**Working Paper** (WP/24-12)

# Financial Stress in ASEAN+3 Economies: Risk Regime Identification and Predictability

Jorge A. Chan-Lau, Michael Wynn, and Hoang Nam Nguyen

October 2024

[This page is intentionally left blank]

# Financial Stress in ASEAN+3 Economies: Risk Regime Identification and Predictability

Prepared by Jorge A. Chan-Lau, Michael Wynn, and Hoang Nam Nguyen [1] [2] [3]

Authorized by Laura Britt Fermo

October 2024

## Abstract

This paper introduces high-frequency country specific financial stress indices (FSIs) for selected ASEAN+3 economies, which are valuable tools for macro-financial surveillance. Firstly, they closely align with regional and global financial stress events. Secondly, when fitted with univariate regime switching models, they serve to identify transitions between low-, medium-, and high stress regimes in real time. Finally, in some economies, momentum-based technical analysis methods can predict regime changes ahead of time with reasonable accuracy, relying solely on the information embedded in the indices. The short-term advance warning may suffice for market practitioners' hedging and tactical decisions, and to alert policy makers about impending distress in the financial sector enabling them to adopt measures aimed at reducing market volatility.

JEL classification: C53, E32, E37, G01

Keywords: Financial stress, financial stability, forecasting, regime switching

[1] Authors' e-mails: Chan-Lau, Jorge.Chan-Lau@amro-asia.org and jchanlau@gmail.com (permanent); Wynn, Michael.Wynn@amro-asia.org; Nguyen, h.nguyen@uniurb.campus.it. Please address correspondence to all authors.

[2] The paper benefits from comments by Laura Britt Fermo, Li Lian Ong, Toan Long Quach, the Bangko Sentral ng Pilipinas, and Bank Indonesia. Any mistakes or omissions are the authors' responsibility.

[3] For brevity, Hong Kong, China is referred to as "Hong Kong" in the text.

## Abbreviations

| | |
|---|---|
| AdaBoost | adaptive boosting |
| AMRO | ASEAN+3 Macroeconomic Research Office |
| ASEAN | Association of South-East Asian Nations (Brunei Darussalam, Cambodia, Indonesia, Lao PDR, Malaysia, Myanmar, Philippines, Singapore, Thailand, Vietnam) |
| ASEAN+3 | ASEAN plus China (including Hong Kong), Japan, Korea |
| AFC | Asian financial crisis |
| COVID-19 | coronavirus disease 2019 |
| ECB | European Central Bank |
| EMBI | Emerging Markets Bond Index |
| FSI | financial stress index |
| GBM | gradient boosting machine |
| GFC | global financial crisis |
| IMF | International Monetary Fund |
| LightGBM | light gradient boosting machine |
| OECD | Organization for Economic Co-operation and Development |
| U.K. | United Kingdom |
| U.S. | United States |

## Table of Contents



### Figures



### Tables



### Appendix Figure



### Appendix Tables

## I. Introduction

The buildup of stresses within the financial system poses a significant threat to financial stability, potentially triggering an economic and financial crisis. The intricate web of interconnected financial institutions and markets, both domestically and globally, can amplify negative shocks rapidly. This heightened vulnerability is exacerbated by factors such as excessive leverage, complex financial instruments, and inadequate risk management practices. Crisis events, like the 2007–2009 global financial crisis, are characterized by liquidity crunches, widespread asset price declines, and the collapse of major financial institutions.

Economic recessions following a financial crisis have substantial costs. The costs are associated not only to the immediate contraction in economic activity as credit supply dries up but also to the protracted post-crisis economic recovery. Following a crisis, the recovery process can take five to ten years (Reinhart and Rogoff 2014), with gross domestic product (GDP) per capita typically lower by about 5 to 6 percent six years after the crisis occurrence (Sufi and Taylor 2022). Reduced investment causes medium-term total factor productivity to fall, leading to protracted output losses (Cerra, Hakamada, and Lama 2021).

Market-based information could alert policy makers about rising financial stress ahead of a crisis event. Excessive credit growth can cause the credit spread between higher and lower grade firms to narrow, foreshadowing credit crunches (López-Salido, Stein, and Zakrajšek 2017; Krishnamurthy and Muir 2024). Equity and property prices could signal financial overheating in real time and could potentially flag banking crises in advance (Chen and Svirydzenka 2021). Market prices and indicators react to increased uncertainty about asset values and investor behaviour, flight to quality and reduced market liquidity (Hakkio and Keeton 2009).[4]

Advance warning on financial stress and imbalances could inform policy responses aimed at reducing financial system vulnerabilities. Possible policy responses include updating regulatory stress test scenarios to reflect increased loss severity in the banking and trading books of systemic financial institution, restricting bank payouts to ensure there are adequate buffers to withstand large losses, discouraging asset overvaluation and hot money flows (short-term capital flows that can rapidly move in and out of a country), ensuring emergency liquidity assistance facilities remain adequate, and more broadly, guide the activation of macro-prudential tools (Johnsson and Bonthron 2013).

A financial stress index (FSI) is a simple yet effective tool to monitor the buildup of risks and imbalances in the financial system. By consolidating market information from various indicators into a single metric, the FSI provides a clear signal of elevated financial stress levels. The FSI offers a more comprehensive view of systemic risk in the financial system compared to analyzing individual indicators in isolation since the latter could be influenced by idiosyncratic factors unrelated to financial stress. Rarely, in the absence of broad financial stress, would all individual indicators move in the same way.

---

[4] Markets can be procyclical and may not always signal impending crises (Borio and Drehmann 2009; Shin 2013). Price bubbles can persist despite known divergence from fundamentals and often burst suddenly without clear triggers (Brunnermeier 2013).

Given their effectiveness in monitoring financial sector risk, FSIs have become integral components of systemic risk management toolkits for central banks and policymaking institutions. Examples include indices developed by the Asian Development Bank (Park and Mercado, 2014), the Bank of Korea (Bank of Korea 2023), the central bank of Mexico (Banco de México 2013), and the European Central Bank (Holló and others 2012), as several U.S. Federal Reserve banks (Hakkio and Keeton 2009; Marks, Kliesen and McCracken 2022). The usefulness of FSIs extends beyond the public sector, with private firms like Goldman Sachs (Hatzius and Stehn 2018) and Citigroup (Citi 2015) also adopting these tools.

This paper introduces several country-specific FSIs for the following selected ASEAN+3 economies: China, Hong Kong, China (hereafter “Hong Kong”), Indonesia, Japan, Korea, Malaysia, the Philippines, Singapore, Thailand, and Vietnam. These FSIs are employed to identify low, medium, and high financial sector risk regimes in each country and assess their potential as early warning indicators. Univariate Markov regime switching models applied to the FSIs reveal that high stress regimes align with historical stress periods, validating their use for real-time risk monitoring.

To evaluate their early warning capabilities, we examine the ability of technical indicators to predict regime shifts using the FSI dynamics. Our findings suggest that technical indicators can signal impending regime changes in some economies, albeit with short lead times. The advance notice may prove valuable for policymakers and market participants alike. Policymakers could employ this information to proactively tighten payout policies, strengthen bank capital adequacy, and prepare emergency liquidity facilities. Market participants may also benefit from such warnings by implementing defensive hedging and loss mitigation strategies and adjusting their positions accordingly. FSIs should be complemented by early warning systems offering longer lead times to implement structural policy changes (Pattillo and others 2000).

The rest of this paper is structured as follows. Section II reviews the academic literature on FSIs; section III describes the data used to construct the FSIs; section IV presents the different methods and models used in the analysis; section V discuss the results and section VI concludes.

## II. Related Literature[5]

FSIs maintained by central banks and policymaking institutions share conceptual similarities but vary in construction, particularly in terms of component variables and aggregation methods. Variable selection is primarily influenced by data availability at the desired monitoring frequency (monthly, weekly, or daily). The choice of aggregation method depends on available data and the modeling team's assessment of how to most effectively capture systemic financial stress.

A simple method for aggregating selected variables into an FSI is to employ variance-equal weights as previously utilized by the International Monetary Fund (IMF 2008) and described by Cardarelli, Elekdag, and Lall (2011). This approach is justified when the number of indicators is limited or when the prior belief is that each indicator, representing a distinct financial sector, contributes equally to overall stress. Research by Park and Mercado (2014)

[5] The review highlights key works relevant to this study. For a comprehensive bibliography, see the cited articles.

indicates that variance-equal weighted FSIs outperform those based on principal component analysis in capturing severe financial stress episodes across advanced and emerging economies.[6]

Correlation-weighted FSIs, where an indicator weight reflects its cross-correlation with other indicators, are an alternative to variance-equal weighted FSIs. The economic intuition underlying the use of correlation weights is that periods of systemic financial stress are characterized by adverse changes affecting all sectors simultaneously. Variance-equal weighted FSIs are a special case of correlation-weighted FSIs since they implicitly assume perfect correlation among the indicators. Compared with correlation-weighted indicators, they yield higher index values during calm period, overestimating financial stress.

Several central banks and policymakers employ correlation-weighted FSIs. The ECB, using market-based indicators split equally into five categories including financial intermediaries, money markets, equity markets, bond markets, and foreign exchange markets, calculates daily and weekly composite indicator of systemic stress (CISS) for the Euro area, individual country members, the U.S., and China (Holló, Kremer, and Lo Duca 2012). The Bank of Canada's FSI, which is an input in the bank's macro-financial risk framework (MacDonald and Traclet 2018), includes indicators associated with equity indices, exchange rates, treasury bill spreads, yield curve data and equity risk premiums (Illing and Liu 2006; Duprey 2020). At AMRO, Tan (2022) developed local stress indices related to local currency bonds and currencies to evaluate the risk of capital outflows in Indonesia, Korea, Indonesia, Malaysia, and the Philippines.

Given the assumption that a limited number of latent factors drive financial stress, dimensionality reduction techniques such as principal component analysis are valuable for FSI construction. Principal component analysis is used at U.S. Federal Reserve banks (FRB), with the FRB of Kansas City producing a monthly FSI including 11 variables (Hakkio and Keeton 2009) and the FRB of St. Louis a weekly FSI based on 18 variables (Kliesen and Smith 2010; Marks, Kliesen and McCracken 2022). Both indices assign weights to the indicators based on their loadings in the first principal component. To incorporate prior beliefs about indicator importance, a two-step approach can be applied, as demonstrated by Poonpatpibul and others (2018) for Asian economies. This involves initially estimating a PCA-based FSI, followed by a constrained regression on the indicators to restrict coefficient values to ranges consistent with economic priors imposed by the index modelers.

Dynamic factor models are used to extract latent common factors which then serve to construct the aggregate FSI. The U.S. Treasury's Office of Financial Research monitors daily financial conditions aided by a FSI that includes 33 market variables. After standardizing each variable, the FSI is set equal to the estimated single latent variable of a dynamic factor model (Monin 2019). The IMF employs financial condition indexes (FCIs) derived from dynamic factor models to monitor financial stresses in several advanced and emerging market economies (IMF 2017). The Bank of Korea, which reports regularly its FSI in its annual Financial Stability Report, follows a different approach. It groups the indicators into five different subsectors: the financial market, the external sector, the real economy, banks, and non-bank financial institutions. For each of them it extracts a subsector-specific

[6] Until August 2023, the ADB published monthly FSIs for Asian countries, the Eurozone, the U.K., and the U.S., following the methodology of Park and Mercado.

common factor using a dynamic factor model. The common factors are then aggregated into a single FSI using variance-equal weights (Bank of Korea 2023).

Once the FSI is available, a threshold-value approach could be used to identify high stress events or regimes. These events are periods during which financial instability impairs the functioning of the financial system and adversely affect the real economy. Their identification requires selecting a threshold value which when exceeded by the FSI signals that the economy is in a high, severe stress regime. The threshold is selected such that that the high stress regimes are closely aligned with declines in real activity, or an expert-based crisis chronology determined separately.[7]

Several studies identify high stress regimes using threshold values. For instance, Lo Duca and Peltonen (2013) and Duprey, Klaus and Peltonen (2017) set the threshold value to the 90th percentile of the distribution of a country's FSI values, as observations above the threshold tend to anticipate GDP deviations from its trend usually observed when economic activity and industrial output experienced large declines. The threshold selection procedure, hence, implicitly captures how financial conditions and the real economy interact.[8]

A more sophisticated approach is to use multi-regime models. The approach assumes that the underlying FSI data generating process can shift between different regimes, one of which is the high risk, stress event regime. The regimes can be identified using multi-regime models such as regime switching or multi-regime regressions. These models can capture the episodic nature of stress events, which are characterised by sudden and abrupt increases of the FSI. One advantage of this approach over the threshold-value approach is that it identifies the regimes endogenously without the need for expert judgement.

Models incorporating multiple regimes usually identify high-stress regimes as those characterized by rising financial instability and a decline in economic activity, explicitly recognizing their interdependence. For instance, David and Hakkio (2010) employ a two-regime Markov switching vector autoregression (MS-VAR) incorporating a FSI and a real activity index, to identify high stress periods aligned with economic downturns. Similar results are obtained by, Holló, Kremer, and Lo Duca (2012) using a bivariate threshold VAR (TVAR), and by Duprey, Klaus and Peltonen (2017) employing a bivariate MS-VAR and TVAR models. Hubrich and Tetlow (2015), identify the regimes with a five-variable MS-VAR model that includes the FSI, measures of economic activity, and policy variables. The inclusion of the latter enables evaluating the effectiveness of monetary policy for steering the economy back to a normal regime after the occurrence of a severe event.

For regime identification purposes, however, it does not seem necessary to model explicitly the interaction between financial stress and economic activity. Regimes identified using univariate switching models where the only variable included is the FSI overlap considerably

[7] Babecký, and others (2014), Laeven and Valencia (2020) and Nguyen, Castron, and Wood (2022) are examples of narrative-based, qualitative crisis chronologies.

[8] In other studies, the thresholds are set arbitrarily to a high percentile value of the FSI distribution, i.e. Illing and Liu (2006) and Cardarelli and others (2011) set the threshold to the historical mean plus one or more standard deviation; Vašíček and others (2017) set it equal to the 80th percentile value.

with those obtained using the multivariable models described previously (Holló, Kremer, and Lo Duca 2012; Duprey, Klaus and Peltonen 2017).

For policy makers the ability to forecast financial stress and especially high stress events is important. The empirical evidence in this regard is mixed. On the one hand, Misina and Tkacz (2009) find that linear and endogenous threshold models including credit and asset price movements as predictors can forecast the Bank of Canada's FSI movements correctly. Kim, Shi, and Kim (2018) show that common factors extracted from a broad range of macroeconomic variables can help to predict the Bank of Korea's FSI up to 12-months ahead. Using cross-country data, Christensen and Li (2014) predict threshold-based stress events in OECD countries, using several economic indicators within a signal extraction approach. Similarly, Lo Duca and Peltonen (2017) find that a discrete choice model with domestic and global macro-financial indicators can predict threshold-based stress events.

On the other hand, finding good performing leading indicators of stress events remains difficult. Vašíček and others (2017) conclude, using a Bayesian model averaging framework, that potential leading indicators of stress perform poorly in predicting out-of-sample FSI changes and stress events. Duprey and Klaus (2022) results suggest that predictive models are not robust as the introduction of new risk factors or policy actions may affect the nature of financial stress. Moreover, the link between severe stress events and the onset of historical economic crises appears weak for OECD economies (Slingenberg and de Haan 2011; Vermeulen and others 2015), and in transition and emerging Asian economies (Cevik, Dibooglu and Kutan 2013; Cevik and others 2016).

Technical analysis methods, though not widely used by in macro-financial analysis, are an alternative approach to forecast stress regimes yet to be explored. Forecasting whether the economy is in either of two states, normal or severe, is like forecasting whether market conditions favour selling or buying an asset. In both cases, the forecasting task is reduced to predicting the outcome of a binary variable. Technical analysis methods, developed by traders and market practitioners, have proven effective to predict "buy" and "sell" regimes for different asset classes, such as stocks (Brock, Lakonishok, and Le Baron 1992; Urquhart, Gebka, and Hudson 2015) and foreign exchange (Menkhoff and Taylor 2007; Neely and Weller 2012; Panopoulou and Souropanis 2019).[9]

Most technical analysis methods require only the past observed time series of the variable of interest, a key data requirement advantage over econometric methods, In the case of buy and sell regimes, the required data are past price observations. In the case of FSI regimes it is sufficient to use the past FSI values. The methods are agnostic regarding the time series analysed: their focus is on anticipating turning points in the series. In trading, the turning points signal transitions between buy and sell regimes. In financial stress monitoring, they signal transitions between normal and high stress regimes, which are previously identified using either the threshold-value approach, multi-regime models, or univariate Markov switching models. Results discussed later in the paper suggest that at short horizons,

---

[9] These methods exploit price predictability driven by market inefficiencies and time-varying risk premiums (Lo 2004). For comprehensive discussions of technical analysis, see Lo and others (2000), Park and Irwin (2007), and Scott, Carr and Cremonie (2016). The latter also provides references to key practitioners' treatises (e.g., Murphy 1999).

technical analysis methods work well for predicting stress events identified using a Markov switching model.

## III. Data Sources and Variable Selection Criteria

Daily FSIs are constructed for the following selected ASEAN+3 economies: China, Hong Kong, Indonesia, Japan, Korea, Malaysia, the Philippines, Singapore, Thailand, and Vietnam. To select the variables included in the FSI, we follow the variable selection criteria suggested by Hakkio and Keeton (2009). Firstly, the variables must capture financial stress aspects associated with increased uncertainty, flight to quality, and the drying up of market liquidity. Secondly, the variables should respond rapidly to changes in financial conditions. Lastly, the variables must be reported at a daily frequency, to facilitate the construction of real-time FSIs. These FSIs, by construction, emphasize heavily market signals.

The selected variables, sourced from Haver Analytics, track price changes and conditions in equity markets, sovereign bonds, money market conditions, and the foreign exchange market (Table 1). The number of variables available differs from country to country with as many as 11 for China and as little as 4 for Indonesia, Thailand, and Vietnam. Several data transformations are applied before including the variables in the FSI.

The data sample covers the period June 1998–December 2023. Observations for economies other than Japan, however, are only available starting at later dates: China (March 2006), Hong Kong (December 2002), Indonesia (May 2004), Korea (November 2001), Malaysia (August 2002), the Philippines (May 2001), Singapore (December 2005), Thailand (December 2001) and Vietnam (November 2005).

## IV. Methods and Models

A common FSI construction method is used for all economies. The method should be simple enough to be updated rapidly and robust to backward looking revisions when new data become available. For these reasons, we select the variance equal weighted method, a choice justified by the findings of Park and Mercado (2014). Their findings suggest that a variance equal weighted FSI, which is adequate when the index only includes few variables, performs as well as indices constructed using dimensionality reduction methods. Variance-equal weighted FSIs do not require backward looking revisions when new data become available. This is not the case for FSIs based on principal component analysis and dynamic factor models: principal components and latent factors previously estimated change when new data are used in the estimation.

Stress regimes in each country are identified using a three-regime univariate Markov switching model that yields low, medium, and high stress regimes. Each model is estimated separately for each country. The choice of a three-regime model instead of a two-regime model explicitly assumes, as in Holló, Kremer, and Lo Duca (2012) and in Hubrich and Tetlow (2015), that the build-up of financial stress when the economy exits a low stress regime, while fast, does not reach levels consistent with a high stress regime immediately.

Data limitations also guide our choice of a univariate model to identify stress regimes. Daily data on economic indicators are not available, which rules out both the use of multivariate, multi-regime models, and of threshold values aligned with changes in economic activity. Although our use of univariate models does not account for the interaction between the financial system and the real economy, earlier empirical studies suggest this might not be a major shortcoming. Holló, Kremer, and Lo Duca (2012) and Duprey, Klaus and Peltonen

(2017), using lower frequency data, found a considerable overlap between regimes identified using univariate switching models, multi-variate switching models, and threshold-value approaches. We expect this would also be the case for daily data.

