deviation within the window:

$\sigma_j = \sqrt{\frac{\sum_{i=1}^{m}\left(x'_{ij} - \bar{x}_j\right)^2}{m-1}}$ (12)

For Eq. (12), σ_j is the standard deviation of indicator j within the 36-month window ending at month t (contrast intensity). m is the number of observations in the window (here m=36), x'_{ij} is the standardized value of indicator j in the i-th month inside the window (ordered from oldest to most recent), and $m-1$ is the degrees-of-freedom adjustment for the sample standard deviation.

Otherwise, the conflict indicator reflects the degree of correlation between the different indicators. If a significant positive correlation exists, then the conflict value is smaller. f_j represents the degree of contradiction between indicator j and the other indicators,

$f_j = \sum_{i=1}^{m}\left(1 - r_{ij}\right)$ (13)

where r_{ij} represents the correlation coefficient between indicators i and j. Lastly, the information carrying capacity, C_j, represents the information-carrying capacity of indicator j. The larger the information-carrying capacity, the greater the weight.

$C_j = \sigma_j f_j$ (14)

Step 3: Calculate weights. Weight w_j of the j −th indicator:

$w_j = \frac{C_j}{\sum_{j=1}^{n} C_j}$ (15)

This normalization ensures that indicators with larger information content receive higher weights in the aggregation.

Step 4: Calculate score:
The score of this paper is estimated using the formula below.

$$S_i = \sum_{j=1}^{n} w_{j,t} x'_{ij} \qquad (16)$$

Where S_i is the financial stress index for time t ;$w_{j,t}$ is the weight of indicator j at time t. x'_{ij} is the standardized value of indicator$j$ for market i at time t. In the formula, the value range of S is [0,1]. A high S value indicates that the market is under significant financial stress during the period. Conversely, a low S value suggests that the market is experiencing less stress.

Results

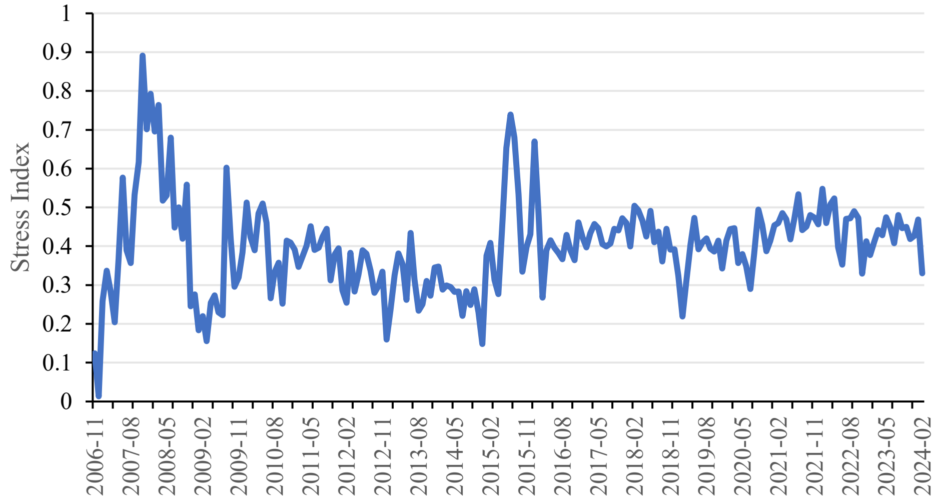
Analysis of Sub-Market Financial Stress Index

Figure 1 presents the equity market stress index for China, Malaysia, Singapore, Indonesia, and the Philippines, revealing pronounced cross-country heterogeneity and strong time-varying characteristics. To recap, since the stress index is normalized to [0,1], values exceeding 0.5 indicate periods of elevated financial stress.

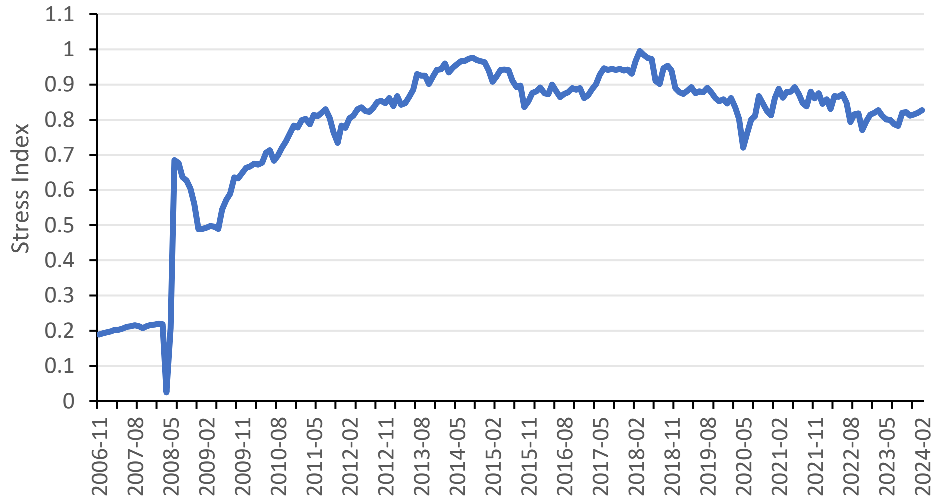
China (Figure 1a) exhibits pronounced stress during the 2008 global financial crisis, with the index approaching 0.8, and a secondary peak in 2015–2016, associated with turbulence in the A-share market following rapid leverage expansion and regulatory tightening. Besides, the volatility in 2015–2016 was closely associated with U.S. monetary policy normalization, rising global risk aversion, and capital-flow reversals from emerging markets, which disproportionately affected economies with greater dependence on external financing and commodity exports.

Outside these episodes, stress remains relatively moderate, reflecting the stabilizing role of market regulation. Malaysia (Figure 1b) exhibits persistently high stress after 2010, frequently remaining above 0.7 and peaking at approximately 0.9 during the COVID-19 pandemic. As a resource-based economy, Malaysia was highly exposed to global commodity price fluctuations, which exacerbated equity market stress during external shocks. Singapore (Figure 1c) records the highest and most sustained stress levels among the five economies, with the index exceeding 0.8 in 2008 and remaining above 0.8 for most of the period after mid-2010. This pattern is consistent with Singapore's status as a highly open international financial center, making it particularly sensitive to global financial disturbances. Indonesia (Figure 1d) exhibits a gradual rise in stress, with heightened volatility during the 2013 taper tantrum and further increases during the pandemic, underscoring its vulnerability to global liquidity conditions and capital-flow reversals. The Philippines (Figure 1e) experiences moderate but persistent stress, with values mainly between 0.3 and 0.7, and temporary increases during major global shocks, reflecting its reliance on foreign capital inflows.

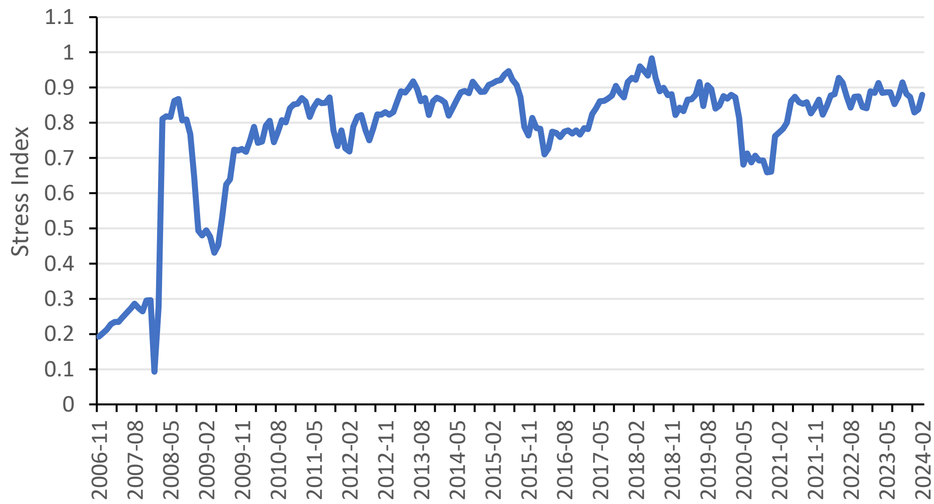
Overall, Singapore and Malaysia experience the most frequent high-risk periods (FSI above 0.5), while China and Indonesia exhibit episodic stress linked to specific shocks, and the Philippines exhibits moderate but sustained vulnerability, underscoring the role of financial openness and economic structure in shaping equity market stress.



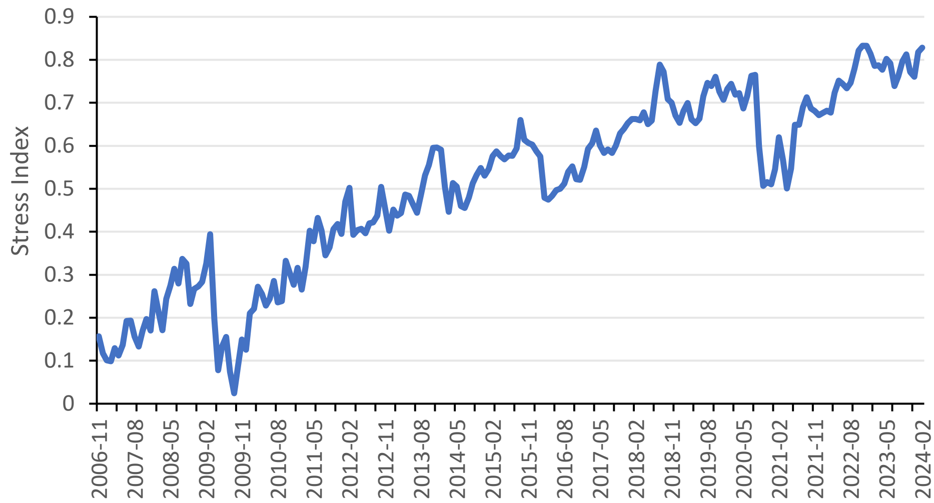
(a) China



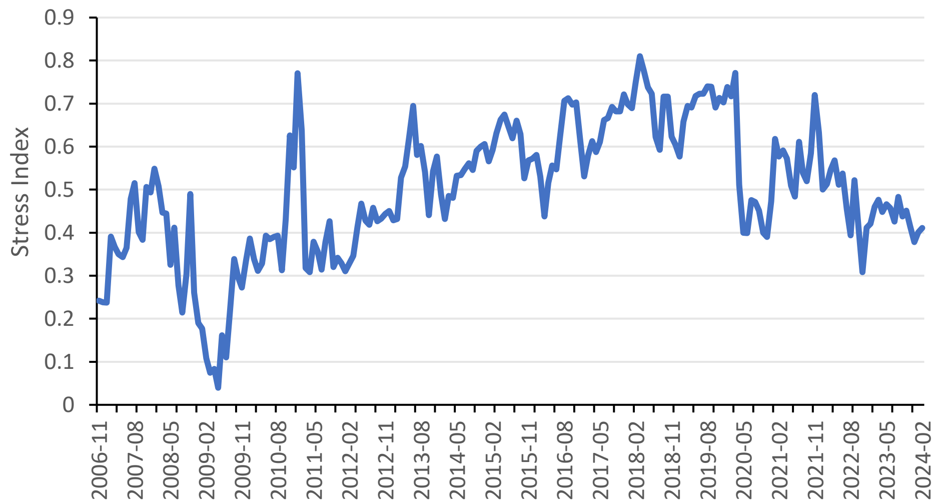
(b) Malaysia



(c) Singapore

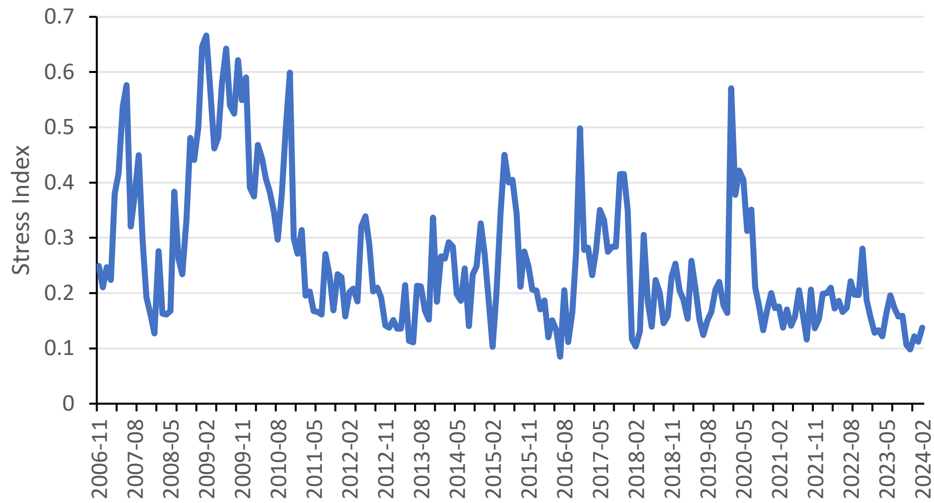


(d) Indonesia

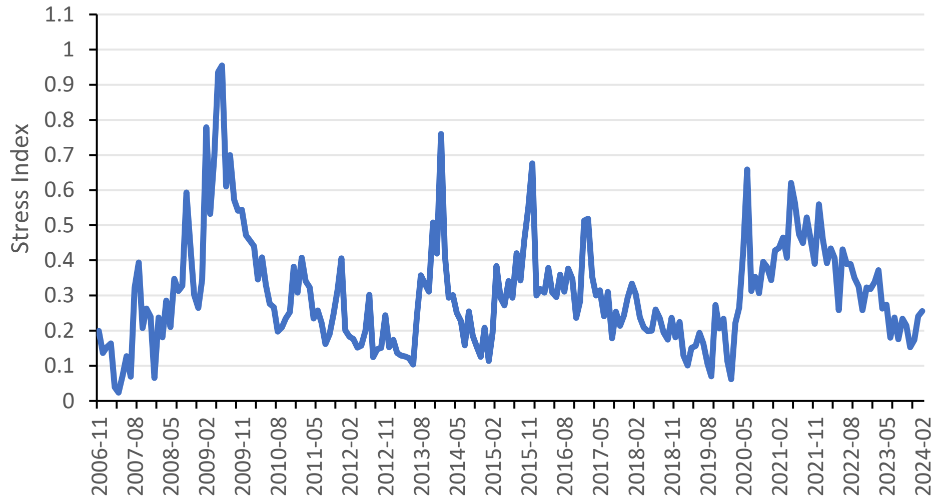


(e) Philippines
Figure 1. Equity Market Stress Index
Source: Author's calculations.

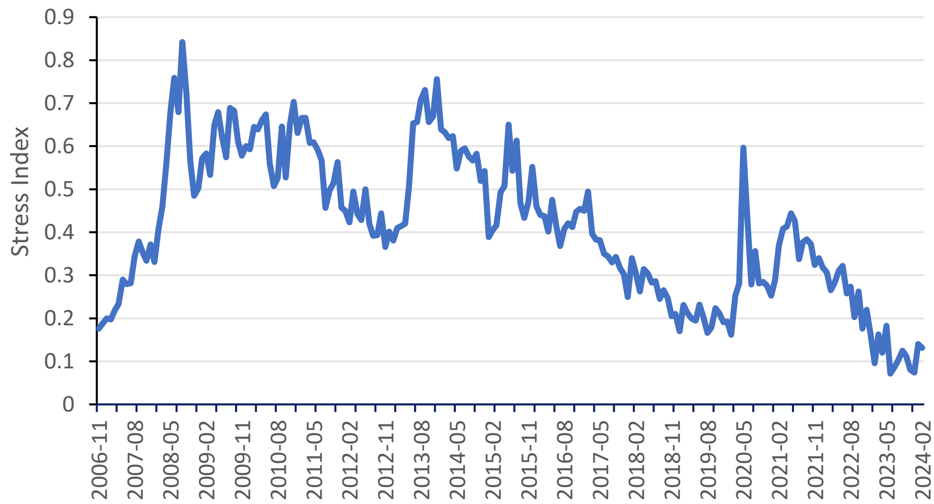
Next, Figure 2 shows bond-market stress clustering in three periods: 2008–2009, 2015–2016, and 2020. In 2008–2009, Malaysia experienced the strongest high-stress episode, with the index peaking at approximately 0.90, substantially higher than the contemporaneous peaks in Singapore (around 0.82), Indonesia (around 0.8), and the Philippines (around 0.65). China showed only brief spikes and was comparatively contained. In 2015–2016, high-stress conditions are most evident in Malaysia and Indonesia, especially Indonesia, which shows a sharp spike in the figure, consistent with spillovers from U.S. policy normalisation and emerging-market risk repricing; Singapore is largely below 0.5, and China is mostly below the threshold (Eickmeier, 2014). During the 2020 pandemic, stress rose again, but it was most pronounced in the Philippines; China showed a short-lived rise near the onset of the pandemic, while Malaysia, Singapore, and Indonesia were mostly below or around 0.5 (International Monetary Fund, 2020). Overall, Malaysia and Indonesia had the highest FSI among other countries during the GFC and the turbulence in 2015-2016, respectively.