**Table 1. Variables Included in Financial Stress Indices**

| Economy | No. | Indicator | Haver Code | Transformation |
|---|---|---|---|---|
| China | 1 | Security Index: Shanghai-Shenzhen 300 | S924SH3@INTDAILY | Computed as Z-score of 20-day volatility of daily returns |
| | 2 | Shanghai Stock Exchange: SSE Index | S924S@INTDAILY | |
| | 3 | Shenzhen Stock Price Index: Composite (New) Index | S924ZNW@INTDAILY | |
| | 4 | Shanghai Stock Price Index: Government Bonds | S924SGB@INTDAILY | |
| | 5 | Shanghai Stock Price Index: Corporate Bonds | S924SCB@INTDAILY | |
| | 6 | Savings Deposit Rate | R924D@INTDAILY | Computed as Z-score of 120-period volatility |
| | 7 | Interbank Repo Fixing Rate | R924R1D@INTDAILY | Computed as Z-score of 180-period volatility |
| | 8 | Wholesale Price 200 Index: Agriculture Products | P924WAP@INTDAILY | Computed as Z-score of the logarithm of the ratio of the indicator to its 20-period moving average |
| | 9 | Required Reserve Ratio | R924RR@INTDAILY | Computed as Z-score of 120-period change |
| | 10 | EMBI Global Sovereign Bond Spread | G924S@EMBI | Computed as Z-score |
| | 11 | J.P Morgan Real Broad Effective Exchange Rate Index--CPI Based: China | X111CCH@INTDAILY | Computed as Z-score of 5-period volatility of daily change |
| Hong Kong | 1 | Stock Price Index: Hang Seng | S532HNG@INTDAILY | Computed as Z-score of 20-period volatility of daily returns |
| | 2 | Discount Window & Liquidity: Overnight HIBOR | R532IOF@INTDAILY | Computed as Z-score of 120-period volatility |
| | 3 | 12-month HKD Interest Settlement Rates | R532K1@INTDAILY | |
| | 4 | 1-Year Government Bond Yield | T532G1@INTDAILY | Computed as Z-score of 120-period volatility of difference to its 120-period moving average |
| | 5 | 5-Year Government Bond Yield | T532G5@INTDAILY | |
| | 6 | 10-Year Government Bond Yield | T532GA@INTDAILY | |
| | 7 | Monetary Base: Total before discount window | M532B@INTDAILY | Computed as Z-score of 120-period volatility of 120-period change |
| | 8 | J.P Morgan Real Broad Effective Exchange Rate Index--CPI Based: Hong Kong | X111CHK@INTDAILY | Computed as Z-score of 5-period volatility of daily change |
| Indonesia | 1 | Jakarta Composite Stock Price Index | S536JKC@INTDAILY | Computed as Z-score of 20-period volatility of daily returns |
| | 2 | Jakarta Interbank IDR Offer Rate JIBOR: 6-month | R536I6M@INTDAILY | Computed as z-score of 180-period volatility |
| | 3 | EMBI Global Sovereign Bond Spread | G536S@EMBI | Computed as Z-score |
| | 4 | J.P Morgan Real Broad Effective Exchange Rate Index--CPI Based: Indonesia | X111CIN@INTDAILY | Computed as Z-score of 5-period volatility of daily change |
| Japan | 1 | Nikkei 300 Stock Price Index | S158NK3@INTDAILY | Computed as Z-score of 20-period volatility of daily returns |
| | 2 | Topix Cash Stock Price Index | S158TPX@INTDAILY | |
| | 3 | Tokyo Overnight Average Rate (TONAR) | R158RDU@INTDAILY | Computed as Z-score of 120-period volatility |
| | 4 | 1-Year Government Bond Yield | R158G1@INTDAILY | Computed as Z-score of 120-period volatility of difference to its 120-period moving average |
| | 5 | 5-Year Government Bond Yield | R158G5@INTDAILY | |
| | 6 | 10-Year Government Bond Yield | R158GA@INTDAILY | |
| | 7 | J.P Morgan Real Broad Effective Exchange Rate Index--CPI Based: Japan | X111CJA@INTDAILY | Computed as Z-score of 5-period volatility of daily change |

Source: Haver Analytics and the authors.

## Table 1 (Cont'd). Variables Included in Financial Stress Indices

| Economy | No. | Indicator | Haver Code | Transformation |
|---|---|---|---|---|
| Korea | 1 | Korea Composite Stock Price Index (KOSPI) | S542CEX@INTDAILY | Computed as Z-score of 20-period volatility of daily returns |
| | 2 | Korea Securities Dealers Association (KOSDAQ) Index | S542DAQ@INTDAILY | |
| | 3 | Bank of Korea Base Rate | R542RD@INTDAILY | Computed as Z-score of 120-period volatility |
| | 4 | 1-Year Government Bond Yield | R542G1@INTDAILY | Computed as Z-score of 120-period volatility of difference to its 120-period moving average |
| | 5 | 5-Year Government Bond Yield | R542G5@INTDAILY | |
| | 6 | 10-Year Government Bond Yield | R542GA@INTDAILY | |
| | 7 | 3-Year AA- Corporate Bond Yield | R542SC3@INTDAILY | |
| | 8 | 3-Year BBB- Corporate Bond Yield | R542S3B@INTDAILY | |
| | 9 | J.P Morgan Real Broad Effective Exchange Rate Index–- CPI Based: Korea | X111CKO@INTDAILY | Computed as Z-score of 5-period volatility of daily change |
| Malaysia | 1 | Stock Price Index: FSTE Bursa Malaysia KLCI | S548KLS@INTDAILY | Computed as Z-score of 20-period volatility of daily returns |
| | 2 | Overnight Interbank Operations Rate | R548IO@INTDAILY | Computed as Z-score of 120-period volatility |
| | 3 | 1-Year Government Bond Yield | R548G1Y@INTDAILY | Computed as Z-score of 120-period volatility of difference to its 120-period moving average |
| | 4 | 5-Year Government Bond Yield | R548G5Y@INTDAILY | |
| | 5 | 10-Year Government Bond Yield | R548GA@INTDAILY | |
| | 6 | EMBI Global Sovereign Bond Spread | G548S@EMBI | Computed as Z-score |
| | 7 | J.P Morgan Real Broad Effective Exchange Rate Index–- CPI Based: Malaysia | X111CMA@INTDAILY | Computed as Z-score of 5-period volatility of daily change |
| Philippines | 1 | Philippine Stock Exchange index (PSEi) | S566MNC@INTDAILY | Computed as Z-score of 20-period volatility of daily returns |
| | 2 | BSP Policy Rate | R566MR@INTDAILY | Computed as Z-score of 120-period volatility |
| | 3 | 3-Month Government Bond Yield | T566G3M@INTDAILY | Computed as Z-score of 120-period volatility of difference to its 120-period moving average |
| | 4 | 5-Year Government Bond Yield | T566G5@INTDAILY | |
| | 5 | 10-Year Government Bond Yield | T566GA@INTDAILY | |
| | 6 | EMBI Global Sovereign Bond Spread | G566S@EMBI | Computed as Z-score |
| | 7 | J.P Morgan Real Broad Effective Exchange Rate Index–- CPI Based: Philippines | X111CPH@INTDAILY | Computed as Z-score of 5-period volatility of daily change |
| Singapore | 1 | Straits Times Index | S576STT@INTDAILY | Computed as Z-score of 20-period volatility of daily returns |
| | 2 | Singapore Overnight Rate Average (SORA) | R576SRA@INTDAILY | Computed as z-score of 120-period volatility |
| | 3 | 1-Year Government Bond Yield | R576G1Y@INTDAILY | Computed as Z-score of 120-period volatility of difference to its 120-period moving average |
| | 4 | 5-Year Government Bond Yield | R576G5Y@INTDAILY | |
| | 5 | 10-Year Government Bond Yield | R576GA@INTDAILY | |
| | 6 | J.P Morgan Real Broad Effective Exchange Rate Index–- CPI Based: Singapore | X111CSI@INTDAILY | Computed as Z-score of 180-period volatility of daily change |
| Thailand | 1 | Stock Price Index: Bangkok SET | S578BST@INTDAILY | Computed as Z-score of 20-period volatility of daily returns |
| | 2 | 5-Year Government Bond Yield | T578G5@INTDAILY | Computed as Z-score of 120-period volatility of difference to its 120-period moving average |
| | 3 | 10-Year Government Bond Yield | T578GA@INTDAILY | |
| | 4 | J.P Morgan Real Broad Effective Exchange Rate Index–- CPI Based: Thailand | X111CTH@INTDAILY | Computed as Z-score of 5-period volatility of daily change |

Source: Haver Analytics and the authors.

**Table 1 (Cont'd). Variables Included in Financial Stress Indices**

| Economy | No. | Indicator | Haver Code | Transformation |
|---|---|---|---|---|
| Vietnam | 1 | Ho Chi Minh Stock Exchange Index | S582VNI@INTDAILY | Computed as Z-score of 20-period volatility of daily returns |
| | 2 | Overnight Interbank Interest Rate | R582ION@INTDAILY | Computed as Z-score of 120-period volatility |
| | 3 | EMBI Global Sovereign Bond Spread | G582S@EMBI | Computed as Z-score |
| | 4 | J.P Morgan Real Broad Effective Exchange Rate Index–- CPI Based: Vietnam | X111CVM@INTDAILY | Computed as Z-score of 5-period volatility of daily change |

Source: Haver Analytics and the authors.

Different classification algorithms are used to evaluate whether it is possible to predict the risk regime in advance using technical indicators as explanatory variables. The evaluation requires consolidating the low and medium regime into a single normal regime to transform the prediction problem to a binary classification problem. The technical indicators used in the classification analysis are the moving average convergence-divergence (MACD), the relative strength index (RSI), and the exponential moving average (EWMA). We describe the methods and models in detail below.

## A. Financial Stress Index Construction

Following Cardarelli and others (2011), each country's FSI is constructed as the sum of the indicators after standardizing them as Z-scores, where a min-max scaling transformation ensures each transformed indicator contributes equally to the index.

Specifically, let $X_{i,k,t}$ be the realization of indicator $k$ for economy $\mathrm{i}$ at time $\mathrm{t}$, with $\mathrm{k} \in K_i$ where the set $K_i$ denotes indicators specific to economy $\mathrm{i}$. The Z-score of the indicator, $Z_{i,k,t}$, is obtained after subtracting the mean $\mu_{i,k}$ and dividing by the indicator's standard deviation, $\sigma_{i,k}$, the latter two values calculated over the full data sample:

$$Z_{i,k,t} = \frac{\{(X\}_{i,k,t} - \mu_{i,k})}{\sigma_{i,k}}, \tag{1}$$

which are then re-scaled using the min-max transformation below:

$$Rescaled\ Z_{i,k,t} = \frac{(Z_{i,k,t} - Z_{i,k,min})}{(Z_{i,k,max} - Z_{i,k,min})}. \tag{2}$$

Afterwards, the FSI is set equal to the sum of the re-scaled indicators:

$$FSI_{i,t} = \sum_{k=1}^{n} Rescaled\ Z_{i,k,t}, \tag{3}$$

and is again-rescaled using the min-max transformation to facilitate comparison across economies:

$$FSI_{i,t} = \frac{(FSI_{i,t} - FSI_{i,min})}{(FSI_{i,max} - FSI_{i,min})} \text{ x } 100. \tag{4}$$

### B. Markov Switching Models and Risk Regime Identification[10]

We use the three-state Markov switching model of Kim, Nelson and Starz (1998) with state dependent means to identify the risk regimes. In the model, the three unobserved states, $S = \{0,1,2\}$, correspond to the low, medium, and high stress regimes, with respective state-dependent means $\mu_s,\ s = 1,\ 2,\ 3$.

Different model specifications are selected for different economies, with the selection based on the robustness and the convergence of the numerical estimation method to ensure the reliability and accuracy of the results. For Hong Kong and the Philippines, the model specification assumes that the mean value of the regime and the error terms depend on the risk regime state $s$:

$$\mathrm{FS}I_{i,t} = \mu_{s,t} + \epsilon_{s,t}, \tag{5}$$

where $\epsilon_{s,t} \sim N(0,\sigma_s^2),\ s \in S$.

For China, an additional lagged value of the FSI is included as an explanatory variable but the distribution of the error-term is assumed the same for all states:

$$\mathrm{FS}I_{i,t} = \mu_{s,t} + \beta_{s,t}\mathrm{FS}I_{i,t-1} + \epsilon_{s,t}, \tag{6}$$

where $\epsilon_{s,t} \sim N(0,\sigma^2),\ s \in S$, and the coefficient $\beta_{s,t} = \beta_{s},\ s \in S$.

For the remaining economies, the model specification is:

$$\mathrm{FS}I_{i,t} = \mu_{s,t} + \beta_{s,t}\mathrm{FS}I_{i,t-1} + \epsilon_{s,t}, \tag{7}$$

where $\epsilon_{s,t} \sim N(0,\sigma_s^2),\ s \in S$, and the coefficient $\beta_{s,t} = \beta_{s},\ s \in S$.

Formally, the transition between states is governed by a time-invariant Markov transition probability matrix $P^*$:

$$P^* = \begin{bmatrix} p_{00} & p_{01} & p_{02} \\ p_{10} & p_{11} & p_{12} \\ p_{20} & p_{21} & p_{22} \end{bmatrix} \tag{8}$$

where $\sum_{j=0}^{2} p_{ij} = 1, \mathrm{i} = 0, \dots 2$.

Parameter estimation is performed using maximum likelihood and the expected maximization (EM) algorithm. Once the parameters are estimated the likelihood of the FSI state at time *t* is evaluated using smoothed and filtered probabilities Smoothed probabilities benefit from hindsight: in any period $t$ in the full sample $[0,T]$ the maximum likelihood is estimated using the full sample information available at time $\mathrm{T} > \mathrm{t}$, $\Psi_{i,T} = \{FSI_{i,j},\ j = 0, \dots, T\}$, which yields the smoothed state probabilities:

[10] See Hamilton (1989, 1990, 1994), and Kim and Nelson (1999) for a comprehensive discussion of regime switching models and estimation methods.

$$\Pr\left(S_{i,t}=j\middle|\Psi_{i,T}\right)=\sum_{k=0}^{2}Pr\left(S_{i,t}=j,S_{i,t-1}=k\middle|\Psi_{i,T}\right). \qquad (9)$$

The smoothed FSI risk regime in country $i$ at time $t$ is set equal to the most likely state, that is, $\mathrm{S_{i,t}}=\mathrm{argmax_k}\Pr\left(\mathrm{S_{i,t}}=\mathrm{k}\middle|\Psi_{i,\mathrm{T}}\right)$.

Real-time monitoring of financial conditions, however, cannot benefit from hindsight since only current and past observations of the FSI are available. In this case, the maximum likelihood estimates rely only on the information set $\Psi_{i,t}=\left\{FSI_{i,j},\ j=0,\dots,t\right\}$, and the filtered state probabilities are:

$$\Pr\left(S_{i,t}=j\middle|\Psi_{i,t}\right)=\sum_{k=0}^{2}Pr\left(S_{i,t}=j,S_{i,t-1}=k\middle|\Psi_{i,t}\right). \qquad (10)$$

Similarly to the previous case, the filtered FSI risk regime is determined as $\mathrm{S_{i,t}}=\mathrm{argmax_k}\Pr\left(\mathrm{S_{i,t}}=\mathrm{k}\middle|\Psi_{i,T}\right)$.

For regime identification, smoothed probabilities are preferred. They are more reliable than filtered probabilities since they are estimated using the information set, $\Psi_{i,T}$, which already contains the information in $\Psi_{i,t}$ (Hamilton 1989).[11] Real-time risk monitoring, however, could be impaired if the dates of the smoothed regimes are very different than those of the filtered regimes. This is not the case for the country FSIs presented in the paper. Hence, while the results presented here correspond to the analysis of smoothed regimes, they would still be valid if filtered regimes were used instead.

### C. Regime Forecasting

Forecasting the risk regime can be reduced to a binary classification problem, where the risk regime either corresponds to a normal regime or to a high stress regime. To perform this reduction, the three switching regimes are consolidated into a normal stress regime, comprising the low and medium stress regimes, and the original high stress regime. The economy is in the normal stress regime whenever the smoothed probability of the high stress regime is less than 0.5 and in the high stress regime otherwise.

One contribution of this paper is the use of technical analysis rather than econometric methods to forecast regime switches ahead of time. Specifically, we construct several momentum indicators widely used by traders to forecast turning points in the time series of asset prices. The three momentum indicators we select are the moving average convergence divergence (MACD) of Appel (1985), the relative strength index (RSI) of Wilder (1978), and the exponential moving average (EMA).[12] The momentum indicators serve as inputs into several binary classification models that attempt to predict ahead of time whether the FSI is in a normal stress regime or a high stress regime. The regimes are assigned the values of 0 and 1 respectively. The indicators are described in detail next.

---

[11] Filtered and smoothed probabilities are calculated with the *sm.tsa.MarkovRegression* routine in the Python library *statsmodel*s, version 0.15.0 (Seabold and Perktold 2010).

[12] See Ramyar (2006) for a comprehensive review of technical analysis applications in financial markets.

### C.1. Technical Momentum Indicators

#### Moving Average Convergence Divergence (MACD)

The MACD is characterized by three parameters, all typically measured in days: a slow time (S), a fast time (F), and a characteristic or histogram time (C). The values of these parameters, which depend on the classification model used, are obtained using cross-validation. The indicator requires the calculation of the MACD line, defined as the difference between the EMAs calculated over the slow time horizon and the fast time horizon; and the signal line, SL, defined as the EMA of the MACD line calculated over its own time horizon. The EMA of the FSI, calculated for a time horizon of $\mathrm{d}$ days, is computed as:

$$\mathrm{EMA(FSI,\ t,\ d)\ =\ FSI_t} \times \frac{\lambda}{1+\mathrm{d}}\ +\ \mathrm{EMA(FSI,\ t-1, d)} \times \left(1\ -\frac{\lambda}{1+\mathrm{d}}\right) \tag{11}$$

where $\lambda$, the smoothing parameter, is set equal to 2. The MACD line and the signal line are then calculated as:

$$\mathrm{MACD(t)}\ =\ \mathrm{EMA}(FSI,\ t, F) - \mathrm{EMA}(FSI,\ t, S), \tag{12}$$

$$\mathrm{SL(t)}\ =\ \mathrm{EMA}(MACD,\ t, C). \tag{13}$$

The momentum of the MACD, $\mathrm{mMACD}$, is defined as:

$$\mathrm{mMACD}(t) = \mathrm{MACD}(t) - \mathrm{SL}(t). \tag{14}$$

In trading, a buy signal is generated when momentum turns positive as it indicates that prices are likely to continue rising, and a sell signal is generated when momentum turns negative for the opposite reason. Similarly, we would expect the same $\mathrm{mMACD}$ dynamics in the FSI, where the equivalent buy (sell) signal anticipates a period characterized by high and rising FSI values consistent with a high (normal) stress regime.

#### Relative Strength Index (RSI)

The RSI is an indicator that takes value within the range of 0 to 100. The computation of the RSI requires specifying a single parameter, the time window $\mathrm{w}$ which serves to calculate the relative strength (RS) of the FSI, which is defined as:

$$\mathrm{RS}(t, w) = \textstyle\sum_{i=t-w+1}^{t} \Delta FSI_i^{+} / \sum_{i=t-w+1}^{t} \Delta FSI_i^{-} \tag{15}$$

where the numerator is the sum of positive daily movements of the $\mathrm{FSI}$ and the denominator the sum of negative daily movements over the time window. The $\mathrm{RSI}(t, w)$ is defined as:

$$\mathrm{RSI}(t,w) = \begin{cases} 100,\ if\ \ \sum_{i=t-w+1}^{t} \Delta FSI_i^{-}\ = 0 \\ 100\ - \frac{100}{1+RS(t,w)}\ ,\ \ otherwise \end{cases} \tag{16}$$

To generate buy and sell signals in trading it is necessary to specify an upper threshold ($\mathrm{U}$) value and a lower threshold value ($\mathrm{L}$). Whenever the $\mathrm{RSI}(t, w)$ crosses the lower threshold value from below it generates a buy signal, and when it crosses the upper threshold value from above it generates a sell signal. As in the case of the MACD momentum indicator, the buy and sell signals serve to forecast stress and normal regimes. For the forecasting exercise, we use the RSI momentum, $\mathrm{mRSI}$, defined as:

$$mRSI(t,w,U,L) = \begin{cases} RSI(s,w) - L & RSI(t_{low}) < L;\ L < RSI(s,w) < U \quad \forall s \in (t_{low}, t] \\ RSI(s,w) - U & RSI(t_{up}) > U;\ L < RSI(s,w) < U \quad \forall s \in (t_{up}, t] \\ 0 & otherwise \end{cases} \quad (17)$$

where $\mathrm{t_{low}}$ is the last time before time $\mathrm{t}$ when the $\mathrm{RSI}$ crossed the lower threshold $\mathrm{L}$ from below $\mathrm{L}$; $\mathrm{t_{up}}$ is the last time before time $\mathrm{t}$ when the $\mathrm{RSI}$ crossed the upper threshold $\mathrm{U}$ from $\mathrm{U}$.

**Exponential Moving Average (EMA)**

The momentum indicator, $\mathrm{mEMA}$, is designed to capture the directional momentum of the FSI. It is constructed based on the EMA in Equation (11) and is defined as the cumulative area between the EMA and the FSI line. When the FSI falls below the EMA, $\mathrm{mEMA}$ takes positive values, indicating undervalued signal or upward pressure. Conversely, when the FSI rises above the EMA, $\mathrm{mEMA}$ turns negative, indicating downward pressure.

## C.2. Classification Models and Estimation

For each country, five classification models are used to forecast high stress regimes across four forecasting horizons: 5, 20, 40, and 60 days. The models are logistic regression, random forest, AdaBoost, gradient boosting machine (GBM), and light gradient boosting machine (LightGBM). We estimate several model specifications, using two types of covariate sets: lagged values of a single momentum indicator and lagged values of all three momentum indicators. For both covariate sets, the lags considered are 5, 10, 15, and 20 days. Prior to estimating the model, it is necessary to specify several hyperparameters, which are needed for constructing the momentum indicators and selecting the best model.

**Classification Models**

Logistic regression is widely used for its simplicity and interpretability (Cox, 1958). It fits a linear model to the logit of the probability of the high stress regime, $\mathrm{p} = \mathrm{P}(Y = 1|X)$, where $Y = 1$ is the high stress regime and $X$ are the covariates used in the equation:

$$\log \frac{p}{1-p} = X \quad (18)$$

Model estimation can be performed, as done in this study, including a regularization term.

The random forest model is an ensemble learning method that leverages multiple decision trees (Breiman 2001). It constructs each tree using a random subset of the training data (bootstrap sampling) and considers only a random feature subset at each split. For binary classification, each tree predicts either the normal ($Y = 0$) or high stress ($Y = 1$) regime. The model's final prediction is determined by majority voting among all trees.

AdaBoost is an ensemble algorithm that combines weak learners (simple models) to create a strong classifier (Freund and Schapire 1997). It iteratively trains weak classifiers (in this case, decision stumps) on weighted versions of the training data. After each iteration, misclassified samples receive higher weights, forcing subsequent learners to focus on them. The final model is a weighted combination of the weak learners, with better performers given higher weights.

GBM is an ensemble technique that sequentially combines weak learners, typically decision trees, to create a robust predictive model (Friedman 2001). GBM builds the model stage-wise, using gradient descent to minimize a loss function. Each stage employs boosting to correct errors made by previous learners.

LightGBM is conceptually similar to GBM but accelerates calculations by improving the tree growth strategy, sampling methods, and implementing covariate dimension reduction (Ke and others 2017). This approach enhances both speed and efficiency in handling large datasets. Since the covariate dimension is low when the three momentum indicators are included in the classifier, we do not expect LightGBM to dominate GBM necessarily.

**Hyperparameter Tuning and Model Selection**

Model selection requires estimating each of the classification models repeatedly across a range of country-specific hyperparameter values. Some hyperparameters are needed to construct the momentum indicators. For example, the MACD momentum indicator requires setting the values of the sow, fast, and signal horizons beforehand. Other hyperparameters are needed to select the best classification model within a class. For example, the number of weak learners could affect the performance of the AdaBoost classifier. Hyperparameter selection is referred to as hyperparameter tuning (Bartz and others 2023, Geron 2022).

Ideally, hyperparameter tuning and model selection are done simultaneously, Specifically, several classification models would be estimated using all possible hyperparameter combinations and the final model is selected based on which delivers the best results according to a performance metric. To prevent overfitting, the estimation uses *k*-fold cross validation, using only part of the data to train and validate the model (train set), and the remainder for out-of-sample evaluation (test set) (Hastie, Tibshirani and Friedman 2009).

However, the simultaneous selection of hyperparameter values and the best classification model is computational costly. Instead, we break the process into two stages. In the first stage, we only tune the hyperparameters necessary for constructing the momentum indicators. In the second stage, we tune the classification models' hyperparameters keeping the momentum indicators' hyperparameters fixed.

In the first stage, the FSI time series data is partitioned into a training set, comprising the first 80 percent of the observations, and a test set comprising the remaining 20 percent, as shown in Table 2. The temporal split ensures we maintain the chronological order of the data and helps to evaluate whether it is possible to forecast the most recent regime changes. If this is the case real-time monitoring is feasible.

For each forecasting horizon, tuning the momentum indicators' hyperparameters requires a systematic approach. First, a range of values for each hyperparameter must be specified for indicators to be as optimally configured. Next, a suitable performance metric is chosen to gauge the model's effectiveness. Finally, a classification model is selected to evaluate the model's performance across different hyperparameter configurations using cross-validation:

- The range of hyperparameter values is set as follows: or the MACD indicator the fast, slow and signal horizons values are allowed to vary from 10 days (two weeks) to 252 days (one year), 20 days (one month) to 252 days, and 10 to 252 days respectively. For the RSI, the time window, upper and lower thresholds can vary from five days (one week) to 252 days, 40 days (two months) to 90 days, and 10 days to 60 (three months) days.

- The performance metric used is the area under the receiver operating characteristic (AUROC). This metric is selected because it balances true and false positive rates of the model: a perfect classification model has an AUROC value of 1.0, with a model performing as well as randomly flipping a coin has an AUROC of 0.5.

- The classification model selected is the univariate logistic regression, in which only a single observation of a momentum indicator is used to forecast the stress regime type over the different forecasting horizons.

- Hyperparameter tuning is performed using 5-fold stratified cross-validation over the train sets listed in Table 2. Stratified sampling ensures that each fold contains roughly the same proportion of normal and high stress regimes in the sample, where the number of former regimes exceed the latter. The regime imbalance could induce a bias towards the majority class (normal stress regime) and the underfitting of the minority class (high stress regime). We address the imbalance using the Synthetic Minority Oversampling Technique (SMOTE) to generate synthetic observations of the high stress regime to generate balanced folds (Chawla and others 2002). There is the possibility, though, that SMOTE could overstate noise rather than the signal.

**Table 2. Financial Stress Indices: Training and Test Sets**

| Economy | Total Obs. | Train set | | Test set | | Starting from |
|---|---|---|---|---|---|---|
| | | N | High stress | N | High stress | |
| China | 4642 | 3714 | 14.0 | 928 | 18.1 | March 16, 2006 |
| Hong Kong | 5485 | 4388 | 24.8 | 822 | 49.3 | December 23, 2002 |
| Indonesia | 5111 | 4089 | 25.2 | 1022 | 23.5 | May 28, 2004 |
| Japan | 6661 | 5329 | 34.9 | 1332 | 25.3 | June 19, 1998 |
| Korea | 5772 | 4618 | 23.5 | 865 | 39.1 | November 15, 2001 |
| Malaysia | 5577 | 4462 | 13.2 | 1115 | 23.8 | August 15, 2002 |
| Philippines | 5906 | 4725 | 22.9 | 1181 | 1.9 | May 11, 2001 |
| Singapore | 4707 | 3766 | 18.7 | 941 | 45.1 | December 15, 2005 |
| Thailand | 5752 | 4602 | 22.9 | 862 | 35.2 | December 13, 2001 |
| Vietnam | 4718 | 3775 | 24.6 | 943 | 14.0 | November 30, 2005 |

Source: Authors' calculations.
Note: the high stress columns show the percentage of observations corresponding to high stress regimes. Total observations before resampling.

**Table 3. Classification Models: Hyperparameter Tuning Options**

| Model | Parameter | Description | Options |
|---|---|---|---|
| LR | solver | Optimization algorithms to use | lbfgs, saga, newton-cg, liblinear |
| | penalty | Regularization term | None, l1, l2 |
| | C | Regularization strength | 0.1, 1.0, 10 |
| RF | n_estimators | Number of trees in the forest | 50, 100 |
| | max_depth | Maximum depth of the tree | None, 5 |
| GBM | n_estimators | Number of boosting stages to be run | 50, 100 |
| | learning_rate | Learning rate | 0.01, 0.1 |
| | max_depth | Maximum depth of the individual regression estimators | 3, 5 |
| AdaBoost | n_estimators | Number of weak learners to train | 50, 100 |
| | learning_rate | Weight applied to each classifier | 0.01, 0.1 |
| LightGBM | n_estimators | Number of boosting stages | 50, 100 |
| | learning_rate | Learning rate | 0.01, 0.1 |
| | num_leaves | Maximum number of leaves in a tree | 31, 62 |

Source: the authors.
Note: newton-cg = Newton-Conjugate Gradient algorithm; lbfgs = Limited-memory Broyden–Fletcher–Goldfarb–Shanno algorithm; saga = Stochastic Average Gradient with L1 regularization; liblinear = Large Linear Classification algorithm; LR = logistic regression; GBM = gradient boosting machine; LGBM = light gradient boosting machine; RF = random forest.

In the second stage, for each forecasting horizon the corresponding momentum indicators are constructed using the hyperparameter values selected in the previous stage. There are several options for the model-specific hyperparameters, which are listed in Table 3. The tuning procedure and model selection is performed jointly with the data sets from the first stage and using the same cross-validation procedure when evaluating each possible hyperparameter combination.

## V. Results

### A. FSIs and Major Global Stress Events

Ideally, we would prefer to contrast the dynamics of the FSI against a country-specific expert-based crisis chronology but to our knowledge, they are not available. Hence, we focus on several major global crisis episodes, some of which might not have the same impact on the economies in the region. Figure 1 shows the FSIs and seven major stress episodes (shaded areas): (a) the Asian financial crisis (AFC), (b) the bursting of the Dot-Com bubble (Mar. 2000–Oct. 2002), (c) the global financial crisis (GFC) (Aug. 2007–Jun. 2009), (d) the European sovereign debt crisis (Mar. 2011–May 2012), (e) the U.S. taper tantrum (Feb. 2013–May 2013), (f) China's stock market turbulence period (Jun. 2015–Feb. 2016), and (g) the COVID-19 pandemic (Mar. 2020–May 2023).

Economies in the region were not necessarily affected equally by major global financial crises. The AFC, the bursting of the Dot-Com bubble and the GFC did have a major impact, with economies' FSIs reaching peak historical levels.[13] The dynamic pattern of the FSIs during the crises is consistent with economic intuition: they rise from very low levels at the onset of the crisis, peak shortly thereafter, and remain at elevated levels during most of the crisis to ease rapidly afterwards.

In contrast, the impact of the European sovereign debt crisis was moderate, with the peak levels of FSIs during this episode being less than half of the GFC peak levels. In Hong Kong, Korea, Malaysia, and Thailand, the FSIs do not seem to record the event as a country-specific stress event as they either remained range bound or declined. This is also the case during the short-lived U.S. taper tantrum, and China's stock market turbulence, which seemingly was a major event only in China, and to a lesser extent in Malaysia and Singapore. Notably, Hong Kong was not affected.

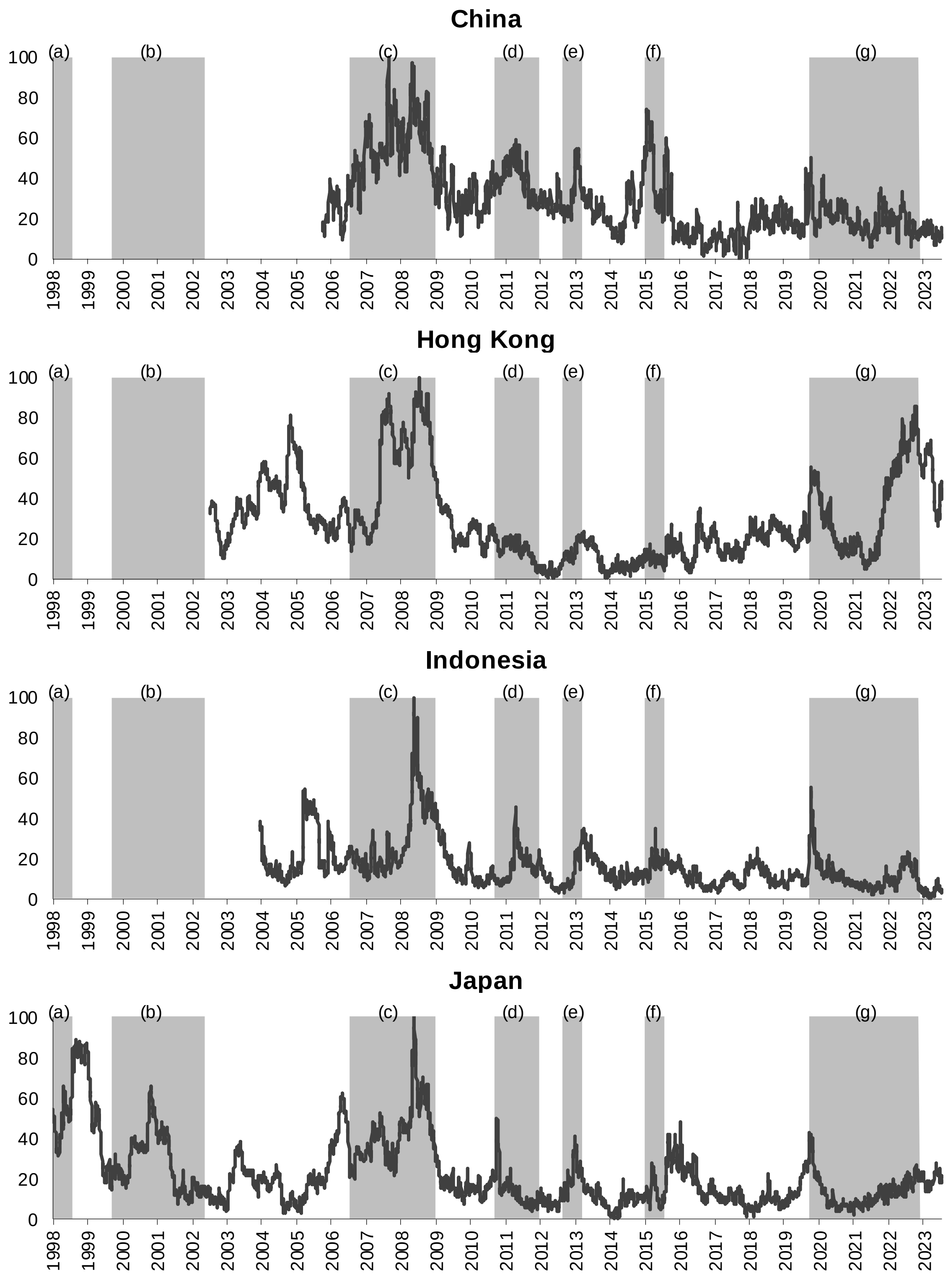
The pandemic stress event has a more nuanced interpretation. Unlike other episodes, several economies, excluding China and Japan, experienced two distinct peaks. While considered a single episode, the pandemic event encompassed two events. The first peak likely reflects the impact of the global lockdowns implemented in early 2020. In contrast with other economic crises, the impact of the lockdowns was short-lived, especially on financial markets, which rebounded and recovered rapidly by the end of 2020 (BIS 2020). The lockdowns, however, affected global supply chains adversely and the supply shock translated into high inflation rates worldwide (IMF 2022). The second peak is arguably mainly associated with the quantitative tightening undertaken by central banks to moderate inflation pressures, especially in advanced economies which drove policy rates upwards

---

[13] FSI data are available only for Japan, Korea, the Philippines and Thailand.

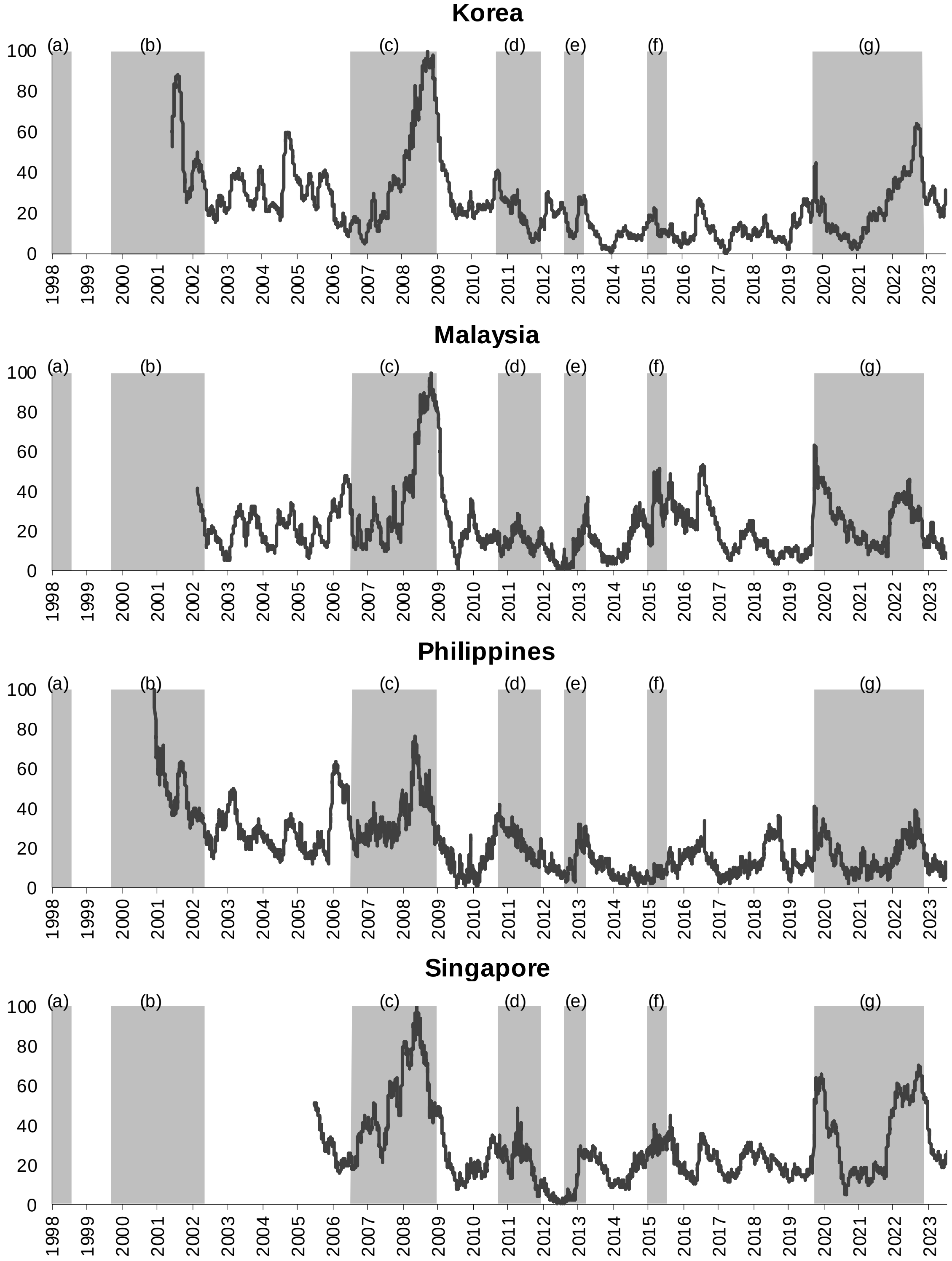
worldwide and raised concerns about a hard landing of the world economy. As concerns eased, FSIs subsequently declined.