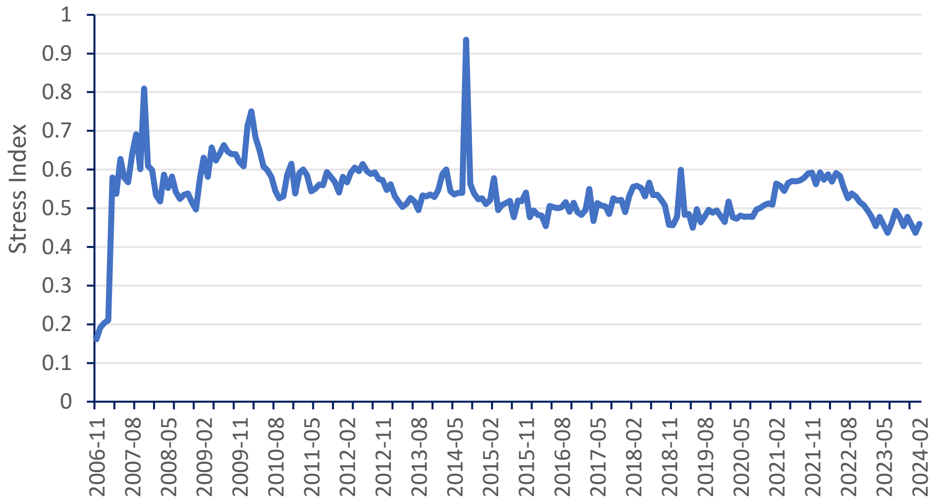
(a) China



(b) Malaysia



(c) Singapore



(d) Indonesia

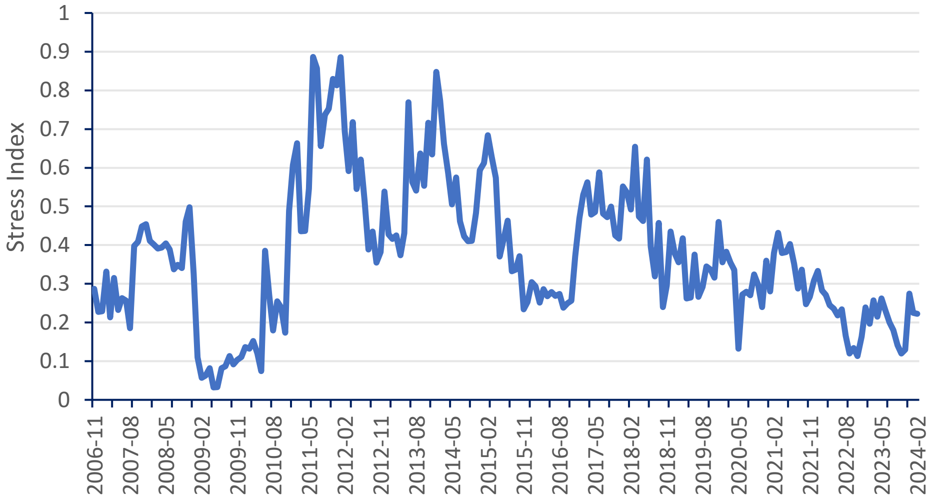
(e) Philippines
Figure 2. Bond Market Stress Index
Source: Author’s calculations.

Figure 3 indicates clear cross-country heterogeneity in banking stress in the 2008 Global Financial Crisis. China remains mostly below the high-stress threshold of 0.5, whereas Malaysia and the Philippines stay predominantly above 0.5 (around 0.6–0.7), and Singapore exhibits the most pronounced spike, approaching 1.0. This ordering is consistent with evidence that banking-sector stress in ASEAN economies can rise sharply during global shocks, particularly in more financially open systems and regional hubs that are more sensitive to external funding conditions and to cross-border risk transmission (Tng et al., 2012; Poonpatpibul et al., 2018).

In the 2015–2016 emerging-market volatility episode, China displays episodic elevations around the threshold, briefly approaching or slightly exceeding 0.5, consistent with a stress environment shaped by domestic financial adjustments and spillovers from global risk repricing. Malaysia remains in a high-stress regime, with the stress index frequently exceeding 0.6, indicating sustained pressure on the banking sector during this episode. Singapore remained below 0.5, implying comparatively stronger banking resilience during that period.

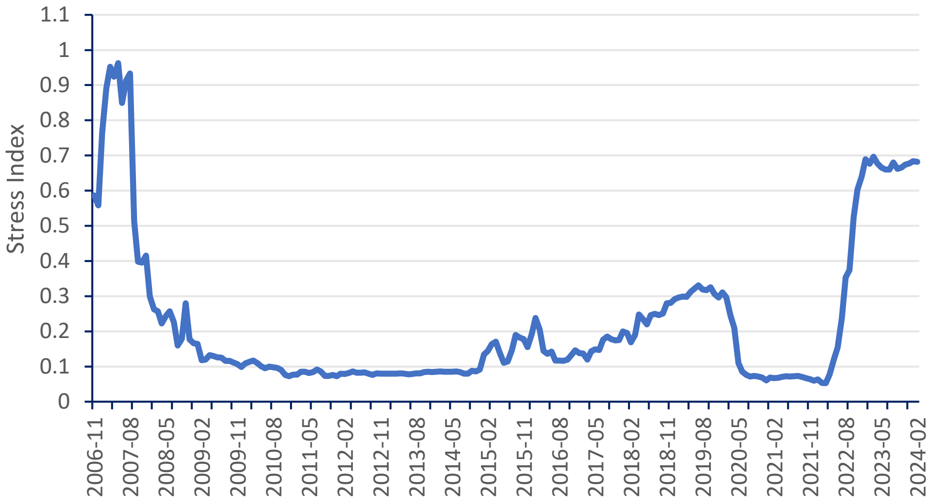
Indonesia records one of the sharpest peaks in the entire figure, with the index approaching 0.8 around 2016, consistent with vulnerability to capital-flow reversals and exchange-rate and financing pressures during economy-wide emerging-market turbulence. The Philippines was largely below 0.5 in 2015–2016 (notwithstanding earlier high stress around 2011–2013), suggesting that the 2015–2016 shock resulted in lower banking stress than in Malaysia and Indonesia. Indeed, compared with other countries, Indonesia's sharp spike and Malaysia's high plateau indicate the highest banking stress in 2015–2016.

In 2020, during the COVID-19 shock, China remained below 0.5, indicating no sustained high-stress banking regime during the pandemic year. This is likely due to the extensive government support measures aimed at stabilizing the banking sector during the pandemic, such as fiscal stimulus and liquidity provisions (Borio, 2020). Malaysia remained at or slightly above the 0.5 threshold in 2020, then dropped sharply in 2021, consistent with a high-stress phase followed by a pronounced easing. Singapore remains below 0.5 in 2020, while Indonesia and the Philippines also remain largely below the high-stress threshold, likely due to similar government interventions that helped mitigate banking-sector pressures during COVID-19 (Demir & Danisman, 2021).