**Figure 1. Financial Stress Indices and Major Financial Stress Episodes**



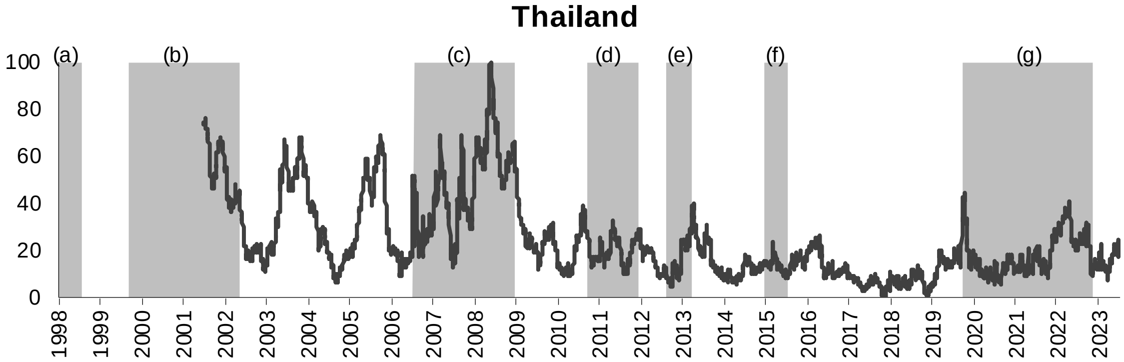

Sources: Haver Analytics; and author's calculations.
Note: FSI plotted as rescaled Z-scores. Shaded areas indicate periods of high financial stress: (a) AFC; (b) Dot-com bubble; (c) GFC; (d) European debt crisis; (e) U.S. taper tantrum; (f) Chinese stock market turbulence; (g) COVID-19 pandemic. Higher FSI values indicate increased financial stress. Daily data from June 19, 1998 to Dec 29, 2023.

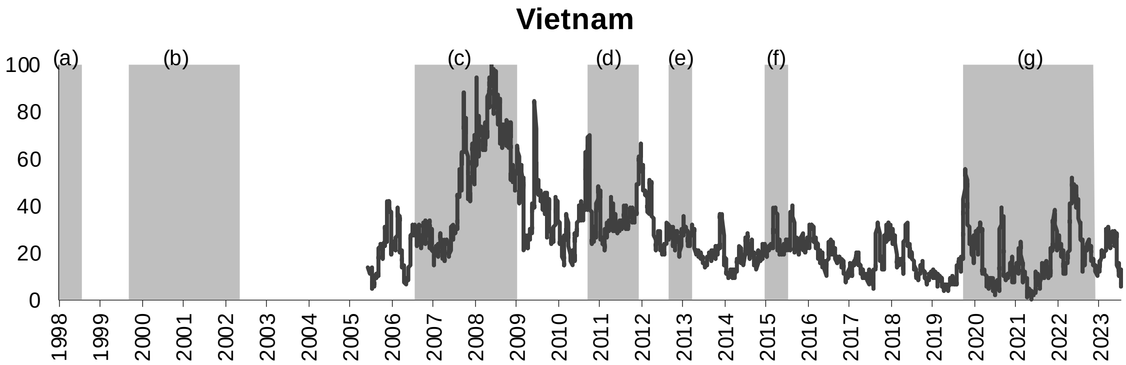
**Figure 1 (Cont'd). Financial Stress Indices and Major Financial Stress Episodes**




Sources: Haver Analytics; and author's calculations.
Note: FSI plotted as rescaled Z-scores. Shaded areas indicate periods of high financial stress: (a) AFC; (b) Dot-com bubble; (c) GFC; (d) European debt crisis; (e) U.S. taper tantrum; (f) Chinese stock market turbulence; (g) COVID-19 pandemic. Higher FSI values indicate increased financial stress. Daily data from June 19, 1998 to Dec 29, 2023.

**Figure 1 (Cont'd). Financial Stress Indices and Major Financial Stress Episodes**




Sources: Haver Analytics; and author's calculations.
Note: FSI plotted as rescaled Z-scores. Shaded areas indicate periods of high financial stress: (a) AFC; (b) Dot-com bubble; (c) GFC; (d) European debt crisis; (e) U.S. taper tantrum; (f) Chinese stock market turbulence; (g) COVID-19 pandemic. Higher FSI values indicate increased financial stress. Daily data from June 19, 1998 to Dec 29, 2023.

### B. Markov Switching Models

The parameter estimates, all statistically significant except for the constant term (Table 4), could serve to characterize two different mechanisms, variance switching and coefficient switching, are responsible for the differences across regimes. As explained in Hubrich and Tetlow (2015), variance switching implies substantial differences of the state dependent volatilities, $\sigma_s^2$, across regimes. When variance switching is present, the realization of an unexpected sequence of shocks drives the economy to switch from one regime to another. In the Markov switching models, which are akin to reduced form models of the economy, shocks are exogenous factors outside the control of economic agents. Coefficient switching, or differences in the values of the coefficients, $\mu_{s,t}$ and $\beta_{s,t}$, indicates that the behavior of the economic agents change across regimes. When the econometric model is viewed as a reduced form representation of the economy, the coefficients should reflect how agents react in different regimes.

There are three possible characterizations of the FSI switching process depending on whether variance switching and/or coefficient switching are present. The first one is pure variance shifting, where the economic response of the agents does not change regardless of the regime, and the nature of the shocks differentiate the regimes. This is the case of the Philippines and Hong Kong. The second characterization is pure coefficient switching, in which the nature of the exogenous shocks is invariant under each regime but not the economic response. This is the case of China.

The final characterization is a combination of variance switching and coefficient switching, with the nature of shocks and the economic response of the agents differing across regimes. This is the case for the remaining economies in our sample. We want to remark that the evidence for coefficient switching between the low and medium stress regimes is weak, as the coefficients $\beta_{s,t}$, for *s=0,*1, while statistically significant, are not different. These results indicate that in this group of economies, the agents' economic behavior is the same in the low and medium stress regimes. Agents, however, react differently when the economy enters the high stress regime.

**Table 4. Selected ASEAN+3 Economies: Markov Regime Switching Models**

| Parameter | China | Hong Kong | Indonesia | Japan | Korea |
|---|---|---|---|---|---|
| $\mu_1$ | 29.300 (0.348) | 10.445 (0.220) | 8.764 (0.139) | 11.129 (0.159) | 15.967 (0.285) |
| $\mu_2$ | 51.628 (0.373) | 23.903 (0.239) | 16.209 (0.160) | 22.094 (0.146) | 26.241 (0.207) |
| $\mu_3$ | 79.299 (0.569) | 56.189 (0.458) | 40.910 (0.670) | 54.007 (0.470) | 52.855 (0.752) |
| $\beta_1$ | -5.56e-3 (0.000) | N.A. | -7.55e-4 (0.000) | -6.89e-4 (0,000) | -1.69e-3 (0.000) |
| $\beta_2$ | -8.57e-3 (0.000) | N.A. | -9.23e-4 (0.000) | -1.43e-3 (0.000) | --1.05e-3 (0.000) |
| $\beta_3$ | -1.20e-2 (0.000) | N.A. | -4.37e-3 (0.000) | --5.01e-3 (0.000) | -2.05e-3 (0.000) |
| $\sigma^{2\backslash\text{ or}\backslash}\sigma_1^2$ | 35.040 (0.749) | 20.082 (1.032) | 4.436 (0.197) | 7.016 (0.227) | 14.039 (0.436) |
| $\sigma_2^2$ | N.A. | 23.903 (1.008) | 7.258 (0.349) | 8.634 (0.300) | 12.036 (0.484) |
| $\sigma_3^2$ | N.A. | 259.50 (9.507) | 151.197(6.144) | 169.504(5.156) | 316.58(11.775) |
| Pr(0,0) | 0.985 (0.000) | 0.990 (0.000) | 0.981 (0.003) | 0.987 (0.002) | 0.994 (0.000) |
| Pr(1,0) | 0.011 (0.002) | 0.009 (0.002) | 0.0017 (0.003) | 0.013 (0.003) | 0.007 (0.002) |
| Pr(2,0) | 0.001 (0.015) | 0.000 (NaN) | 0.000 (NaN) | 0.000 (NaN) | 0.000 (NaN) |
| Pr0,1) | 0.014 (0.003) | 0.010 (0.002) | 0.019 (0.003) | 0.013 (0.002) | 0.006 (0.000) |
| Pr(1,1) | 0.977 (0.003) | 0.986 (0.003) | 0.971 (0.004) | 0.981 (0.003) | 0.986 (0.003) |
| Pr(2,1) | 0.036 (0.007) | 0.005 (0.002) | 0.021 (0.004) | 0.006 (0.002) | 0.008 (0.002) |
| **Parameter** | **Malaysia** | **Philippines** | **Singapore** | **Thailand** | **Vietnam** |
| $\mu_1$ | 13.989 (0.181) | 9.031 (0.086) | 5.996 (0.358) | 19.997 (0.172) | 18.971 (0.812) |
| $\mu_2$ | 27.294 (0.208) | 23.216 (0.126) | 24.898 (0.274) | 35.775 (0.226) | 29.691 (0.610) |
| $\mu_3$ | 65.526 (1.202) | 45.348 (0.393) | 56.493 (0.810) | 61.312 (0.469) | 62.657 (0.924) |
| $\beta_1$ | -6.59e-4 (0.000) | N.A. | 2.49e-3 (0.000) | -2.70e-3 (0.000) | -1.89e-3 (0.000) |
| $\beta_2$ | -4.30e-4 (0.000) | N.A. | 3.62e-4 (0.000) | -4.23e-3 (0,000) | -1.59e-3 (0.000) |
| $\beta_3$ | -5.05e-3 (0.000) | N.A. | -9.27e-4 (0.000) | -6.10e-3 (0.000) | -6.83e-3 (0.001) |
| $\sigma_1^2$ | 19.769 (0.543) | 13.225 (0.436) | 18.628 (0.701) | 11.429 (0.350) | 18.854 (0.729) |
| $\sigma_2^2$ | 16.811 (0.664) | 24.360 (0.812) | 20.040 (0.837) | 11.098 (0.444) | 13.691 (0.592) |
| $\sigma_3^2$ | 219.372(9.880) | 149.112(6.365) | 217.995(9.470) | 122.233(4.670) | 201.506 (9.45) |
| Pr(0,0) | 0.991 (0.002) | 0.993 (0.003) | 0.992 (0.000) | 0.992 (0.000) | 0.988 (0.160) |
| Pr(1,0) | 0.015 (0.003) | 0.007 (0.002) | 0.008 (0.002) | 0.011 (0.002) | 0.014 (0.003) |
| Pr(2,0) | 0.000 (NaN) | 0.000 (NaN) | 0.000 (NaN) | 0.000 (NaN) | 0.000 (NaN) |
| Pr0,1) | 0.009 (0.002) | 0.007 (0.002) | 0.008 (0.000) | 0.009 (0.000) | 0.013 (0.006) |
| Pr(1,1) | 0.982 (0.003) | 0.989 (0.002) | 0.988 (0.003) | 0.981 (0.003) | 0.975 (0.009) |
| Pr(2,1) | 0.006 (0.002) | 0.008 (0.003) | 0.007 (0.003) | 0.010 (0.003) | 0.017 (0.005) |

Source: Authors' calculations.
Note: p-values in parentheses. For most economies, there are no observed transitions between state 2 (high stress) to state 0 (low stress) which yields a NaN standard deviation value.

For economies fitted with the model specification, Equation (7), the FSI exhibits mean reversion in all regimes except Singapore, as reflected by the one-day lagged FSI coefficients ($\beta$). Mean reversion increases with the severity of the stress regime, excluding Malaysia, where mean reversion in the low stress regime exceeds that in the medium stress regime (Table 5). In normal stress regimes, shocks could have a half-life as long as three years as is the case in Malaysia and Indonesia. In Singapore, mean reversion is present only in the high stress regime, where the half-life is two years.

In Singapore, interestingly, a shock occurring in normal and medium stress regimes would not banish over time. Instead, the FSI would continue to trend higher. However, since the lagged FSI coefficients are small, absent any other subsequent shocks and assuming the FSI initial value is equal to the constant term in the low stress regime, long periods should elapse for the FSI to explode. One year and half must elapse for the economy to shift from the low to the medium stress regime, and another six years to enter the high stress regime.

**Table 5. Selected ASEAN+3 Economies: Half-Life of FSI shocks, in days**

| **Stress regime** | **China** | **Hong Kong** | **Indonesia** | **Japan** | **Korea** |
|---|---|---|---|---|---|
| Low | 124 | N.A. | 917 | 1006 | 410 |
| Medium | 81 | N.A. | 751 | 484 | 657 |
| High | 57 | N.A. | 158 | 138 | 337 |
| **Stress regime** | **Malaysia** | **Philippines** | **Singapore** | **Thailand** | **Vietnam** |
| Low | 1051 | N.A. | N.A. | 257 | 366 |
| Medium | 1610 | N.A. | N.A. | 163 | 436 |
| High | 137 | N.A. | 748 | 113 | 102 |

Source: Authors' calculations.

The transition probability estimates indicate that regimes are highly persistent and that transitions between the low and severe stress regimes seldom occur. For all economies, except China, the economy a high stress regime is followed by a medium stress regime. In China, the high stress regime can be followed by a low stress regime and vice-versa. But the probability of observing such transition is less than 1 in 1000.

Under the assumption that the financial stress drivers and associated transmission mechanisms remain unchanged, we can estimate how often economies would experience different stress regimes over the long run (Table 6). Malaysia and China are the economies less prone to experience high stress events. In contrast, more than half of the time Indonesia would be under a high stress regime. Moreover, low stress periods would occur infrequently, suggesting a two-regime switching model could also be used to identify stress regimes.

**Table 6. Selected ASEAN+3 Economies: Steady State Regime Probabilities, in percent**

| **Stress regime** | **China** | **Hong Kong** | **Indonesia** | **Japan** | **Korea** |
|---|---|---|---|---|---|
| Low | 36 | 31 | 4 | 33 | 38 |
| Medium | 48 | 31 | 42 | 33 | 33 |
| High | 16 | 34 | 54 | 33 | 29 |
| **Stress regime** | **Malaysia** | **Philippines** | **Singapore** | **Thailand** | **Vietnam** |
| Low | 53 | 40 | 39 | 45 | 41 |
| Medium | 32 | 40 | 39 | 33 | 36 |
| High | 16 | 20 | 22 | 22 | 23 |

Source: Authors' calculations.

### C. Regime Identification

We would like to note that the discussion in this section and the next are based on the results corresponding to smoothed regimes derived from smoothed probabilities, which are deemed more reliable than filtered probabilities. However, filtered regimes, obtained using the latter, are better suited for real-time risk monitoring. A multiclass classification analysis shows that differences between the smoothed and filtered risk regimes are negligible (Appendix I). Hence the findings and analysis presented in the two sections remain valid regardless of whether smoothed or filtered risk regimes are used.[14]

Differences in the response of FSIs to global and regional shocks across economies are expected. The FSIs are designed to capture domestic financial stress, whose sensitivity to external shocks is partly determined by the linkages of the domestic economy to the countries or economic and financial sectors where the shock originates. This is evident in Figure 2, that shows the historical global stress episodes discussed earlier have impacted stress regimes differently. Only the AFC and the GFC had a severe impact across the region, while other episodes only affected a few economies.[15]

Stress events. originating in the region and elsewhere seem to have a large impact on Indonesia. Model-based high stress periods overlap with the dates of major historical stress episodes regardless of whether the initial shocks originated in the Americas, Europe, or Asia. In contrast, the European sovereign debt crisis seems to have been a non-event for other economies in the region, either because their FSIs remained in the low and medium stress bounds, or because after raising to high stress levels, they fell rapidly to normal stress levels (China, Korea, the Philippines, and Singapore). This finding is consistent with Indonesia's high stress steady state probability (Table 6).

Among economies highly integrated in the financial system, Japan experienced the most frequent instances of high stress in the period following the GFC. It was also affected, albeit briefly, by the US taper tantrum and problems in the Chinese stock market. Remarkably, this event was barely noticeable in the FSIs of the two major financial centers in the region, Hong Kong and Singapore.

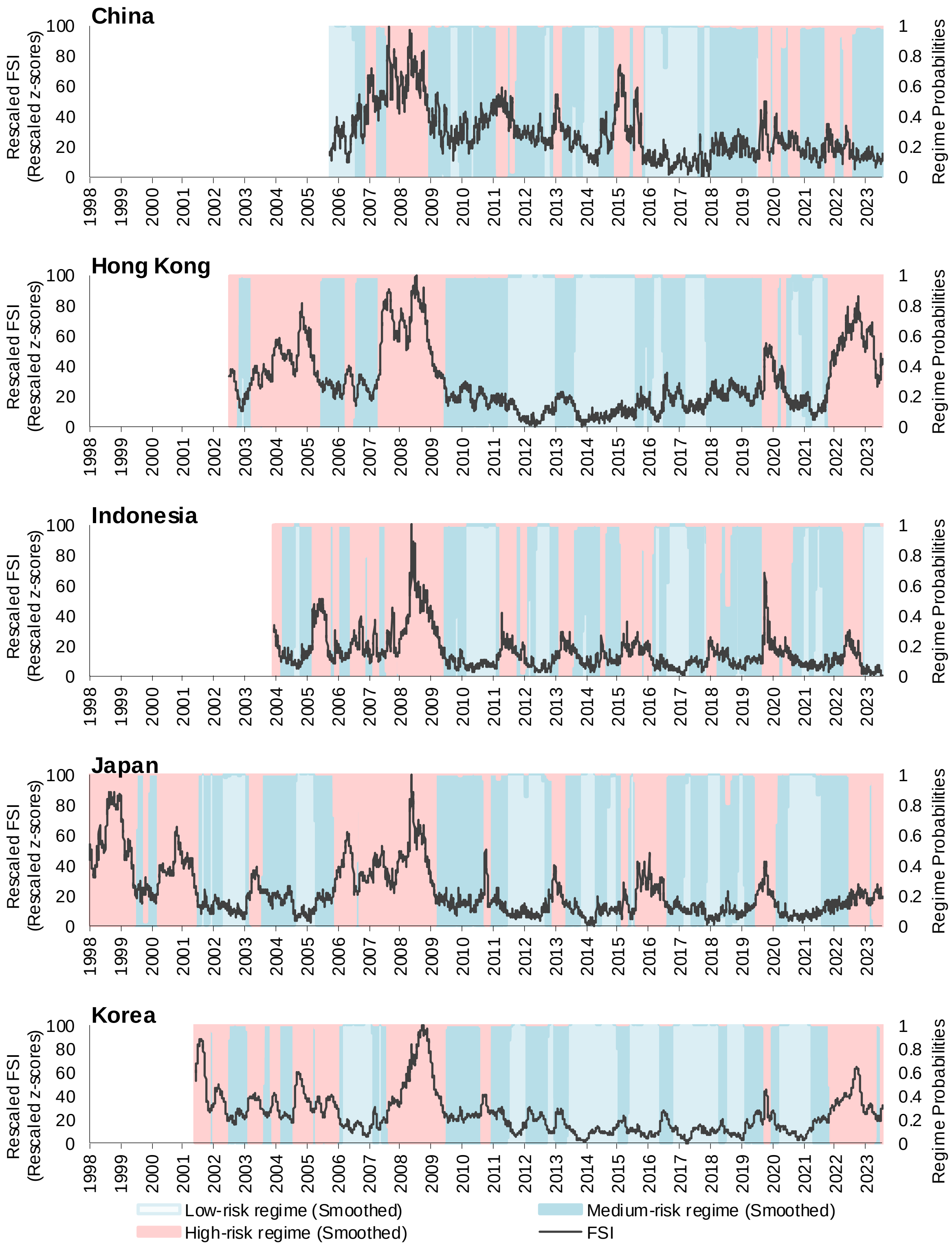
During the pandemic, financial stress peaked rapidly and severely impacted Hong Kong, Indonesia, Malaysia, and Singapore, with their FSIs reaching levels not seen since the GFC. Despite the protracted disruptions to the real economy due to lockdowns and the dislocation of global supply chains, financial stress rapidly subsided as financial markets recovered and stabilized in late 2020. However, this stabilization was short-lived, as financial stress surged again in 2022 due to policy rate hikes in advanced economies, particularly in the United States. These hikes increased financial stress in Japan, Korea, Singapore, and Thailand. China also shifted to a high stress regime, though at levels significantly lower those

[14] One caveat when interpreting these results is that the FSIs' reflect mainly high-frequency financial market stress and not necessarily macroeconomic, fiscal, or systemic financial vulnerabilities. FSIs are one tool that complements a more comprehensive financial stability assessment, such as those conducted jointly by the IMF and the World Bank under their Financial Sector Assessment Program.

[15] See Appendix II for a detailed analysis that assumes historical events are the ground truth and evaluates the ability of the smoothed and filtered regimes to identify them.

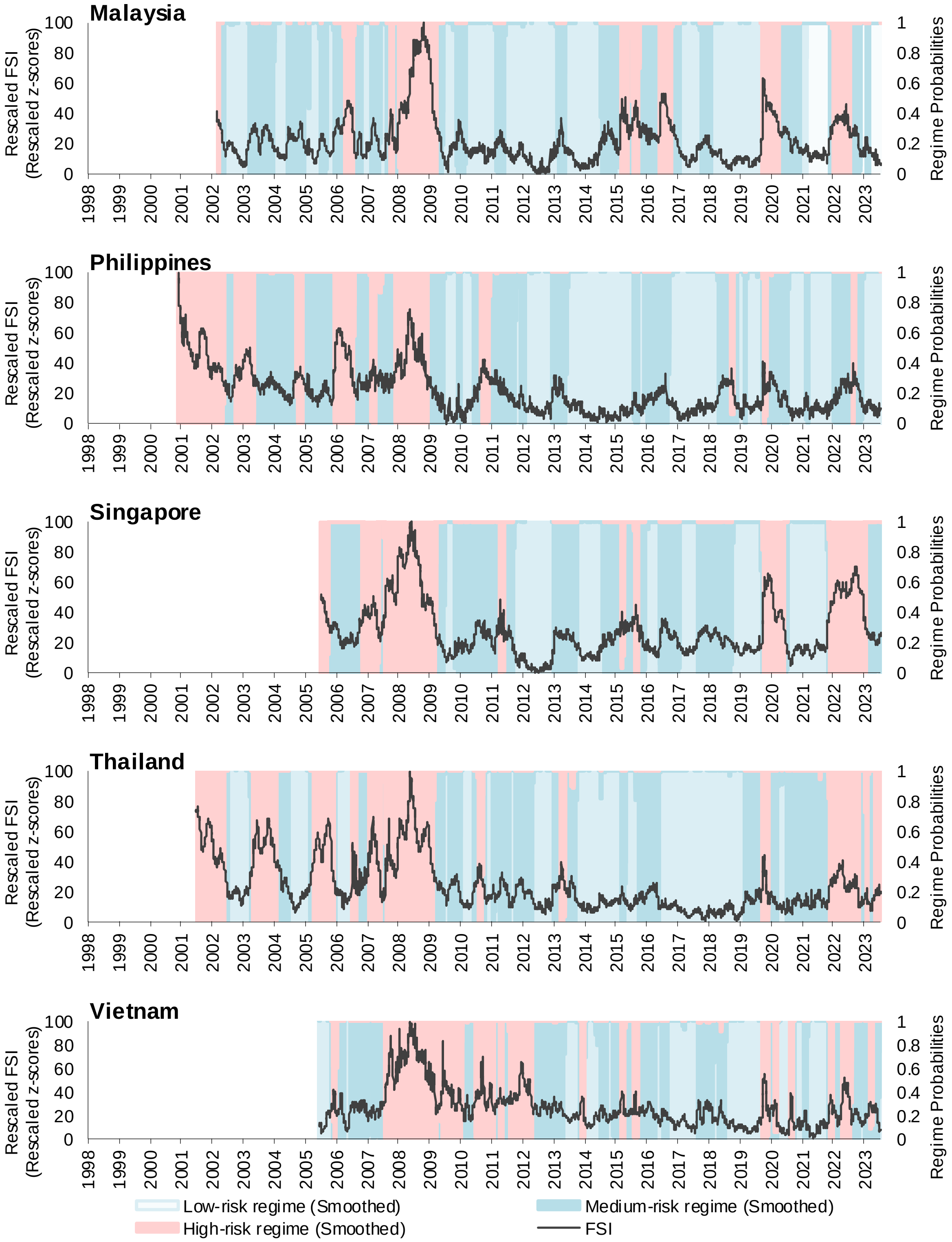
observed during the GFC and the stock market disruption episode. Around the same time, the financial system also was subject to adverse shocks from the failure of large property developers. By mid-2023, the FSIs suggest economies' financial stresses were back to low and medium levels, except Hong Kong, Japan, and Thailand.

**Figure 2. Financial Stress Indices: Risk Regime Smoothed Probabilities**




Sources: Haver Analytics; and authors' calculations.
Note: FSI and smoothed regime probabilities shown. Left y-axis: FSI rescaled Z-scores (0-100). Right y-axis: Probability (0-1) of FSI in low (light blue)-, medium (blue)-, or high-risk regimes (red). Data in daily frequency.

**Figure 2 (Cont'd). Financial Stress Indices: Risk Regime Smoothed Probabilities**




Sources: Haver Analytics; and authors' calculations.
Note: FSI and smoothed regime probabilities shown. Left y-axis: FSI rescaled Z-scores (0-100). Right y-axis: Probability (0-1) of FSI in low (light blue)-, medium (blue)-, or high-risk regimes (red). Data in daily frequency.

### D. Risk Regime Predictability

Table 7 shows the hyperparameters used to construct the momentum indicators, which then serve as inputs in the different classification models. As explained in the method section, the selected hyperparameters maximize the area under the curve of a univariate logistic classification model tasked with predicting the regime type at several horizon values: 5, 20, 40, and 60 days. Only the lagged observation is included as the explanatory variable.

Afterwards, several classification models are estimated after tuning their hyperparameters. The classification models are constructed using the momentum indicators as covariates, considering various lag combinations (1–5, 1–10, 1–15, 1–20) and forecasting horizons (5, 20, 40, 60 days).[16] The best classification models, for each country and each forecasting horizon, are selected based on the AUROC metrics. Figures 3 to 6 summarize their AUROC performance along five other several metrics: recall, specificity, precision, balanced accuracy, and the F1 score.[17]

Logistic regression generally yields the best performance across most economies and forecasting horizons. Typically, with up to five lags of the momentum indicator or all three indicators, logistic regression outperforms other models. However, in some economies like Korea, Thailand, and Vietnam, GBMs and their variants show better results. While the RSI is often the preferred single indicator, in Hong Kong and Korea, models that incorporate all three indicators are most effective.

While AUROCs remain high across all forecasting horizons, precision is notably low for some economies, including Japan, the Philippines, and Vietnam. These low precision values likely indicate differences in class imbalances between the training and test datasets, suggesting a potential dataset shift. In particular, the Philippines, where only two percent of the test sample observations fall into the high-stress class, shows negligible precision across all forecasting horizons, raising concerns about the predictability of its FSIs.

As expected, the models perform better at shorter forecast horizons. At these horizons, high stress regimes can be predicted in advance. Excluding the Philippines, weighted metrics (balanced accuracy and F1 score) suggest that FSIs' past behaviour may provide sufficient information to forecast high stress regimes 5 days in advance for all economies, and up to 60 days for Hong Kong, Singapore, and Thailand.

It is noteworthy that including additional indicator lags (10 and above) does not improve model performance for any of the economies studied. In the case of China, performance metrics deteriorate substantially, suggesting the classifiers might overfit the training data. The decline in performance highlights the importance of carefully selecting the appropriate

---

[16] Given $L$ lags and a forecasting horizon $H$, the model forecast the risk regime at time $t$ using covariate values observed in periods $t-1-H$, $t-2-H$, …, $t-L-H$. See methods section for details on the estimation procedure.

[17] True positives are defined as correct predictions of the high stress regime. Recall (sensitivity) measures the model's ability to identify positive instances correctly (ratio of true positives to true positives and false negatives); specificity, measures whether negative instances are identified correctly (ratio of true negatives to true negatives and false positives); precision; measures the accuracy of the positive predictions (ratio of true positives to true positives and false positives). Two measures that weight the tradeoff between identifying correctly positive and negative instances are balanced accuracy, defined as the arithmetic mean of sensitivity and specificity, and the F1 score, the harmonic mean of precision and sensitivity. The tables in Appendix III provide additional performance details, listing the best classification models and the covariates they use.

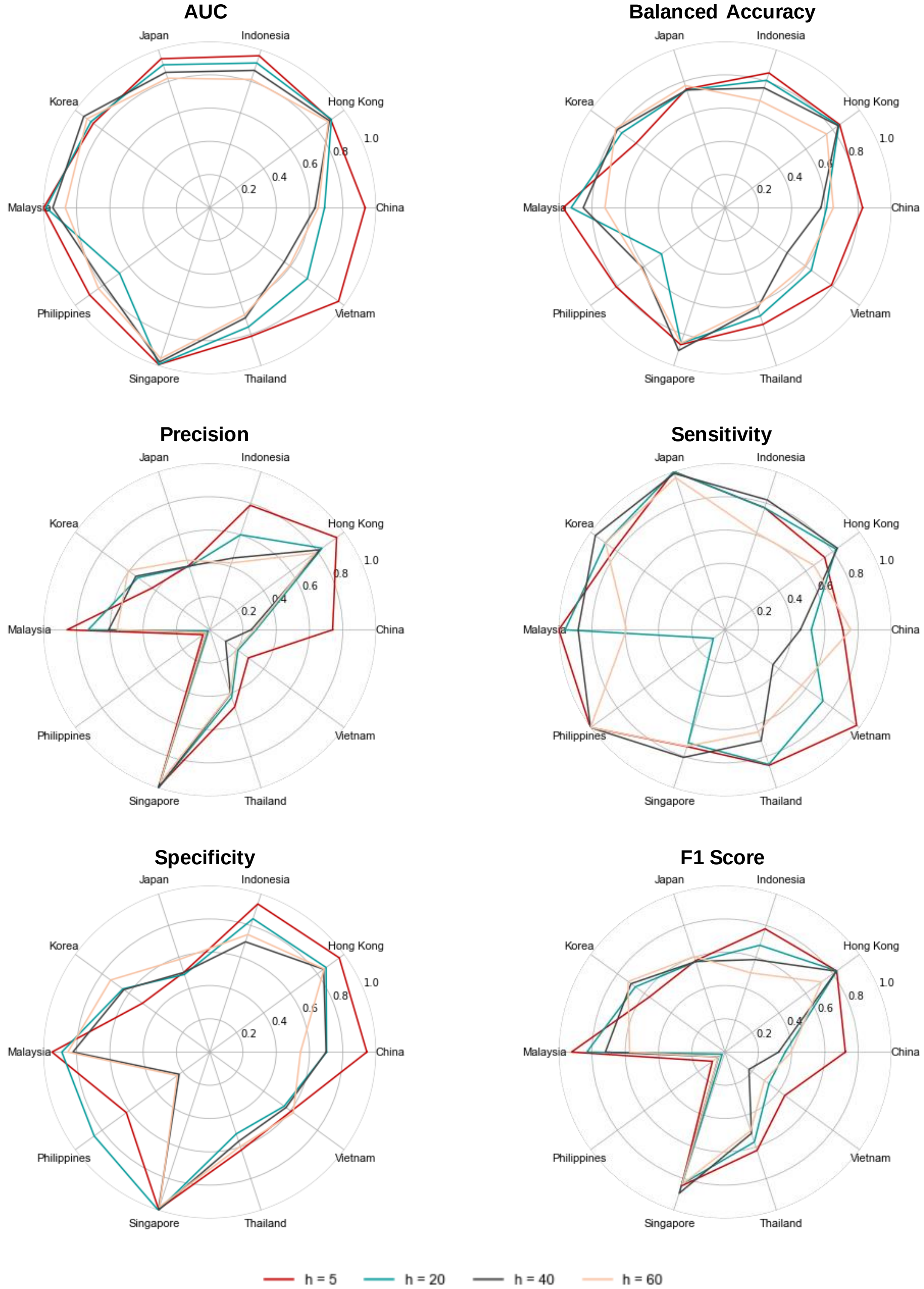
number of lags to ensure model robustness, as more data does not necessarily yield better results.

**Table 7. Momentum Indicators: Hyperparameters**

| Economy | Horizon | MACD | | | | RSI | | | | EMA | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Fast | Slow | Signal | AUC | Window | Upper | Lower | AUC | Period | AUC |
| China | 5 | 222 | 236 | 9 | 0.58 | 187 | 50 | 10 | 0.44 | 230 | 0.42 |
| | 20 | 42 | 56 | 39 | 0.56 | 247 | 60 | 50 | 0.44 | 230 | 0.49 |
| | 40 | 12 | 56 | 39 | 0.53 | 187 | 60 | 50 | 0.43 | 230 | 0.50 |
| | 60 | 72 | 116 | 69 | 0.50 | 187 | 50 | 10 | 0.55 | 230 | 0.51 |
| Hong Kong | 5 | 12 | 236 | 189 | 0.51 | 127 | 70 | 40 | 0.63 | 230 | 0.52 |
| | 20 | 222 | 236 | 219 | 0.56 | 127 | 70 | 40 | 0.62 | 230 | 0.52 |
| | 40 | 222 | 236 | 219 | 0.58 | 127 | 70 | 40 | 0.60 | 230 | 0.56 |
| | 60 | 222 | 236 | 219 | 0.60 | 127 | 70 | 40 | 0.59 | 230 | 0.53 |
| Indonesia | 5 | 222 | 236 | 219 | 0.53 | 247 | 70 | 50 | 0.59 | 230 | 0.46 |
| | 20 | 222 | 236 | 219 | 0.50 | 247 | 70 | 50 | 0.53 | 230 | 0.49 |
| | 40 | 222 | 236 | 219 | 0.44 | 247 | 70 | 60 | 0.38 | 230 | 0.48 |
| | 60 | 222 | 236 | 219 | 0.43 | 247 | 70 | 60 | 0.36 | 230 | 0.51 |
| Japan | 5 | 222 | 236 | 219 | 0.65 | 247 | 60 | 50 | 0.46 | 230 | 0.59 |
| | 20 | 222 | 236 | 219 | 0.64 | 247 | 60 | 50 | 0.44 | 230 | 0.51 |
| | 40 | 222 | 236 | 159 | 0.56 | 247 | 60 | 50 | 0.45 | 230 | 0.52 |
| | 60 | 222 | 236 | 129 | 0.56 | 247 | 60 | 50 | 0.47 | 230 | 0.52 |
| Korea | 5 | 222 | 236 | 219 | 0.58 | 247 | 70 | 50 | 0.45 | 230 | 0.48 |
| | 20 | 222 | 236 | 219 | 0.63 | 247 | 70 | 50 | 0.46 | 230 | 0.49 |
| | 40 | 222 | 236 | 219 | 0.65 | 97 | 80 | 30 | 0.73 | 230 | 0.49 |
| | 60 | 222 | 236 | 219 | 0.53 | 97 | 80 | 30 | 0.73 | 230 | 0.58 |
| Malaysia | 5 | 222 | 236 | 219 | 0.61 | 247 | 50 | 10 | 0.57 | 230 | 0.33 |
| | 20 | 222 | 236 | 219 | 0.63 | 247 | 50 | 10 | 0.44 | 230 | 0.33 |
| | 40 | 222 | 236 | 219 | 0.61 | 217 | 70 | 40 | 0.47 | 230 | 0.60 |
| | 60 | 162 | 236 | 219 | 0.58 | 217 | 70 | 40 | 0.50 | 230 | 0.52 |
| Philippines | 5 | 192 | 236 | 219 | 0.49 | 247 | 50 | 40 | 0.35 | 200 | 0.50 |
| | 20 | 222 | 236 | 219 | 0.49 | 247 | 50 | 40 | 0.36 | 200 | 0.50 |
| | 40 | 222 | 236 | 189 | 0.53 | 67 | 60 | 40 | 0.45 | 200 | 0.51 |
| | 60 | 192 | 206 | 189 | 0.55 | 67 | 60 | 40 | 0.45 | 170 | 0.51 |
| Singapore | 5 | 222 | 236 | 219 | 0.54 | 187 | 60 | 40 | 0.46 | 230 | 0.47 |
| | 20 | 222 | 236 | 219 | 0.54 | 187 | 60 | 40 | 0.51 | 230 | 0.46 |
| | 40 | 222 | 236 | 219 | 0.56 | 187 | 60 | 40 | 0.51 | 230 | 0.45 |
| | 60 | 222 | 236 | 219 | 0.57 | 187 | 60 | 40 | 0.52 | 230 | 0.46 |
| Thailand | 5 | 222 | 236 | 219 | 0.60 | 247 | 40 | 10 | 0.45 | 230 | 0.50 |
| | 20 | 222 | 236 | 219 | 0.52 | 217 | 50 | 40 | 0.48 | 230 | 0.46 |
| | 40 | 222 | 236 | 189 | 0.52 | 217 | 50 | 40 | 0.49 | 200 | 0.47 |
| | 60 | 132 | 236 | 189 | 0.53 | 217 | 50 | 40 | 0.59 | 200 | 0.49 |
| Vietnam | 5 | 162 | 236 | 99 | 0.52 | 247 | 50 | 10 | 0.45 | 230 | 0.47 |
| | 20 | 222 | 236 | 69 | 0.51 | 247 | 50 | 10 | 0.49 | 230 | 0.50 |
| | 40 | 222 | 236 | 69 | 0.51 | 247 | 50 | 10 | 0.49 | 230 | 0.47 |
| | 60 | 222 | 236 | 69 | 0.50 | 247 | 50 | 10 | 0.49 | 230 | 0.56 |

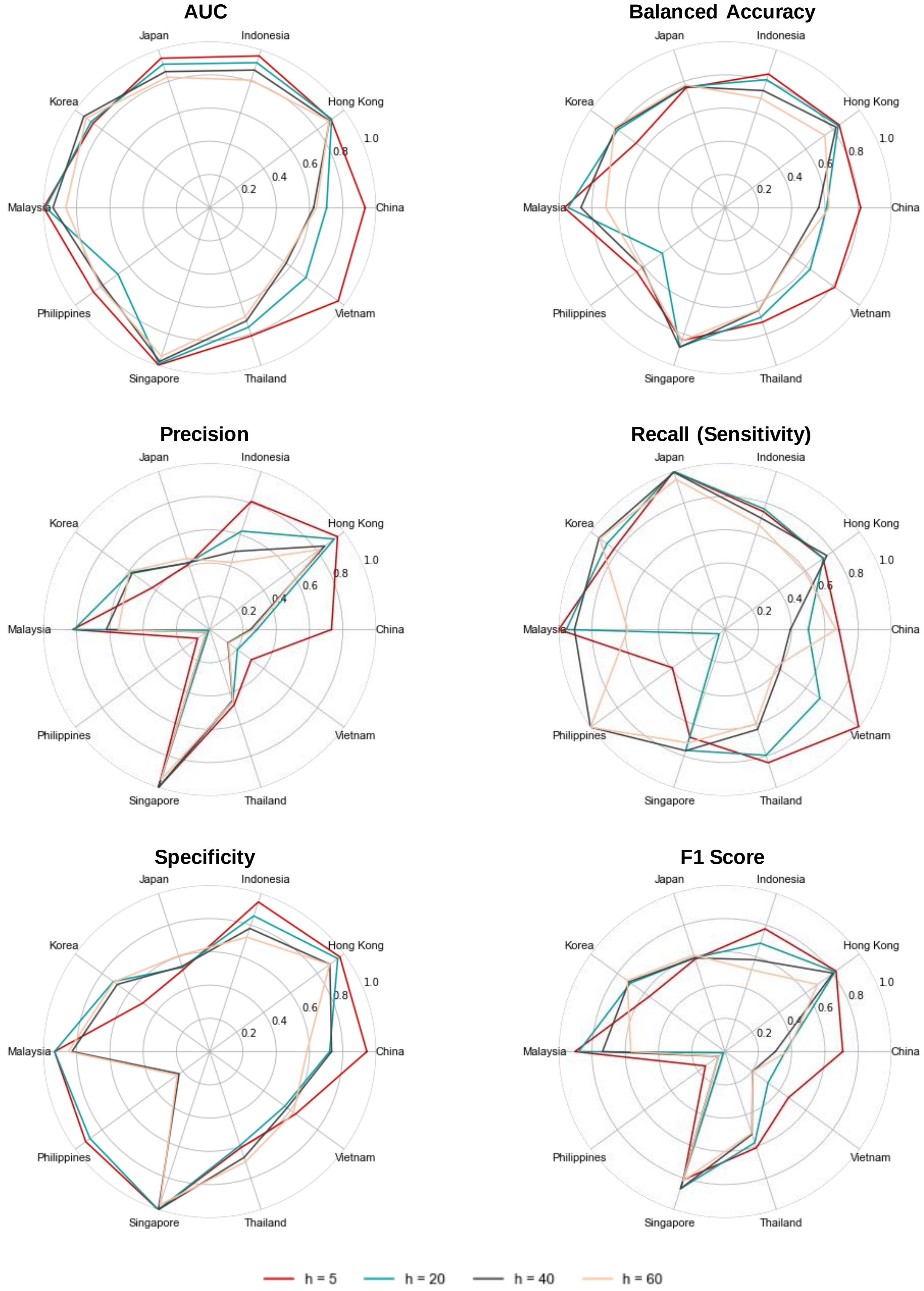
Source: Authors' calculations.
Note: MACD = Moving Average Convergence Divergence; RSI = Relative Strength Index; EMA = exponential moving average; AUC = Area under the Receiver Operating Characteristics curve.