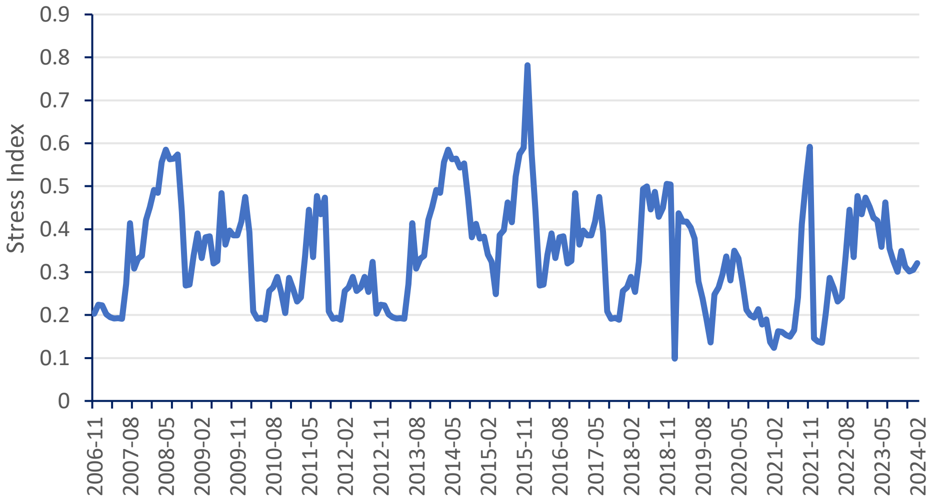


(a) China

(b) Malaysia



(c) Singapore

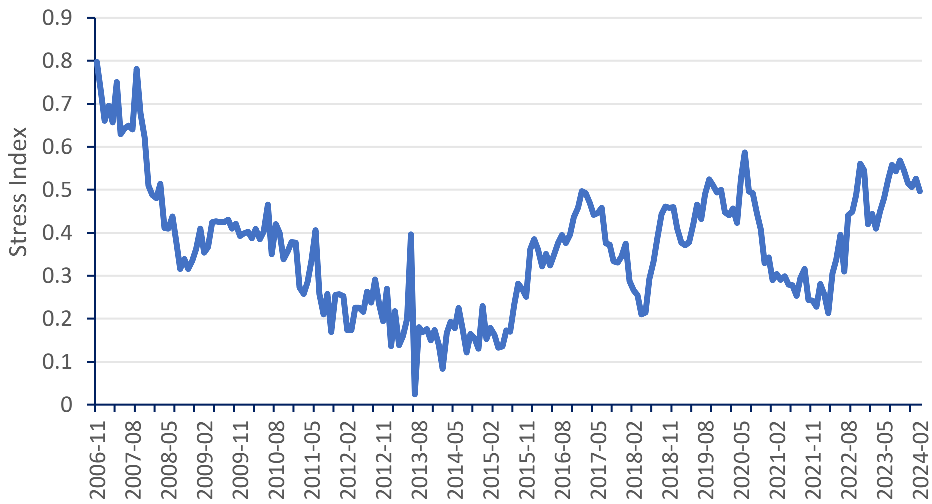


(d) Indonesia

(e) Philippines
Figure 3. Banking Market Stress Index
Source: Author’s calculations.

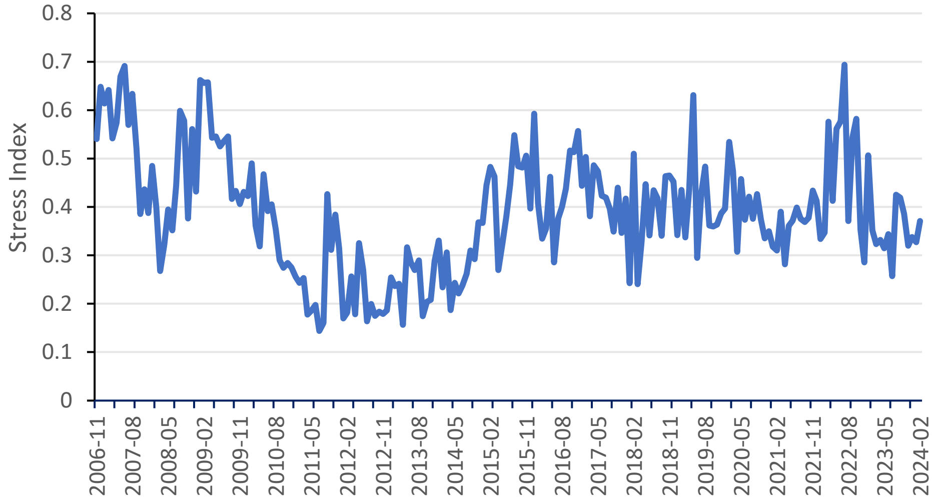
Figure 4 reports the foreign-exchange market stress index for China and four ASEAN economies. Focusing on high-risk readings above the 0.5 threshold, the 2008 global crisis episode stands out (notably 2008), as Singapore is the only economy to enter the high-stress regime clearly, consistent with its sensitivity to cross-border funding and liquidity shocks as an international financial center. In contrast, China and Malaysia remain elevated but mostly below 0.5, while Indonesia and the Philippines also stay largely below the high-stress threshold, indicating comparatively milder FX stress in this phase.

A broader and more persistent high-stress pattern emerges during the period of emerging-market volatility (notably 2015–2016) and the pandemic shock (notably 2020). Malaysia and Indonesia have maintained readings above 0.5 since around 2015–2016, consistent with tighter external financing conditions and heightened risk repricing in commodity- and capital-flow–sensitive economies. During the COVID-19 shock, high-stress readings became more widespread: Malaysia and Indonesia remained above 0.5, the Philippines shifted into the high-stress regime, and China and Singapore showed temporary spikes around the threshold, indicating episodic but less persistent foreign exchange stress relative to Malaysia and Indonesia, notably in 2020.

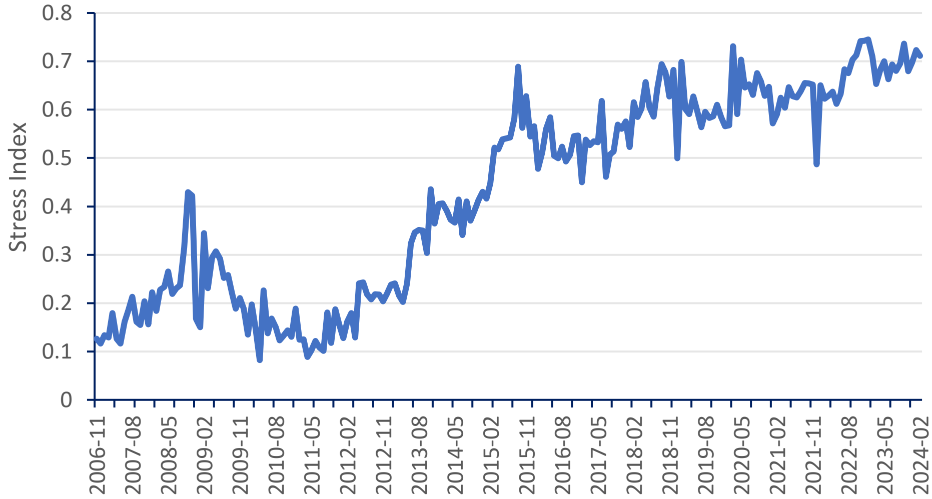


(a) China

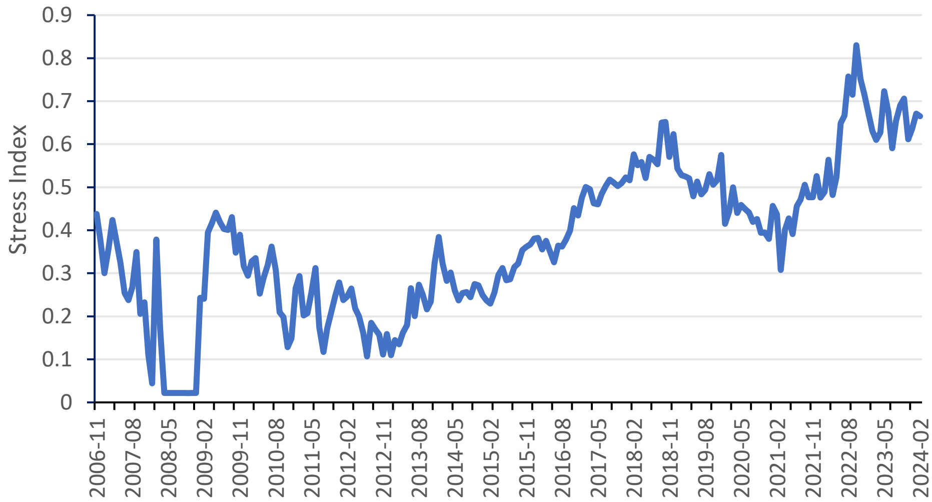
(b) Malaysia



Singapore (c)



(d) Indonesia



(e) Philippines

Figure 4. Foreign Exchange Market Stress Index

Source: Author's calculations.

Aggregated Financial Stress Index

The General Comparison of Financial Stress Indexes.