**Figure 3. Best Performing Models, 1 to 5 Lags: Test-Sample Performance Metrics**



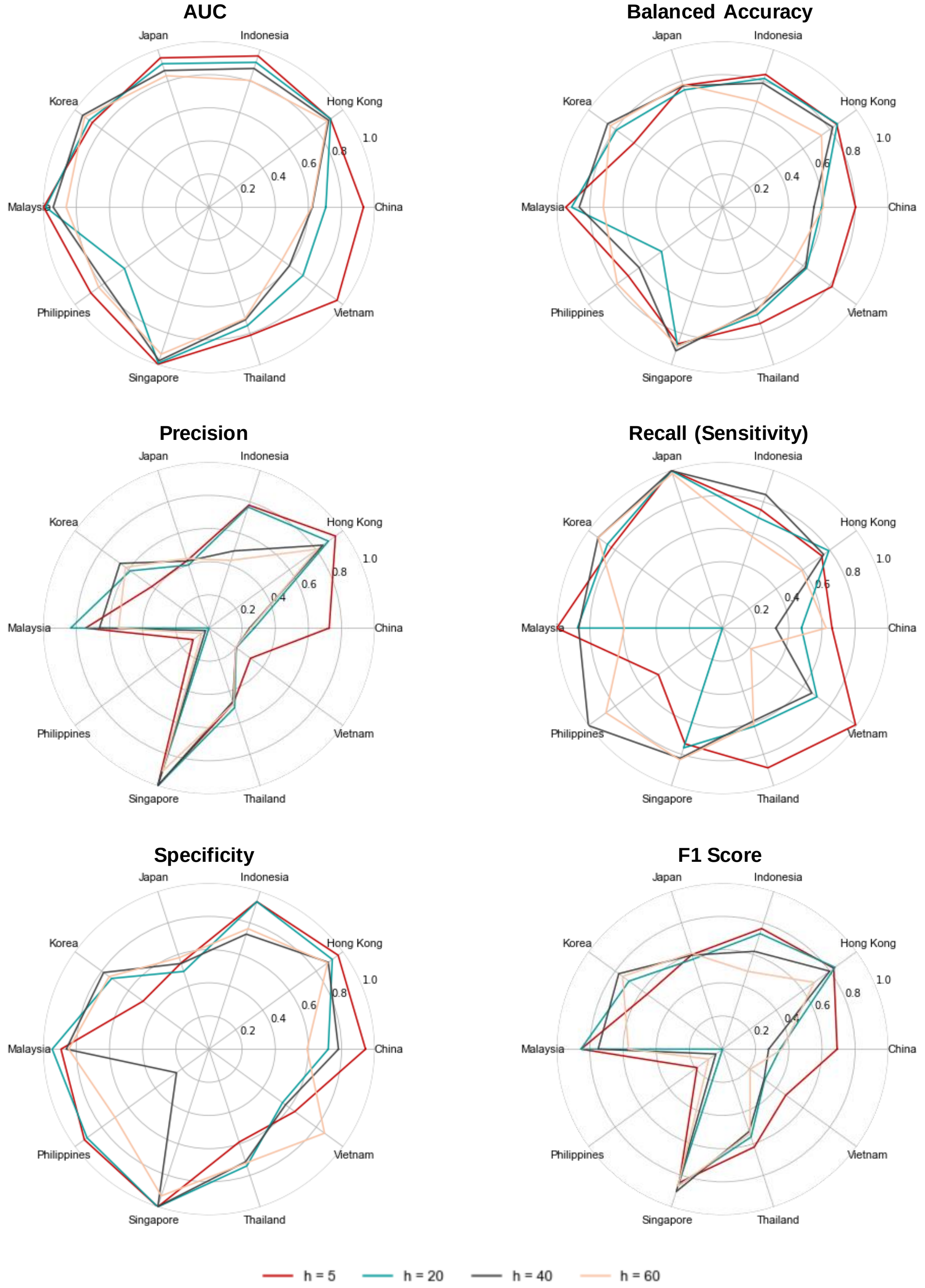

Source: Authors.

**Figure 4. Best Performing Models, 1 to 10 Lags: Test-Sample Performance Metrics**



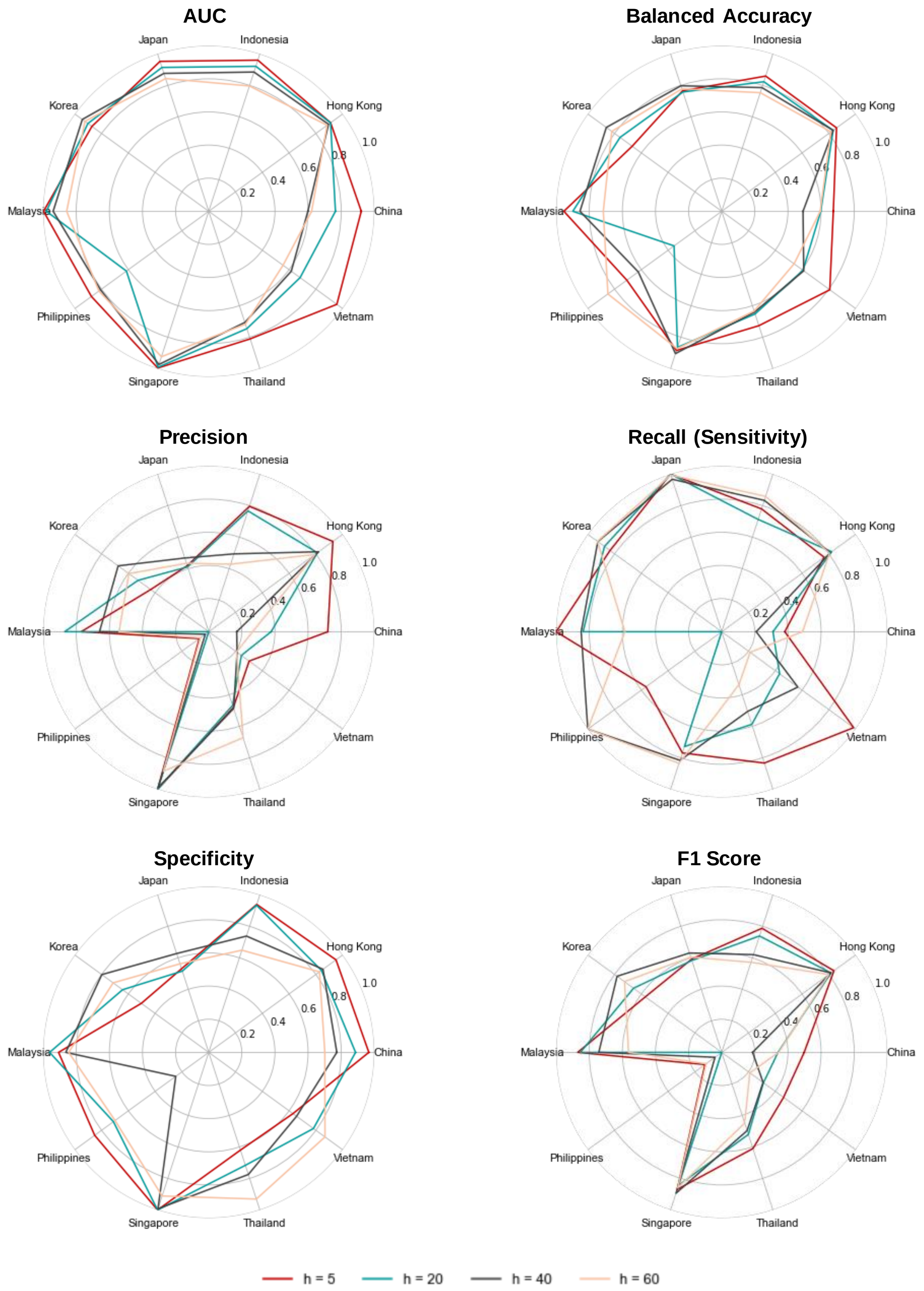

Source: Authors.

**Figure 5. Top Performing Models, 1 to 14 Lags: Test-Sample Performance Metrics**




Source: Authors.

**Figure 6. Top Performing Models, 1 to 20 Lags: Test-Sample Performance Metrics**




Source: Authors.

## VI. Conclusions

Macro-financial surveillance and safeguarding financial stability requires implementing practical tools for monitoring financial system stress. This study, building on the insights of prior work on FSIs, suggest that daily, high frequency equal variance weighted country-specific indices could be very useful for monitoring financial stress in China, Japan, Korea, and several other ASEAN+3 economies. Moreover, when regime switching models are used to model their dynamic behavior, it is possible to identify low, medium, and high stress regimes. These risk regimes seem consistent with observed historical stress episodes. Simple momentum-based technical methods prove useful for predicting regime changes in advance and could be integrated in early warning systems.

Our results indicate that the FSIs effectively capture upward financial stress pressures arising from major, world-wide global financial crises such as the global financial crisis in 2008–9. The FSIs also reveal cross-country differences during more localized financial stress events such as the European sovereign debt crisis and the stock market turbulence China experienced in 2015. The differences suggest that it is worth analyzing in detail, the economies' financial linkages among themselves and the rest of the world, as well as exploring and understanding potential shock transmission channels.

Understanding how shocks originate, diffuse, and are transmitted both domestically and across borders is crucial, as they can have lasting effects on the economy. The transition probability matrices associated with regime-switching models suggest that it may take two to three years for the impact of a single shock to be reduced by half. Additionally, the steady-state probabilities derived from these transition matrices indicate the likelihood of economies experiencing high-stress events over the long run.

Besides risk regime identification, it is of interest to forecast regime changes as this could give policy makers advance warning to implement mitigation measures. Rather than relying on econometric methods, we choose to examine whether momentum indicators developed in the technical analysis literature could forecast the turning points of the FSIs. Our examination delivers positive results. Technical indicators constructed using only past observations of the FSIs can provide short-term signals of impending regime changes when used as inputs in several machine learning classification models. The advance warning may suffice for market practitioners' hedging and tactical decisions, and to alert policy makers about impending distress in the financial sector and adopt measures aimed at reducing market volatility.

In summary, our findings underscore the usefulness of FSIs for short-term risk monitoring and highlight the ongoing challenges in developing long-term predictive tools for policymakers. These results suggest a dual focus for future research: enhancing the precision of FSIs for immediate risk assessment and advancing methodologies to develop more reliable long-term forecasting instruments for policymakers.

## Appendix I. Smoothed Risk Regimes vs. Filtered Risk Regimes

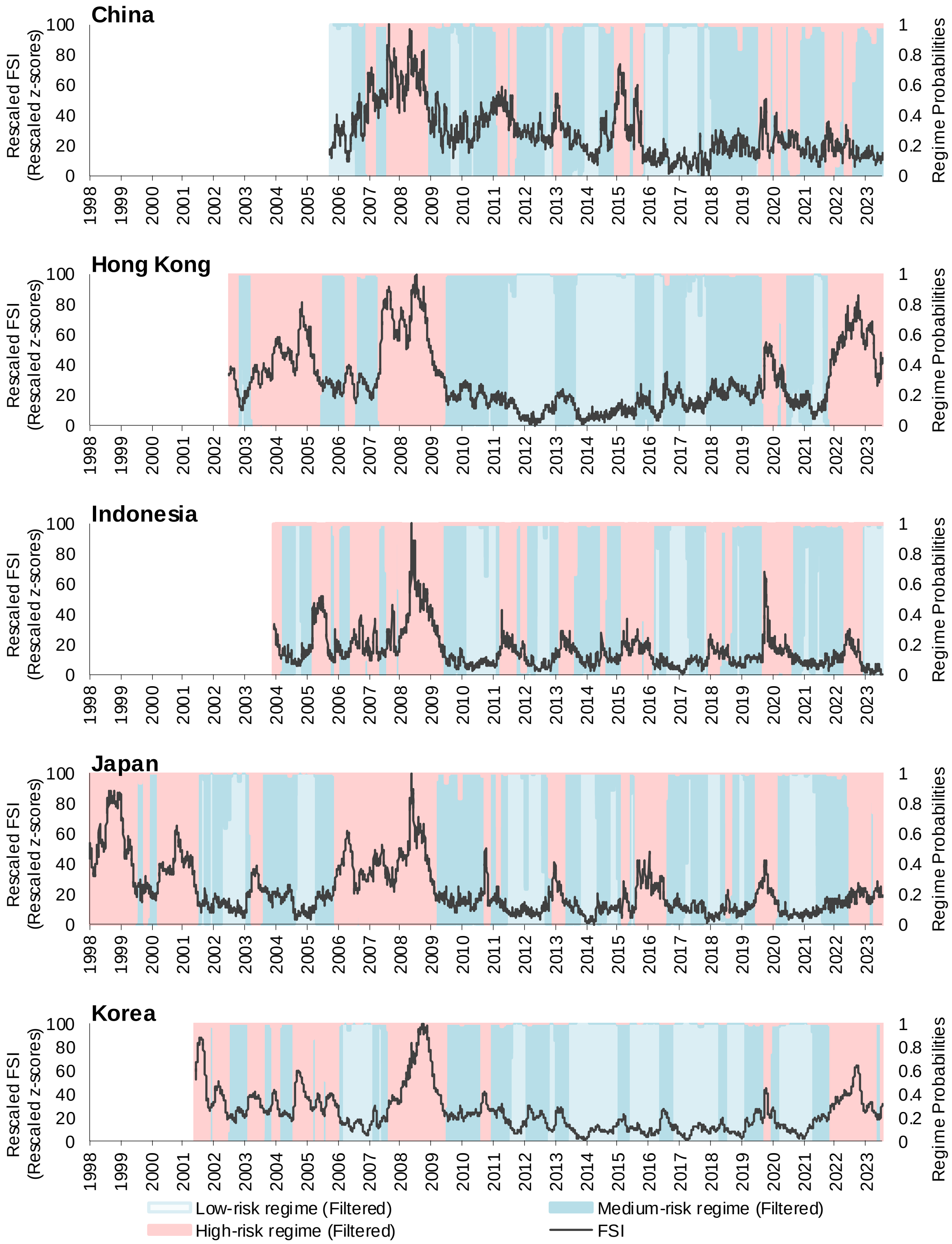
We evaluate whether there are substantial differences between regimes identified using smoothed probabilities and filtered probabilities. Assuming that the smoothed regimes are the ground truth, we perform a multiclass classification analysis. Appendix Table 1 shows that the performance metrics exceed 0.90 for all economies and regimes, and 0.95 for a substantial number of them. This suggests that filtered risk regimes are not much different from the smoothed risk regimes, which is also observed by comparing Appendix Figure 1 with Figure 2.

### Appendix Table 1. Filtered Risk Regimes: Performance Metrics Vis-à-vis Smoothed Risk Regimes

| | Risk regime | | | Risk regime | | |
|---|---|---|---|---|---|---|
| | Low | Medium | High | Low | Medium | High |
| | | **China** | | | **Hong Kong** | |
| Recall (Sensitivity) | 0.94 | 0.94 | 0.91 | 0.96 | 0.95 | 0.98 |
| Specificity | 0.97 | 0.93 | 0.99 | 0.98 | 0.97 | 0.99 |
| Precision | 0.95 | 0.93 | 0.94 | 0.97 | 0.95 | 0.97 |
| Balanced Accuracy | 0.96 | 0.94 | 0.95 | 0.97 | 0.96 | 0.99 |
| F1 Score | 0.95 | 0.94 | 0.92 | 0.96 | 0.95 | 0.98 |
| | | **Indonesia** | | | **Japan** | |
| Recall (Sensitivity) | 0.95 | 0.93 | 0.96 | 0.96 | 0.94 | 0.98 |
| Specificity | 0.98 | 0.95 | 0.98 | 0.98 | 0.97 | 0.99 |
| Precision | 0.96 | 0.93 | 0.94 | 0.96 | 0.94 | 0.98 |
| Balanced Accuracy | 0.96 | 0.94 | 0.97 | 0.97 | 0.96 | 0.99 |
| F1 Score | 0.95 | 0.93 | 0.95 | 0.96 | 0.94 | 0.98 |
| | | **Korea** | | | **Malaysia** | |
| Recall (Sensitivity) | 0.98 | 0.95 | 0.97 | 0.98 | 0.94 | 0.96 |
| Specificity | 0.98 | 0.97 | 0.99 | 0.98 | 0.97 | 0.99 |
| Precision | 0.98 | 0.95 | 0.97 | 0.98 | 0.94 | 0.96 |
| Balanced Accuracy | 0.98 | 0.96 | 0.98 | 0.98 | 0.96 | 0.98 |
| F1 Score | 0.98 | 0.95 | 0.97 | 0.98 | 0.94 | 0.96 |
| | | **Philippines** | | | **Singapore** | |
| Recall (Sensitivity) | 0.97 | 0.96 | 0.97 | 0.96 | 0.97 | 0.98 |
| Specificity | 0.98 | 0.97 | 0.99 | 0.99 | 0.97 | 0.99 |
| Precision | 0.97 | 0.96 | 0.96 | 0.98 | 0.95 | 0.98 |
| Balanced Accuracy | 0.98 | 0.96 | 0.98 | 0.97 | 0.97 | 0.99 |
| F1 Score | 0.97 | 0.96 | 0.96 | 0.97 | 0.96 | 0.98 |
| | | **Thailand** | | | **Vietnam** | |
| Recall (Sensitivity) | 0.97 | 0.95 | 0.98 | 0.96 | 0.94 | 0.95 |
| Specificity | 0.98 | 0.97 | 0.99 | 0.98 | 0.96 | 0.99 |
| Precision | 0.98 | 0.94 | 0.97 | 0.96 | 0.93 | 0.96 |
| Balanced Accuracy | 0.98 | 0.96 | 0.98 | 0.97 | 0.95 | 0.97 |
| F1 Score | 0.97 | 0.94 | 0.97 | 0.96 | 0.93 | 0.96 |

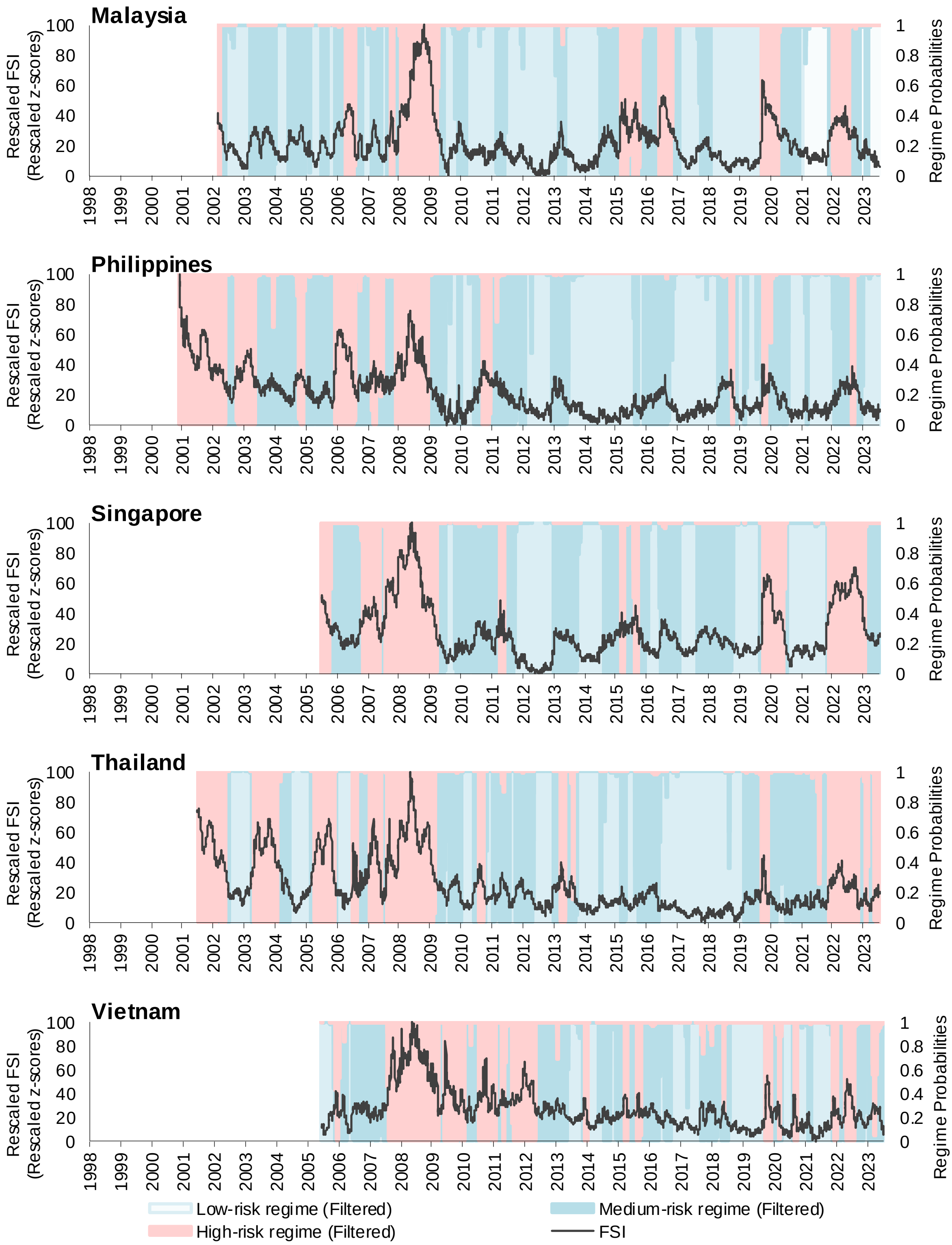
Source: Authors' calculations.
Note: Metrics calculated assuming that smoothed risk regimes are the ground truth.

**Appendix Figure 1. Financial Stress Indices: Risk Regime Filtered Probabilities**




Sources: Haver Analytics; and authors' calculations.
Note: FSI and filtered regime probabilities shown. Left y-axis: FSI rescaled Z-scores (0-100). Right y-axis: Probability (0-1) of FSI in low (light blue)-, medium (blue)-, or high-risk regimes (red). Data in daily frequency.

**Appendix Figure 1 (Cont'd). Financial Stress Indices: Risk Regime Filtered Probabilities**




Sources: Haver Analytics; and authors' calculations.
Note: FSI and filtered regime probabilities shown. Left y-axis: FSI rescaled Z-scores (0-100). Right y-axis: Probability (0-1) of FSI in low (light blue)-, medium (blue)-, or high-risk regimes (red). Data in daily frequency.

## Appendix II. Risk Regimes and Historical Stress Episodes

Appendix Table 2 shows that, based on balanced accuracy and F1 scores, country-specific shocks may be more important in determining financial stress at the country level, barring major global financial disruptions. These findings justify constructing separate FSIs for each country and assessing their predictability on a country-by-country basis.

### Appendix Table 2. Filtered and Smoothed Risk Regimes: Performance Metrics Vis-à-vis Narrative-based Financial Stress Episodes

| | High stress regimes | | | |
|---|---|---|---|---|
| **Metric** | **Filtered** | **Smoothed** | **Filtered** | **Smoothed** |
| | **China** | | **Hong Kong** | |
| Recall (Sensitivity) | 0.90 | 0.89 | 0.50 | 0.50 |
| Specificity | 0.63 | 0.63 | 0.67 | 0.67 |
| Precision | 0.29 | 0.29 | 0.38 | 0.38 |
| Balanced Accuracy | 0.76 | 0.76 | 0.58 | 0.58 |
| F1 Score | 0.44 | 0.44 | 0.43 | 0.43 |
| | **Indonesia** | | **Japan** | |
| Recall (Sensitivity) | 0.62 | 0.63 | 0.60 | 0.60 |
| Specificity | 0.66 | 0.66 | 0.64 | 0.64 |
| Precision | 0.38 | 0.38 | 0.45 | 0.45 |
| Balanced Accuracy | 0.64 | 0.65 | 0.62 | 0.62 |
| F1 Score | 0.47 | 0.48 | 0.52 | 0.52 |
| | **Korea** | | **Malaysia** | |
| Recall (Sensitivity) | 0.60 | 0.60 | 0.69 | 0.70 |
| Specificity | 0.66 | 0.66 | 0.67 | 0.67 |
| Precision | 0.37 | 0.37 | 0.28 | 0.28 |
| Balanced Accuracy | 0.63 | 0.63 | 0.68 | 0.69 |
| F1 Score | 0.46 | 0.46 | 0.39 | 0.40 |
| | **Philippines** | | **Singapore** | |
| Recall (Sensitivity) | 0.69 | 0.68 | 0.85 | 0.85 |
| Specificity | 0.64 | 0.64 | 0.68 | 0.68 |
| Precision | 0.31 | 0.30 | 0.46 | 0.46 |
| Balanced Accuracy | 0.67 | 0.66 | 0.77 | 0.77 |
| F1 Score | 0.43 | 0.42 | 0.60 | 0.60 |
| | **Thailand** | | **Vietnam** | |
| Recall (Sensitivity) | 0.65 | 0.65 | 0.65 | 0.64 |
| Specificity | 0.68 | 0.67 | 0.62 | 0.61 |
| Precision | 0.39 | 0.39 | 0.33 | 0.33 |
| Balanced Accuracy | 0.66 | 0.66 | 0.63 | 0.63 |
| F1 Score | 0.49 | 0.49 | 0.43 | 0.43 |

Source: Authors' calculations.

Note: Major stress episodes, based on a historical narrative, include: (a) Asian financial crisis; (b) Dot-com bubble; (c) Global financial crisis; (d) European debt crisis; (e) U.S. taper tantrum; (f) Chinese stock market turbulence; (g) COVID-19 pandemic. Higher FSI values indicate increased financial stress. The calculations assume that these stresss epiodes are the ground truth.

## Appendix III. Best Classification Models: Test-Sample Performance Metrics

### Appendix Table 3. Classification Models Including 1 to 5 Lags

| | Horizon (days) | | | | Horizon (days) | | | |
|---|---|---|---|---|---|---|---|---|
| **Metric** | **5** | **20** | **40** | **60** | **5** | **20** | **40** | **60** |
| | **China** | | | | **Hong Kong** | | | |
| AUC | 0.93 | 0.69 | 0.63 | 0.65 | 0.90 | 0.90 | 0.89 | 0.88 |
| Balanced Accuracy | 0.83 | 0.61 | 0.58 | 0.65 | 0.85 | 0.84 | 0.84 | 0.75 |
| Precision | 0.74 | 0.28 | 0.25 | 0.27 | 0.94 | 0.84 | 0.82 | 0.78 |
| Recall (Sensitivity) | 0.71 | 0.52 | 0.45 | 0.76 | 0.74 | 0.82 | 0.84 | 0.66 |
| Specificity | 0.94 | 0.70 | 0.70 | 0.55 | 0.96 | 0.87 | 0.85 | 0.85 |
| F1 Score | 0.72 | 0.36 | 0.32 | 0.40 | 0.83 | 0.83 | 0.83 | 0.72 |
| Covariates | RSI | RSI | RSI | MACD | EMA | M, R, E | M, R, E | M, R, E |
| Model | LR | LR | RF | AdaBoost | LR | LR | LR | LR |
| | **Indonesia** | | | | **Japan** | | | |
| AUC | 0.96 | 0.92 | 0.87 | 0.81 | 0.94 | 0.91 | 0.86 | 0.82 |
| Balanced Accuracy | 0.85 | 0.81 | 0.76 | 0.68 | 0.75 | 0.75 | 0.75 | 0.77 |
| Precision | 0.79 | 0.60 | 0.45 | 0.42 | 0.41 | 0.40 | 0.40 | 0.44 |
| Recall (Sensitivity) | 0.77 | 0.77 | 0.82 | 0.61 | 1.00 | 1.00 | 0.99 | 0.96 |
| Specificity | 0.94 | 0.84 | 0.70 | 0.74 | 0.50 | 0.49 | 0.50 | 0.59 |
| F1 Score | 0.78 | 0.68 | 0.58 | 0.50 | 0.58 | 0.57 | 0.57 | 0.60 |
| Covariates | RSI | RSI | RSI | RSI | RSI | RSI | RSI | RSI |
| Model | LR | LR | LR | RF | LR | LR | LR | GBM |
| | **Korea** | | | | **Malaysia** | | | |
| AUC | 0.86 | 0.88 | 0.94 | 0.91 | 1.00 | 0.98 | 0.94 | 0.87 |
| Balanced Accuracy | 0.66 | 0.77 | 0.80 | 0.81 | 0.97 | 0.93 | 0.85 | 0.72 |
| Precision | 0.43 | 0.53 | 0.55 | 0.61 | 0.86 | 0.73 | 0.61 | 0.56 |
| Recall (Sensitivity) | 0.82 | 0.89 | 0.96 | 0.89 | 1.00 | 0.96 | 0.88 | 0.59 |
| Specificity | 0.50 | 0.65 | 0.64 | 0.74 | 0.95 | 0.89 | 0.82 | 0.85 |
| F1 Score | 0.56 | 0.67 | 0.70 | 0.72 | 0.92 | 0.83 | 0.72 | 0.57 |
| Covariates | RSI | M, R, E | M, R, E | EMA | RSI | RSI | RSI | MACD |
| Model | LR | LGBM | LGBM | RF | LR | LR | RF | LR |
| | **Philippines** | | | | **Singapore** | | | |
| AUC | 0.89 | 0.67 | 0.78 | 0.83 | 0.99 | 0.99 | 0.98 | 0.95 |
| Balanced Accuracy | 0.81 | 0.47 | 0.61 | 0.62 | 0.87 | 0.86 | 0.90 | 0.86 |
| Precision | 0.05 | 0.01 | 0.03 | 0.03 | 0.99 | 1.00 | 1.00 | 0.97 |
| Recall (Sensitivity) | 1.00 | 0.09 | 1.00 | 1.00 | 0.74 | 0.71 | 0.81 | 0.74 |
| Specificity | 0.62 | 0.86 | 0.23 | 0.24 | 0.99 | 1.00 | 1.00 | 0.98 |
| F1 Score | 0.09 | 0.02 | 0.05 | 0.05 | 0.85 | 0.83 | 0.89 | 0.84 |
| Covariates | RSI | M, R, E | RSI | RSI | RSI | RSI | RSI | RSI |
| Model | LR | RF | RF | LR | LR | LR | LR | LR |
| | **Thailand** | | | | **Vietnam** | | | |
| AUC | 0.81 | 0.75 | 0.70 | 0.68 | 0.96 | 0.73 | 0.55 | 0.59 |
| Balanced Accuracy | 0.74 | 0.68 | 0.63 | 0.62 | 0.79 | 0.64 | 0.46 | 0.59 |
| Precision | 0.49 | 0.43 | 0.41 | 0.40 | 0.29 | 0.21 | 0.12 | 0.20 |
| Recall (Sensitivity) | 0.86 | 0.85 | 0.70 | 0.65 | 0.98 | 0.73 | 0.36 | 0.57 |
| Specificity | 0.62 | 0.52 | 0.56 | 0.60 | 0.61 | 0.55 | 0.57 | 0.62 |
| F1 Score | 0.62 | 0.57 | 0.51 | 0.50 | 0.44 | 0.33 | 0.18 | 0.29 |
| Covariates | RSI | RSI | RSI | RSI | RSI | RSI | RSI | M, R, E |
| Model | LR | GBM | LGBM | LGBM | LGBM | LR | GBM | GBM |

Source: Authors' calculations.

Note: MACD = moving average convergence divergence; RSI = relative strength Index; EMA = exponential moving average; M, R, E = MACD, RSI, and EMA; LR = logistic regression; GBM = gradient boosting machine; LGBM = light gradient boosting machine; RF = random forest.

## Appendix Table 4. Classification Models Including 1 to 10 lags

| | Horizon(days) | | | | Horizon (days) | | | |
|---|---|---|---|---|---|---|---|---|
| **Metric** | **5** | **20** | **40** | **60** | **5** | **20** | **40** | **60** |
| | **China** | | | | **Hong Kong** | | | |
| AUC | 0.93 | 0.70 | 0.62 | 0.64 | 0.90 | 0.91 | 0.89 | 0.89 |
| Balanced Accuracy | 0.81 | 0.61 | 0.56 | 0.63 | 0.85 | 0.84 | 0.82 | 0.74 |
| Precision | 0.73 | 0.28 | 0.25 | 0.26 | 0.95 | 0.93 | 0.85 | 0.82 |
| Recall (Sensitivity) | 0.68 | 0.50 | 0.39 | 0.67 | 0.73 | 0.73 | 0.76 | 0.59 |
| Specificity | 0.94 | 0.72 | 0.73 | 0.58 | 0.97 | 0.95 | 0.89 | 0.89 |
| F1 Score | 0.71 | 0.36 | 0.30 | 0.38 | 0.82 | 0.82 | 0.80 | 0.69 |
| Covariates | RSI | RSI | RSI | MACD | EMA | EMA | M, R, E | EMA |
| Model | LR | LR | RF | AdaBoost | LR | LR | LR | LR |
| | **Indonesia** | | | | **Japan** | | | |
| AUC | 0.96 | 0.92 | 0.87 | 0.81 | 0.95 | 0.91 | 0.86 | 0.83 |
| Balanced Accuracy | 0.85 | 0.81 | 0.74 | 0.69 | 0.76 | 0.77 | 0.77 | 0.78 |
| Precision | 0.81 | 0.62 | 0.49 | 0.42 | 0.41 | 0.42 | 0.42 | 0.45 |
| Recall (Sensitivity) | 0.75 | 0.76 | 0.70 | 0.66 | 1.00 | 1.00 | 0.99 | 0.95 |
| Specificity | 0.95 | 0.86 | 0.78 | 0.72 | 0.52 | 0.53 | 0.54 | 0.61 |
| F1 Score | 0.78 | 0.69 | 0.58 | 0.52 | 0.58 | 0.59 | 0.59 | 0.61 |
| Covariates | RSI | RSI | RSI | RSI | RSI | RSI | RSI | RSI |
| Model | LR | LR | AdaBoost | RF | LR | AdaBoost | RF | AdaBoost |
| | **Korea** | | | | **Malaysia** | | | |
| AUC | 0.87 | 0.88 | 0.94 | 0.92 | 1.00 | 0.99 | 0.94 | 0.87 |
| Balanced Accuracy | 0.66 | 0.80 | 0.81 | 0.82 | 0.97 | 0.94 | 0.87 | 0.72 |
| Precision | 0.43 | 0.58 | 0.58 | 0.60 | 0.82 | 0.82 | 0.62 | 0.55 |
| Recall (Sensitivity) | 0.83 | 0.88 | 0.94 | 0.93 | 1.00 | 0.95 | 0.91 | 0.58 |
| Specificity | 0.50 | 0.72 | 0.69 | 0.71 | 0.93 | 0.93 | 0.83 | 0.85 |
| F1 Score | 0.56 | 0.70 | 0.71 | 0.73 | 0.90 | 0.88 | 0.74 | 0.57 |
| Covariates | RSI | M, R, E | M, R, E | EMA | RSI | MACD | RSI | MACD |
| Model | LR | LGBM | LGBM | LGBM | LR | LR | GBM | LR |
| | **Philippines** | | | | **Singapore** | | | |
| AUC | 0.86 | 0.68 | 0.79 | 0.81 | 1.00 | 0.99 | 0.97 | 0.94 |
| Balanced Accuracy | 0.66 | 0.47 | 0.61 | 0.62 | 0.84 | 0.88 | 0.88 | 0.84 |
| Precision | 0.09 | 0.01 | 0.03 | 0.03 | 1.00 | 1.00 | 1.00 | 0.95 |
| Recall (Sensitivity) | 0.39 | 0.04 | 1.00 | 1.00 | 0.68 | 0.76 | 0.77 | 0.72 |
| Specificity | 0.92 | 0.89 | 0.23 | 0.24 | 1.00 | 1.00 | 1.00 | 0.97 |
| F1 Score | 0.15 | 0.01 | 0.05 | 0.05 | 0.81 | 0.87 | 0.87 | 0.82 |
| Covariates | M, R, E | M, R, E | RSI | RSI | RSI | RSI | RSI | RSI |
| Model | RF | RF | RF | LGBM | LR | LR | LR | LR |
| | **Thailand** | | | | **Vietnam** | | | |
| AUC | 0.81 | 0.76 | 0.72 | 0.69 | 0.96 | 0.72 | 0.57 | 0.55 |
| Balanced Accuracy | 0.72 | 0.69 | 0.65 | 0.65 | 0.82 | 0.63 | 0.49 | 0.50 |
| Precision | 0.48 | 0.45 | 0.45 | 0.45 | 0.31 | 0.21 | 0.14 | 0.14 |
| Recall (Sensitivity) | 0.84 | 0.80 | 0.63 | 0.60 | 0.99 | 0.70 | 0.41 | 0.38 |
| Specificity | 0.61 | 0.59 | 0.67 | 0.70 | 0.64 | 0.56 | 0.58 | 0.62 |
| F1 Score | 0.61 | 0.58 | 0.52 | 0.52 | 0.47 | 0.32 | 0.20 | 0.20 |
| Covariates | RSI | RSI | RSI | RSI | RSI | RSI | RSI | MACD |
| Model | LR | GBM | GBM | LGBM | LR | LR | RF | GBM |

Source: Authors' calculations.

Note: MACD = moving average convergence divergence; RSI = relative strength Index; EMA = exponential moving average; M, R, E = MACD, RSI, and EMA; LR = logistic regression; GBM = gradient boosting machine; LGBM = light gradient boosting machine; RF = random forest.