Table 2 reveals clear cross-country heterogeneity in aggregate financial stress. The discussions center on the range of the aggregated FSI, its mean, peak periods and levels, and the FSI standard deviation. Based on Table 2 and using 0.5 as the high-risk threshold, stress concentration becomes most visible across three major event windows. During the 2008 global financial crisis, the high-stress regime was most evident in Singapore and Malaysia. Singapore's economy reached a peak stress level of 0.683, and Malaysia reached 0.680. Malaysia, with the index of 0.683, and Indonesia, with the index of 0.657, clearly fell within the high-stress regime in 2015-2016. China, by comparison, rises only to its sample peak of 0.481, consistent with intensified domestic stress surrounding the 2015 equity market correction and the associated deleveraging process. During the 2020 COVID-19 shock, the most pronounced high-stress readings were observed in the Philippines, where the stress index peaked at 0.705. In contrast, China and Singapore remain below the high-risk threshold for most of the period, while Malaysia and Indonesia do not exhibit a sustained high-stress plateau, indicating that foreign exchange stress during this phase was more transitory.

Interestingly, Table 2 also reveals that Singapore exhibits the largest volatility dispersion among the five economies, with a standard deviation of 0.170 and an index range of 0.284-0.680, indicating the strongest transmission of global funding shocks and risk repricing into domestic financial conditions. By contrast, China's stress index remains within a much narrower range from 0.102 to 0.481, suggesting that stress episodes were largely episodic rather than persistent.

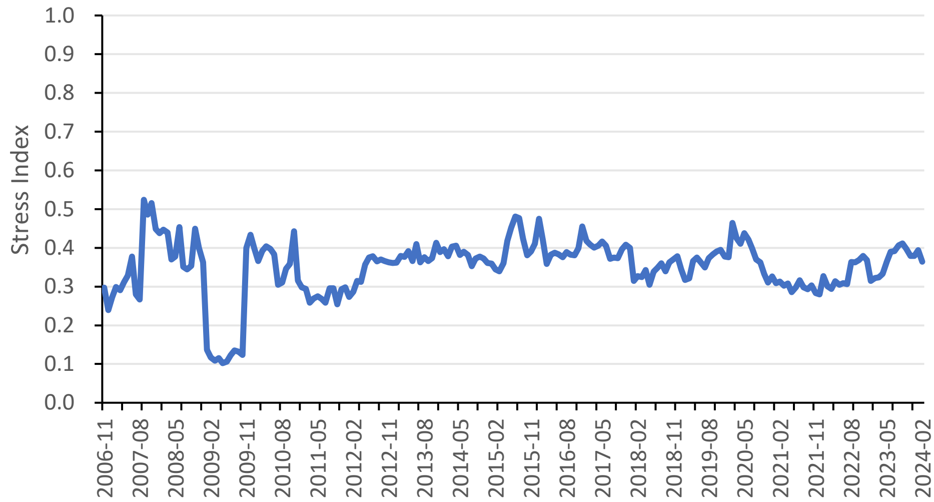
In conclusion, China exhibits the lowest and most stable profile, with the index confined to a relatively narrow band and reaching its local maximum only around 2015–2016, indicating that high-stress conditions are episodic rather than persistent. By contrast, the ASEAN economies exhibit higher average stress and greater volatility. Singapore exhibits the largest dispersion, consistent with a more shock-sensitive profile in an open financial hub, and, together with Malaysia and the Philippines, attains the highest peak level observed in the sample. Indonesia peaks slightly lower but shows a more sustained increase since the mid-2010s, suggesting prolonged exposure to adverse external conditions rather than a single short-lived spike.

Table 2
Statistics on the Volatility Characteristics of the Aggregate Financial Stress Index

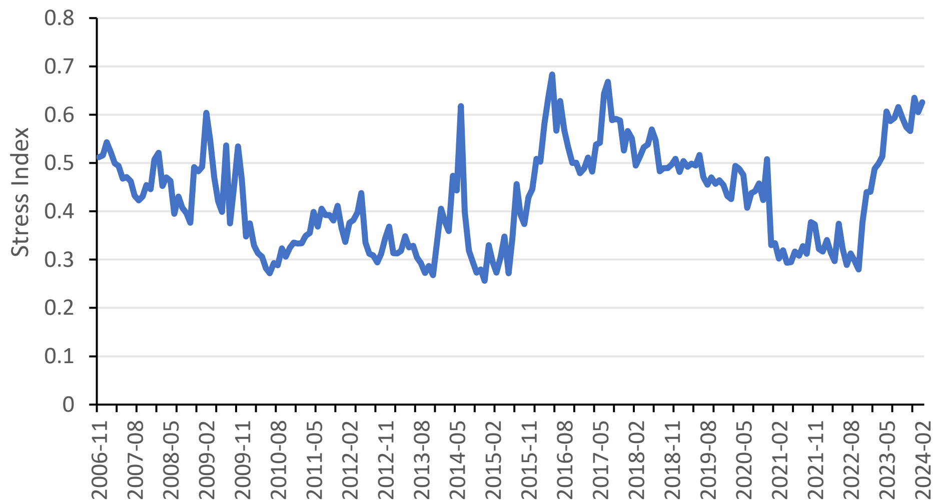
Country	Index range	Mean	Peak Period	Peak Level	Std. dev.
China	0.102–0.481	0.337	2015–2016	0.481	0.075
Malaysia	0.256–0.683	0.428	2008, 2015–2016	0.683	0.105
Singapore	0.284–0.680	0.464	2008, 2012	0.680	0.170
Indonesia	0.294–0.657	0.448	2014–2016	0.657	0.120
Philippines	0.171–0.705	0.465	2014, 2020	0.705	0.110

Dynamic Financial Stress Indexes for China and ASEAN-4 Economies

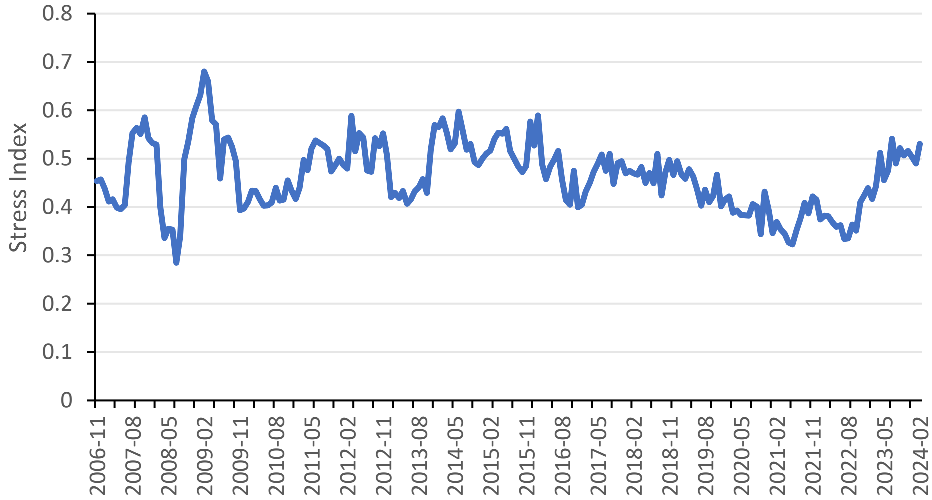
In this section, the key development in the aggregated FSI for each examined country is presented. Figure 5(a) suggests that the index rose sharply in China around 2008, reflecting a rapid increase in financial stress, likely driven by spillover effects from the global financial crisis and domestic adjustments. By late 2009, the index stabilized at a higher level, suggesting that financial stress had entered a relatively steady phase. After a clear peak around 2015–2016, China's post-2016 path is comparatively smooth, with stress reverting to its mid-range relatively quickly after temporary upticks, indicating limited persistence of shocks in the aggregate index. In addition, the 2020 episode appears as a contained, short-lived elevation rather than a structural upward shift, suggesting that system-wide stress did not remain elevated for an extended period in the aggregate measure, while Singapore's average financial stress level was higher, but mainly manifested as a short-term, event-driven mode rather than long-term stress events.



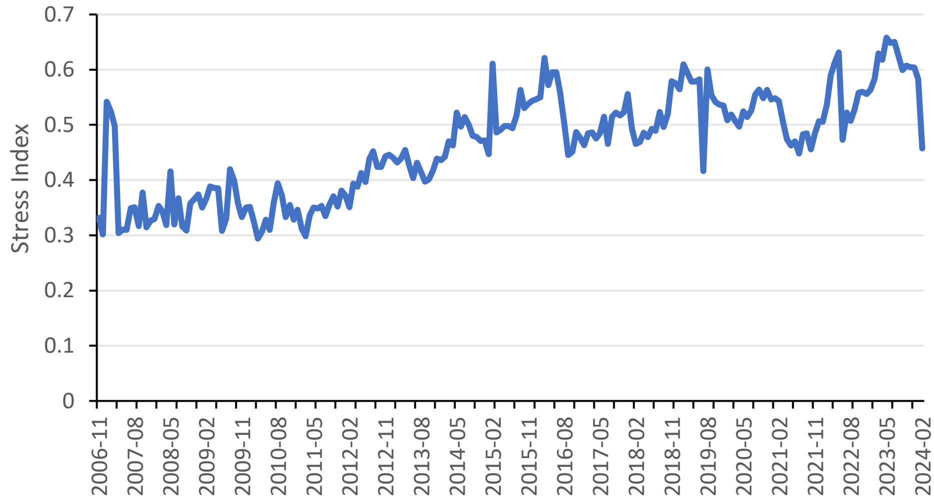
(a) China



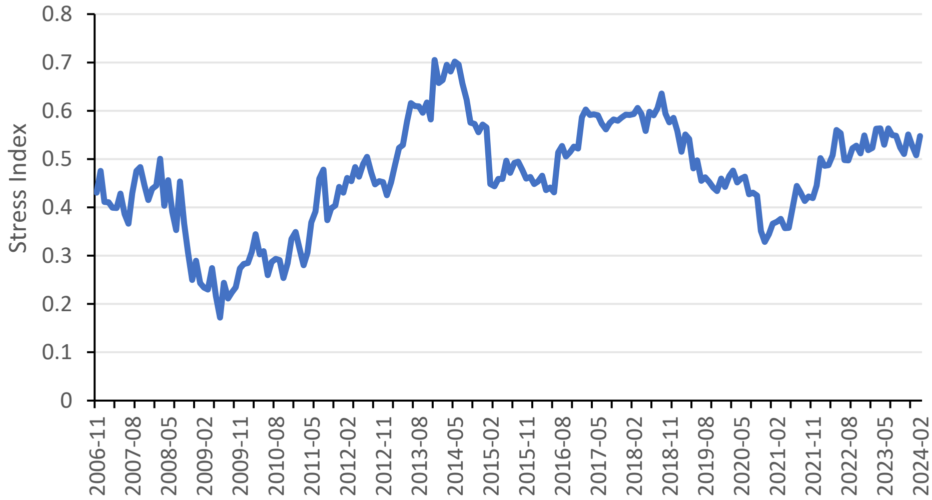
(b) Malaysia



(c) Singapore



(d) Indonesia



(e) Philippines

Figure 5. Dynamics Financial Stress Index
Source: Author’s calculations.

Figure 5(b) shows that Malaysia's index remained elevated throughout 2008–2009, with visible short-run oscillations and pronounced increases in 2015–2016, and remained in the 0.55–0.65 range in recent years, indicating high levels given Malaysia’s exposure to commodity cycles and US-dollar funding conditions. The spike in 2015–2016 was closely linked to the global commodity price collapse, particularly the drop in oil prices, which significantly affected Malaysia's fiscal revenue and external financing, further exacerbating financial stress. Additionally, the depreciation of the Malaysian Ringgit and the strength of the US dollar increased the cost of external debt, further tightening liquidity. The spike in 2020 was primarily due to the COVID-19 pandemic, which caused a global economic contraction and tightened both external and domestic liquidity. Malaysia's financial markets were severely affected by a sharp decline in demand across key sectors, including tourism and manufacturing. During the COVID-19 shock, Malaysia’s FSI increased moderately but remained lower than its earlier peaks, reflecting the mitigating effects of policy support and regulatory forbearance.

As illustrated in Figure 5(c), Singapore displays a highly responsive but less persistent stress profile. Financial stress rises sharply during 2008–2009, consistent with its exposure to global funding and liquidity shocks as an international financial center. Additional short-term fluctuations are evident around 2011–2012, corresponding to heightened global uncertainty during the European sovereign debt crisis. During the 2015–2016 emerging-market volatility episode, Singapore’s stress index exhibits only mild and short-lived fluctuations rather than a pronounced spike, indicating relative resilience to U.S. monetary policy normalization and emerging-market risk repricing. Another temporary increase occurs in 2020, reflecting disruptions in global capital flows during the pandemic. However, in contrast to Malaysia and Indonesia, these stress episodes are relatively short-lived, with the index reverting quickly toward its mid-range level, consistent with Singapore’s deep financial markets and effective exchange-rate-centered policy framework.

Figure 5(d) shows that Indonesia's index rises rapidly from very low pre-crisis levels to a moderate plateau during 2008–2009. After that, Indonesia displays the sharpest peaks and greatest volatility with brief surges in 2015–2016 and 2018, followed by another notable increase in 2022 and gradual normalization, signaling high elasticity to shifts in global risk appetite and capital flows. In 2007-2008, Indonesia's financial stress index increased significantly, mainly reflecting spillover effects from the global financial crisis, the reversal of capital flows, and depreciation pressure on the Indonesian rupiah (Chen et al., 2015). During this stage, global liquidity has tightened, and risk aversion has increased, limiting Indonesia's external financing environment. In 2015–2016, global commodity price fluctuations, particularly in oil and natural gas, significantly affected Indonesia, given its reliance on commodity exports. The depreciation of the Indonesian rupiah and tighter external financing conditions during this period exacerbated the financial stress. In 2018, shifts in global investor sentiment, combined with capital outflows and a stronger US dollar, led to further spikes. The 2022 increase in FSI was primarily driven by a surge in global commodity prices, particularly in the energy and food sectors, which was influenced by geopolitical events such as the Russia-Ukraine conflict. These spikes reflect Indonesia’s sensitivity to global risk appetite and its dependence on external financing and commodity market trends.

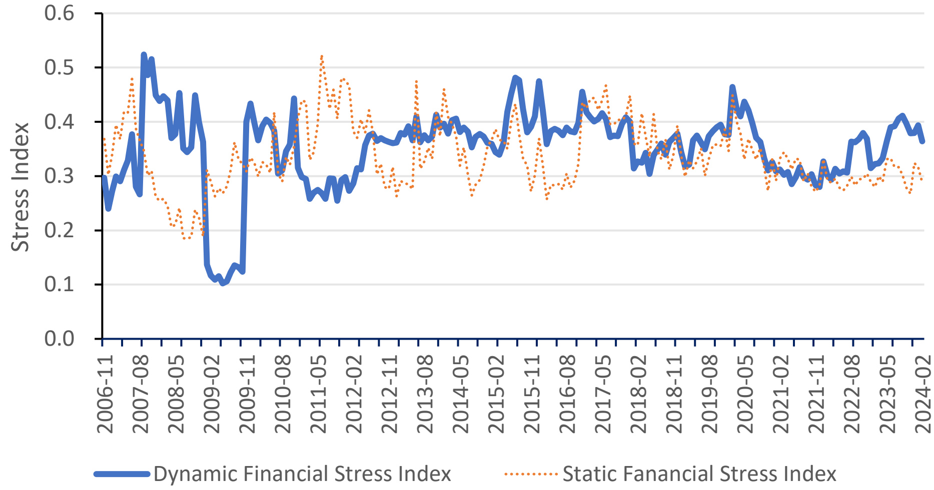
As shown in Figure 5(e), the Philippines shows that the FSI declined through 2008–2009, moving from moderate stress in 2007–2008 to lower readings in 2009, suggesting earlier easing than in Malaysia and Singapore. After the Philippines showed a decrease around 2013-2014 and maintained a relatively high level in the subsequent period, it showed a phase transition. The first jump in 2013 was largely influenced by global liquidity repricing and changes in external financing conditions. In 2020, the COVID-19 pandemic triggered a severe global economic contraction, which exacerbated financial stress slightly in the Philippines. These factors contributed to higher levels of financial stress observed during 2013 to 2020 than at the end of the 2010s.

Overall, across the five time-series data presented in Figure 5, the FSI generally increases in tandem with an “event-driven, mean-reverting” dynamic, although the reversion is not full. during well-defined global stress windows and subsequently subsides after the stress. Besides, the stress levels in China are relatively lower and more stable; the Philippines and Singapore have higher overall stress levels; Indonesia has greater volatility; and Malaysia showed the "double peak" features of 2008 and 2015-2016. At the regional level, some common regional stress movements are consistent with exposure to global risk repricing and dollar liquidity conditions, which are transmitted to the international bond market and broader financial conditions (Albagli et al., 2018; Chen et al., 2015). The cross-national differences in the continuous increase in FSI readings are more likely attributable to heterogeneity in external financing dependency, commodity sensitivity, and the depth of domestic financial markets.

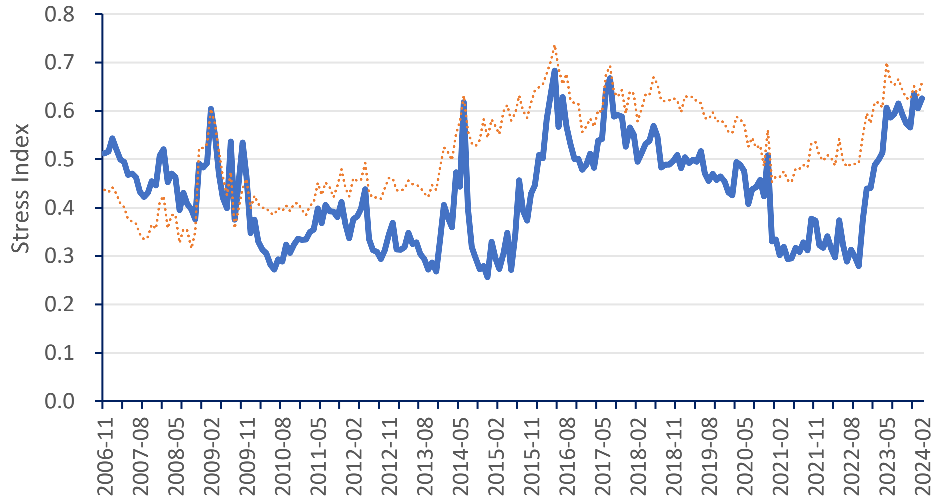
Comparative Analysis of Dynamic CRITIC Method and Static CRITIC Method

Sensitivity to stress episodes differs materially between the dynamic and static CRITIC-based FSIs. Overall, dynamic CRITIC can reflect the evolution of related structures and volatility characteristics between sub-markets by allowing weights to change over time; static CRITIC methods[1] uses fixed weights, so the sequence is relatively smoother. It should be emphasized that dynamic methods do not necessarily have to be "higher" in all periods; they assign higher weights to different sub-markets at different stages, highlighting different pressure windows. The blue curve in Figure 6 represents the dynamic CRITIC index, and the orange represents the static CRITIC index.

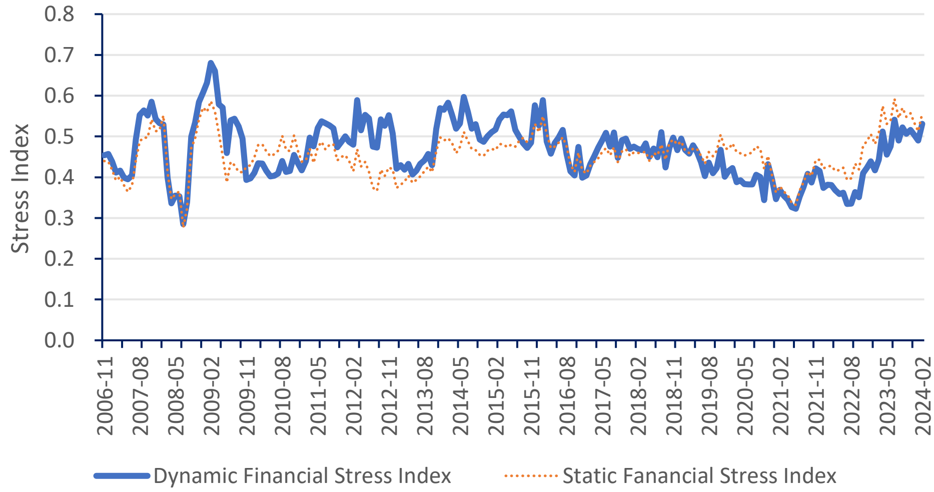
1 Static CRITIC calculates the weights of each indicator based on the full sample at once (determined by the comparison strength and indicator conflict) and maintains them unchanged throughout the entire sample period.



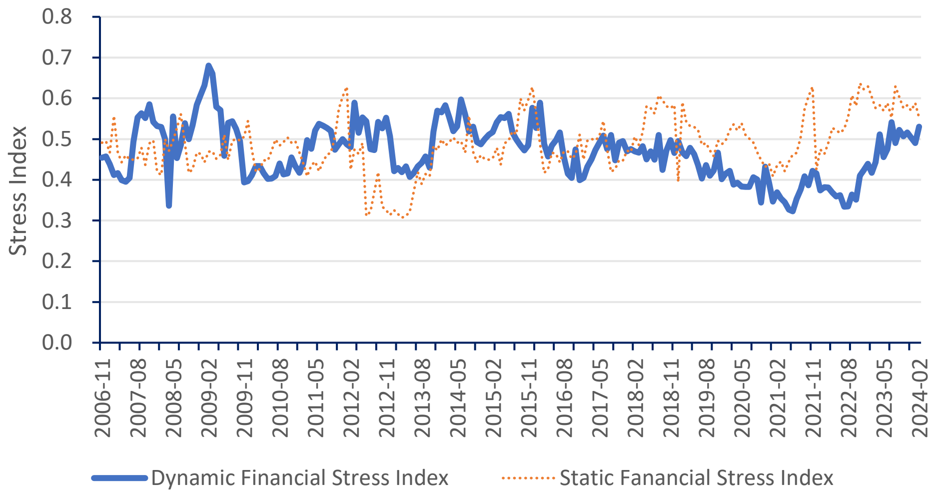
(a) China



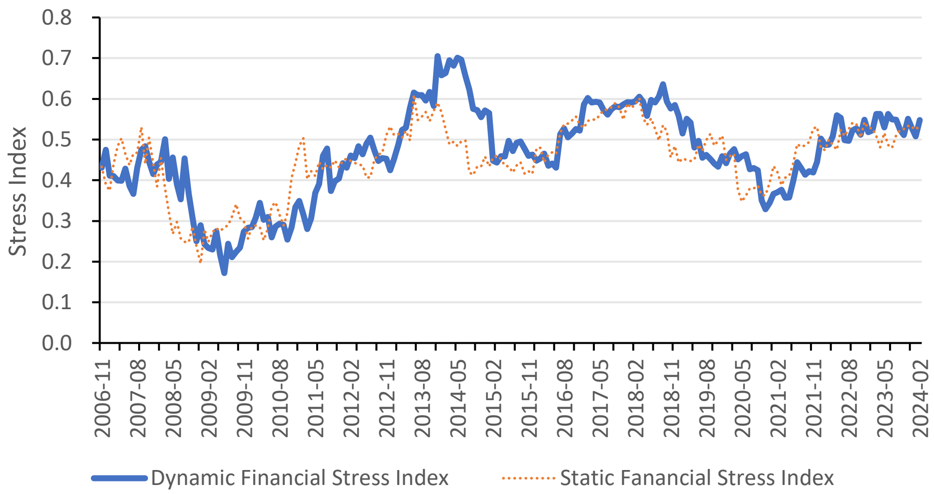
(b) Malaysia



(c) Singapore



(d) Indonesia



(e) Philippines

Figure 6. Comparison of Dynamic and Static Financial Stress Indices
Source: Author’s calculations.

Figure 6 compares the dynamic-CRITIC FSI with its static-CRITIC counterpart for China and ASEAN-4 economies. Both series broadly identify the same high- and low-risk phases, indicating that each weighting scheme captures the common timing of stress episodes. However, the dynamic FSI is generally more responsive, whereas the static FSI is smoother and tends to adjust more gradually when stress rises abruptly. This difference is most pronounced in major shocks, where time-varying weights amplify the contributions of sub-markets whose volatility and co-movement intensify under stress.

During the 2008–2009 global financial crisis, the dynamic FSI rose more steeply than the static index in most countries. The Philippines, otherwise, shows a similar pattern between the dynamic and static FSI. Besides, its short-run volatility is generally higher. This is especially evident in Singapore and Malaysia, where the dynamic series exhibits pronounced crisis spikes while the static series increases more moderately, consistent with the dynamic scheme reacting more strongly to abrupt changes in cross-market dependence and volatility.

China's dynamic series also shows a clearer crisis-response pattern than the static line, though the amplitude is comparatively smaller.

In the 2015–2016 episode of emerging-market volatility, the gap between the two measures widens again in several economies, notably China's dynamic FSI, which exhibits a more pronounced stress pulse around the RMB regime adjustment in 2015, heightening exchange-rate uncertainty and propagating to broader financial conditions. Malaysia and Indonesia similarly exhibit more pronounced dynamic movements during this period, consistent with greater sensitivity to risk repricing and external financing conditions, whereas the static index remains comparatively muted.

Finally, during 2020–2022, the dynamic FSI generally responded more promptly to the pandemic shock and the subsequent tightening of global financial conditions, resulting in more pronounced fluctuations than the static FSI. For instance, in Indonesia, the dynamic FSI shows an earlier upward trend in mid-2020, reflecting the initial pandemic-induced stress, while the static series starts to rise later in the year. Similarly, in Singapore, the dynamic series exhibits a sharper initial increase around the same period, whereas the static series reacts more gradually, missing the early spikes. These findings in the dynamic FSI across multiple economies underscore its ability to detect and adjust to rapidly evolving stress conditions ahead of static measures, making it a more timely and informative indicator during sudden market shifts during the pandemic.

Contribution of Different Financial Markets to Financial Stress

The analysis of the weights of the financial sub-markets in China, Malaysia, Singapore, Indonesia, and the Philippines revealed significant structural differences across these countries' financial systems. Figure 7 decomposes the overall financial stress of various countries into the contribution ratios of four sub-markets (banks, stocks, foreign exchange, and domestic bonds); the sum of the four for each economy is 100%. The results show significant structural differences in the sources of stress across countries. China and Malaysia exhibit relatively pronounced bank-dominated features, with bank contributions of 33.7% and 31.2%, respectively, followed by domestic bonds (23.1% in China; 20.1% in Malaysia). Singapore's structure is more balanced: the key contributors are the banking sector (29.1%), stocks (26.7%), and foreign exchange (24.9%). The proportion of domestic bonds is relatively small (19.2%). In Indonesia, stress contributions are mainly concentrated in stocks (31.0%) and domestic bonds (26.0%), while foreign exchange contributions are relatively low (14.0%). In contrast, the Philippines exhibits a distinct foreign exchange dominance, with foreign exchange contributing 34.0%, higher than that of banks (26.8%) and stocks (22.1%). Overall, although financial stress index levels are similar, stress-driven markets differ across economies. Therefore, when interpreting the FSI, it is necessary to conduct targeted observations and monitoring in combination with the sub-market structure.

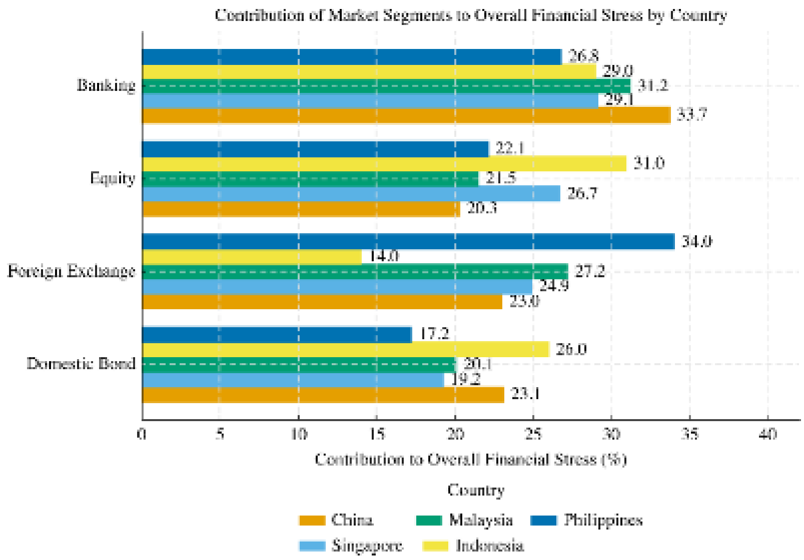


Figure 7. Contribution of Market Segments to Overall Financial Stress (%)
Source: Author's calculations.

Conclusions and Policy Recommendations

This study assessed financial stress in China and the ASEAN-4 countries by constructing financial stress indices for four sub-markets (banking, bonds, stocks, and foreign exchange) and for China and the ASEAN-4 countries (Malaysia, Singapore, the Philippines, and Indonesia). By adopting a dynamic CRITIC weighting method, the proposed framework allows the contribution of each sub-market to evolve, thereby providing a more adaptive measure of financial stress than the static-weight method.

This study draws some conclusions. Firstly, there is significant heterogeneity in financial stress across countries, and the dynamic CRITIC weighting method captures the time-varying risk mechanisms underlying this heterogeneity. Specifically, China's Financial Stress Index has the smallest range, from 0.10 to 0.50, with an average of 0.32. This performance fully reflects the buffering effect of capital controls and policy interventions in mitigating risk shocks. In contrast, the overall financial stress levels across the four ASEAN countries examined are generally high, with Singapore exhibiting the most pronounced fluctuations. This fully confirms its high sensitivity to global risks as a highly open financial center. Indonesia and the Philippines have higher average stress levels, with means of 0.41 and 0.45, respectively, suggesting greater exposure to persistent stress than in China. Moreover, while dynamic CRITIC offers the advantage of adjusting its weights in real time based on volatility fluctuations and cross-market correlations, it does not necessarily outperform static CRITIC in every scenario. The primary strength of dynamic CRITIC lies in its ability to adapt to changing market conditions, making it especially useful during periods of heightened financial stress. Its responsiveness and ability to track volatility make it a valuable complement to traditional static aggregation methods, particularly during significant market turbulence. Therefore, the focus of empirical results should be on highlighting the volatility and adaptability of dynamic FSI, rather than asserting its superiority in all cases.

Furthermore, Figure 7 shows that there are significant differences in the "source structure" of financial stress among countries: in China (33.7%), Malaysia (31.2%), and Singapore (29.1%), the stress is mainly contributed by the banking sector, indicating that credit and liquidity conditions are at the core of stress formation. The Philippines is more affected by foreign exchange stress (34.0%), indicating greater susceptibility to transmitting stress through external shocks and exchange-rate channels. Indonesia's foreign exchange contribution was relatively low (14.0%), but stocks (31.0%) and domestic bonds (26.0%) contributed more, suggesting that market pricing and domestic debt conditions were more critical to its stress fluctuations.

This study puts forward the following policy recommendations. First, our comparison shows that the dynamic and static CRITIC weighting methods can diverge during stress episodes because dynamic weights adjust to changes in market volatility and cross-market correlations, whereas static weights remain fixed. This divergence implies that relying solely on a static, single-perspective stress gauge may understate the pace and structure of risk accumulation in crises. Therefore, regulatory authorities should complement conventional static monitoring with a multi-market dashboard that jointly tracks stress across banking, bond, equity, and foreign-exchange markets, and routinely review stress signals under both static and dynamic specifications to obtain a more comprehensive assessment of systemic risk. Second, these countries could establish a stress-monitoring panel to track financial stress in each country. Given the different structures of pressure sources, the monitoring focus and early-warning threshold should be set around the dominant sub-markets identified in this paper to avoid a "one-size-fits-all" approach.

Related to the second implication, the third policy suggestion is that policymakers should calibrate policy tools to the dominant channels. In bank-dominated economies (i.e., China, Malaysia, and Singapore), it is necessary to enhance liquidity and balance-sheet resilience. A high proportion of bank contributions means that policies should focus more on liquidity support, capital buffers, and stress tests for maturity mismatches and cross-border Risk, especially during the shock window period. Moreover, counter-cyclical management in the banking sector needs to be strengthened. Otherwise, the Philippines, under greater pressure from foreign-exchange dominance, needs to strengthen its external buffers and hedging capabilities. When foreign exchange contributions are at their peak, particular attention should be paid to the adequacy of reserves, the pro-cyclicality of short-term external debt and capital flows, and to improving the availability of hedging tools and markets to reduce the amplification of exchange rate pressure during the external tightening stage. Finally, Indonesia, an economy more sensitive to stock and bond markets, needs to enhance its domestic market capacity. When the contribution of stocks and bonds is higher, market depth, investor structure stability, and the shape of the yield curve directly affect the stress process, especially during the post-pandemic external tightening stage, which is even more crucial.

Future research could investigate the interplay between financial stress and other macroeconomic variables, such as unemployment and inflation, to provide deeper insights into the broader economic implications of financial risks in the examined countries. Lastly, integrating real-time data and applying machine learning techniques could enhance the timeliness and accuracy of financial stress indicators and warrant further investigations.

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