## Appendix Table 5. Classification Models Including 1 to 15 lags

| | Horizon (days) | | | | Horizon (days) | | | |
|---|---|---|---|---|---|---|---|---|
| **Metric** | **5** | **20** | **40** | **60** | **5** | **20** | **40** | **60** |
| | **China** | | | | **Hong Kong** | | | |
| AUC | 0.93 | 0.71 | 0.62 | 0.62 | 0.91 | 0.91 | 0.89 | 0.88 |
| Balanced Accuracy | 0.80 | 0.60 | 0.55 | 0.61 | 0.85 | 0.86 | 0.82 | 0.74 |
| Precision | 0.73 | 0.27 | 0.25 | 0.25 | 0.94 | 0.89 | 0.85 | 0.81 |
| Recall (Sensitivity) | 0.66 | 0.48 | 0.32 | 0.63 | 0.74 | 0.79 | 0.75 | 0.59 |
| Specificity | 0.94 | 0.72 | 0.78 | 0.59 | 0.96 | 0.92 | 0.89 | 0.89 |
| F1 Score | 0.69 | 0.35 | 0.28 | 0.36 | 0.83 | 0.84 | 0.80 | 0.68 |
| Covariates | RSI | RSI | RSI | MACD | EMA | M, R, E | M, R, E | EMA |
| Model | LR | LR | LGBM | GBM | LR | LR | LR | LR |
| | **Indonesia** | | | | **Japan** | | | |
| AUC | 0.96 | 0.92 | 0.88 | 0.80 | 0.95 | 0.91 | 0.87 | 0.83 |
| Balanced Accuracy | 0.84 | 0.82 | 0.79 | 0.67 | 0.77 | 0.74 | 0.77 | 0.78 |
| Precision | 0.78 | 0.77 | 0.49 | 0.43 | 0.43 | 0.40 | 0.42 | 0.44 |
| Recall (Sensitivity) | 0.75 | 0.70 | 0.85 | 0.58 | 1.00 | 1.00 | 1.00 | 0.98 |
| Specificity | 0.93 | 0.93 | 0.73 | 0.76 | 0.55 | 0.49 | 0.54 | 0.58 |
| F1 Score | 0.76 | 0.73 | 0.62 | 0.49 | 0.60 | 0.57 | 0.60 | 0.61 |
| Covariates | RSI | RSI | RSI | RSI | RSI | RSI | RSI | RSI |
| Model | LR | LR | GBM | RF | LR | RF | RF | GBM |
| | **Korea** | | | | **Malaysia** | | | |
| AUC | 0.87 | 0.89 | 0.94 | 0.93 | 1.00 | 0.98 | 0.94 | 0.86 |
| Balanced Accuracy | 0.66 | 0.79 | 0.86 | 0.84 | 0.95 | 0.91 | 0.86 | 0.72 |
| Precision | 0.43 | 0.59 | 0.66 | 0.62 | 0.74 | 0.83 | 0.66 | 0.55 |
| Recall (Sensitivity) | 0.83 | 0.86 | 0.93 | 0.93 | 1.00 | 0.88 | 0.87 | 0.59 |
| Specificity | 0.49 | 0.73 | 0.79 | 0.74 | 0.89 | 0.95 | 0.86 | 0.85 |
| F1 Score | 0.56 | 0.70 | 0.77 | 0.75 | 0.85 | 0.85 | 0.75 | 0.57 |
| Covariates | RSI | M, R, E | M, R, E | EMA | RSI | MACD | RSI | MACD |
| Model | LR | LGBM | LGBM | GBM | LR | LR | LR | LR |
| | **Philippines** | | | | **Singapore** | | | |
| AUC | 0.88 | 0.63 | 0.78 | 0.82 | 1.00 | 0.99 | 0.97 | 0.93 |
| Balanced Accuracy | 0.70 | 0.45 | 0.62 | 0.78 | 0.87 | 0.88 | 0.91 | 0.88 |
| Precision | 0.12 | 0.00 | 0.03 | 0.05 | 1.00 | 1.00 | 1.00 | 0.91 |
| Recall (Sensitivity) | 0.48 | 0.00 | 1.00 | 0.87 | 0.73 | 0.76 | 0.83 | 0.83 |
| Specificity | 0.93 | 0.91 | 0.24 | 0.70 | 1.00 | 1.00 | 1.00 | 0.93 |
| F1 Score | 0.19 | 0.00 | 0.05 | 0.10 | 0.85 | 0.86 | 0.90 | 0.87 |
| Covariates | M, R, E | M, R, E | RSI | EMA | RSI | RSI | RSI | EMA |
| Model | RF | RF | LR | LR | LR | LR | LR | AdaBoost |
| | **Thailand** | | | | **Vietnam** | | | |
| AUC | 0.81 | 0.75 | 0.71 | 0.71 | 0.96 | 0.70 | 0.60 | 0.54 |
| Balanced Accuracy | 0.74 | 0.68 | 0.65 | 0.66 | 0.82 | 0.63 | 0.62 | 0.54 |
| Precision | 0.48 | 0.50 | 0.47 | 0.48 | 0.31 | 0.20 | 0.20 | 0.20 |
| Recall (Sensitivity) | 0.89 | 0.62 | 0.59 | 0.61 | 0.99 | 0.70 | 0.67 | 0.21 |
| Specificity | 0.59 | 0.74 | 0.71 | 0.72 | 0.64 | 0.55 | 0.57 | 0.86 |
| F1 Score | 0.62 | 0.56 | 0.52 | 0.54 | 0.47 | 0.31 | 0.31 | 0.21 |
| Covariates | RSI | RSI | RSI | RSI | RSI | RSI | M, R, E | EMA |
| Model | LR | LGBM | GBM | LGBM | LR | LR | LGBM | AdaBoost |

Source: Authors' calculations.

Note: MACD = moving average convergence divergence; RSI = relative strength Index; EMA = exponential moving average; M, R, E = MACD, RSI, and EMA; LR = logistic regression; GBM = gradient boosting machine; LGBM = light gradient boosting machine; RF = random forest.

## Appendix Table 6. Classification Models Including 1 to 20 lags

| | Horizon (days) | | | | Horizon (days) | | | |
|---|---|---|---|---|---|---|---|---|
| **Metric** | **5** | **20** | **40** | **60** | **5** | **20** | **40** | **60** |
| | **China** | | | | **Hong Kong** | | | |
| AUC | 0.92 | 0.77 | 0.60 | 0.62 | 0.91 | 0.91 | 0.89 | 0.88 |
| Balanced Accuracy | 0.67 | 0.60 | 0.49 | 0.59 | 0.86 | 0.83 | 0.83 | 0.82 |
| Precision | 0.72 | 0.38 | 0.17 | 0.27 | 0.93 | 0.81 | 0.82 | 0.79 |
| Recall (Sensitivity) | 0.38 | 0.31 | 0.21 | 0.49 | 0.76 | 0.82 | 0.81 | 0.80 |
| Specificity | 0.97 | 0.89 | 0.77 | 0.70 | 0.95 | 0.84 | 0.85 | 0.83 |
| F1 Score | 0.50 | 0.34 | 0.19 | 0.34 | 0.84 | 0.82 | 0.82 | 0.80 |
| Covariates | M, R, E | RSI | RSI | MACD | EMA | M, R, E | M, R, E | EMA |
| Model | AdaBoost | LGBM | RF | GBM | LR | RF | LGBM | LGBM |
| | **Indonesia** | | | | **Japan** | | | |
| AUC | 0.96 | 0.92 | 0.88 | 0.80 | 0.95 | 0.91 | 0.88 | 0.84 |
| Balanced Accuracy | 0.86 | 0.82 | 0.79 | 0.75 | 0.77 | 0.76 | 0.80 | 0.78 |
| Precision | 0.80 | 0.77 | 0.49 | 0.43 | 0.42 | 0.41 | 0.47 | 0.43 |
| Recall (Sensitivity) | 0.78 | 0.71 | 0.83 | 0.86 | 1.00 | 1.00 | 0.97 | 0.99 |
| Specificity | 0.94 | 0.93 | 0.74 | 0.65 | 0.53 | 0.52 | 0.63 | 0.56 |
| F1 Score | 0.79 | 0.74 | 0.62 | 0.57 | 0.59 | 0.58 | 0.63 | 0.60 |
| Covariates | RSI | RSI | RSI | MACD | RSI | RSI | RSI | RSI |
| Model | AdaBoost | LR | RF | AdaBoost | LR | RF | GBM | GBM |
| | **Korea** | | | | **Malaysia** | | | |
| AUC | 0.87 | 0.90 | 0.94 | 0.92 | 1.00 | 0.98 | 0.94 | 0.86 |
| Balanced Accuracy | 0.67 | 0.76 | 0.86 | 0.82 | 0.95 | 0.90 | 0.86 | 0.72 |
| Precision | 0.43 | 0.53 | 0.68 | 0.60 | 0.77 | 0.87 | 0.66 | 0.54 |
| Recall (Sensitivity) | 0.83 | 0.88 | 0.93 | 0.93 | 1.00 | 0.84 | 0.85 | 0.58 |
| Specificity | 0.50 | 0.64 | 0.80 | 0.71 | 0.91 | 0.96 | 0.86 | 0.85 |
| F1 Score | 0.57 | 0.66 | 0.78 | 0.73 | 0.87 | 0.85 | 0.74 | 0.56 |
| Covariates | RSI | EMA | M, R, E | EMA | RSI | MACD | RSI | MACD |
| Model | LR | LGBM | GBM | GBM | LR | LR | LR | LR |
| | **Philippines** | | | | **Singapore** | | | |
| AUC | 0.88 | 0.61 | 0.81 | 0.82 | 1.00 | 0.99 | 0.97 | 0.92 |
| Balanced Accuracy | 0.71 | 0.36 | 0.62 | 0.85 | 0.88 | 0.86 | 0.90 | 0.87 |
| Precision | 0.07 | 0.00 | 0.03 | 0.06 | 1.00 | 1.00 | 0.99 | 0.89 |
| Recall (Sensitivity) | 0.57 | 0.00 | 1.00 | 1.00 | 0.77 | 0.73 | 0.82 | 0.83 |
| Specificity | 0.85 | 0.71 | 0.25 | 0.70 | 1.00 | 1.00 | 0.99 | 0.91 |
| F1 Score | 0.13 | 0.00 | 0.05 | 0.12 | 0.87 | 0.84 | 0.89 | 0.86 |
| Covariates | RSI | M, R, E | RSI | EMA | RSI | RSI | RSI | EMA |
| Model | LGBM | AdaBoost | LR | LR | LR | LR | LR | AdaBoost |
| | **Thailand** | | | | **Vietnam** | | | |
| AUC | 0.81 | 0.75 | 0.71 | 0.72 | 0.96 | 0.68 | 0.62 | 0.55 |
| Balanced Accuracy | 0.73 | 0.65 | 0.64 | 0.63 | 0.81 | 0.61 | 0.61 | 0.54 |
| Precision | 0.48 | 0.47 | 0.49 | 0.67 | 0.30 | 0.24 | 0.21 | 0.21 |
| Recall (Sensitivity) | 0.83 | 0.59 | 0.51 | 0.34 | 0.98 | 0.43 | 0.57 | 0.21 |
| Specificity | 0.62 | 0.72 | 0.77 | 0.93 | 0.63 | 0.78 | 0.66 | 0.87 |
| F1 Score | 0.61 | 0.52 | 0.50 | 0.45 | 0.46 | 0.31 | 0.31 | 0.21 |
| Covariates | RSI | RSI | RSI | RSI | RSI | RSI | M, R, E | M, R, E |
| Model | LR | AdaBoost | RF | RF | LR | LR | LGBM | LR |

Source: Authors' calculations.

Note: MACD = moving average convergence divergence; RSI = relative strength Index; EMA = exponential moving average; M, R, E = MACD, RSI, and EMA; LR = logistic regression; GBM = gradient boosting machine; LGBM = light gradient boosting machine; RF = random forest.

**References**

Appel, G. 1985. "The Moving Average Convergence-Divergence Trading Method." Traders Press.

Banco de México. 2013. "Financial Market Stress Index and Its Components." Box 2 in Financial System Report, Mexico City, Mexico, September. https://www.banxico.org.mx/publications-and-press/financial-system-reports/financial-system-reports-supe.html

Babecký, J., T. Havránek, J. Matějů, M. Rusnák, K. Šmídková, and B. Vašíček. 2014. "Banking, Debt, and Currency Crises in Developed Countries: Stylized Facts and Early Warning Indicators." *Journal of Financial Stability* 15: 1–17.

Bank for International Settlements. 2020. *BIS Quarterly Review*. December. https://www.bis.org/publ/qtrpdf/r_qt2012.pdf

Bank of Korea. 2023. "Results of Financial Stress Index (FSI) Reform." Box 7 in Financial Stability Report, Seoul, South Korea, December. https://www.bok.or.kr/eng/bbs/E0000737/view.do?nttId=10082745&menuNo=400205

Bartz, E., T. Bartz-Beielstein, M. Zaefferer, and O. Mersmann, editors. 2023. *Hyperparameter Tuning for Machine and Deep Learning with R: A Practical* Guide. Springer

Bergstra, J., and Y. Bengio. 2012. "Random Search for Hyper-Parameter Optimization." *The Journal of Machine Learning Research* 13, 281–305. https://dl.acm.org/doi/10.5555/2188385.2188395

Borio, C. and M. Drehmann. 2009. "Towards and Operational Framework for Financial Stability: Fuzzy Measurement and its Consequences." BIS Working Papers No. 284. Bank for International Settlements, Basel, Switzerland, June 11. https://www.bis.org/publ/work284.htm

Breiman, L.. 2001. "Random Forests." *Machine Learning* 45 (1): 5–32. https://link.springer.com/article/10.1023/A:1010933404324

Brock, W, J. Lakonishok, and B. LeBaron. 1992. "Simple Technical Trading Rules and the Stochastic Properties of Stock Returns." *The Journal of Finance* 47 (5): 1731–64.

Brunnermeier, M.K. and M. Oehmke. "Bubbles, Financial Crises, and Systemic Risk." In Handbook of the Economics of Finance 2, Part B: 1221–1288: 2013, edited by George M. Constantinides, M. Harris, and Rene M. Stulz. Elsevier, Amsterdam, Netherlands.

Cardarelli, R., S. Elekdag, and S. Lall. 2011. "Financial Stress and Economic Contractions." *Journal of Financial Stability* 7: 78–97.

Cerra, V., M. Hakamada, and R. Lama. 2021. "Financial Crises, Investment Slumps, and Slow Recoveries." IMF Working Paper No. 2021/170, International Monetary Fund, Washington, DC, June 25. https://www.imf.org/en/Publications/WP/Issues/2021/06/25/Financial-Crises-Investment-Slumps-and-Slow-Recoveries-461271

Cevik, E.I., S. Dibooglu, and A.M. Kutan. 2013. "Measuring Financial Stress in Transition Economies." *Journal of Financial Stability* 9 (4): 597–611.

Cevik, E.I., S. Dibooglu, and T. Kenc. 2016. "Financial Stress and Economic Activity in Some Emerging Asian Economies." *Research in International Business and Finance* 36: 127–139.

Chawla, N.V., K.W. Bowyer, L. O. Hall, and W. P. Kegelmeyer. 2002. "SMOTE: Synthetic Minority Over-sampling Technique." *Journal of Artificial Intelligence Research* 16: 321–57. https://www.jair.org/index.php/jair/article/view/10302

Chen, S., and K. Svirydzenka. 2021. "Financial Cycles – Early Warning Indicators of Banking Crises." Working Paper No. 2021/116, International Monetary Fund, Washington, DC, April 29. https://www.imf.org/en/Publications/WP/Issues/2021/04/29/Financial-Cycles-Early-Warning-Indicators-of-Banking-Crises-50257

Christensen, I., and F. Li. 2014. "Predicting Financial Stress Events: A Signal Extraction Approach." Staff Working Paper 2014-37, Bank of Canada, Ottawa, Canada, August. https://doi.org/10.34989/swp-2014-37

Citi. 2015. "Citi Risk Aversion Indicator – Index Methodology. Citi Investment Strategies." Citigroup, October 16. https://investmentstrategies.citi.com/citicis/eppublic/docs/us/Citi_Risk_Aversion_Indicator_Index_Conditions.pdf

Cox, D. R. 1958. "The Regression Analysis of Binary Sequences." *Journal of the Royal Statistical Society: Series B (Methodological)* 20 (2): 215–232.

Davig, T., and C.S. Hakkio. 2010. "What is the Effect of Financial Stress on Economic Activity?" *Economic Review* 95: 35–62.

Duprey, T. 2020. "Canadian Financial Stress and Macroeconomic Condition." *Canadian Public Policy* 46 (S3): S236–S260. https://doi.org/10.3138/cpp.2020-047

Duprey, T., and B. Klaus. 2022. "Early Warning or Too Late? A (Pseudo-)Real-Time Identification of Leading Indicators of Financial Stress." *Journal of Banking and Finance* 138, 106196. https://doi.org/10.1016/j.jbankfin.2021.106196

Duprey, T.. B. Klaus, and T. Peltonen. 2017. "Dating Systemic Financial Stress Episodes in the EU Countries." *Journal of Financial Stability* 32: 30–56.

Fawcett, T.. 2006. “An Introduction to ROC Analysis.” *Pattern Recognition Letters* 27 (8): 861–874.

Freund, Y., R.E. Schapire. 1997. A Decision-Theoretic Generalization of On-Line Learning and an Application to Boosting. *Journal of Computer and System Sciences* 55 (1), 119–139. https://www.sciencedirect.com/science/article/pii/S002200009791504X

Fang, J., B. Jacobsen, and Y. Qin. 2013. “Predictability of the Simple Technical Trading Rules: An Out-of-Sample Test,” *Review of Financial Economics* 23 (1): 30–45.

Friedman J.. 2001. ‘‘Greedy Function Approximation: A Gradient Boosting Machine.’’ *The Annals of Statistics* 29 (5): 1189–1232. https://projecteuclid.org/journals/annals-of-statistics/volume-29/issue-5/Greedy-function-approximation-A-gradient-boosting-machine/10.1214/aos/1013203451.full

Geron, A. 2022. *Hands-On Machine Learning with Scikit-Learn, Keras, and Tensorflow: Concepts, Tools, and Techniques to Build Intelligent Systems*. Third edition. O’Reilly.

Hakkio, S.C. and W.R. Keeton. 2009. “Financial Stress: What Is It, How Can It Be Measured, and Why Does It Matter?” *Economic Review* 94 (Q II): 5–50. https://ideas.repec.org/a/fip/fedker/y2009iqiip5-50nv.94no.2.html

Hamilton, J.D. 1989. “A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle.” *Econometrica* 57 (2): 357–84.

Hamilton, J.D. 1990. “Analysis of Time Series Subject to Changes in Regime.” *Journal of Econometrics* 45: 39–70.

Hamilton, J.D. 1994. *Time Series Analysis*. Princeton University Press.

Hastie, T., R. Tibshirani, and J. Friedman. 2009. *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*. Springer.

Hatzius, J., and S. J. Stehn. 2018. “The Case for a Financial Conditions Index.” Global Economics Paper, Goldman Sachs, New York, New York, United States, July 16. https://www.goldmansachs.com/intelligence/pages/case-for-financial-conditions-index.html

Holló, D., M. Kremer, and M. Lo Duca. 2012. “CISS – A Composite Indicator of Systemic Stress in the Financial System.” Working Paper No. 1426, European Central Bank, Frankfurt, Germany, March 19. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2018792

Hsu, P.., M.P. Taylor, and Z. Wang. 2016. “Technical Trading: Is It Still Beating the Foreign Exchange Market?” *Journal of International Economics* 102: 188–208.

Hubrich, K., and R.J. Tetlow. 2015. “Financial Stress and Economic Dynamics: the Transmission of Crises.” *Journal of Monetary Economics* 70: 100–115.

Illing, M., and Y. Liu. 2006. “Measuring Financial Stress in a Developed Country: An Application to Canada.” *Journal of Financial Stability* 2 (3): 243–265.

International Monetary Fund. 2008. *World Economic Outlook*. April. https://www.imf.org/en/Publications/WEO/Issues/2016/12/31/Financial-Stress-Downturns-and-Recoveries

______. 2017. *Global Financial Stability Report.* October. https://www.imf.org/en/Publications/GFSR/Issues/2017/09/27/global-financial-stability-report-october-2017

______. 2022. *World Economic Outlook.* October. https://www.imf.org/en/Publications/WEO/Issues/2022/10/11/world-economic-outlook-october-2022

Johansson, T., Bonthron, F., 2013. “Further development of the index for financial stress for Sweden.” *Sveriges Riksbank Economic Review* 1: 1–20. https://archive.riksbank.se/Documents/Rapporter/POV/2013/2013_1/rap_pov_artikel_3_130321_eng.pdf

Ke, G., Q. Meng, T. Finley, T. Wang, W. Chen, W. Ma, Q. Ye, and T.-Y. Liu. 2017. “LightGBM: A Highly Efficient Gradient Boosting Decision Tree.” *Advances in Neural Information Processing Systems (NIPS)* 30, 3146–3154. https://papers.nips.cc/paper_files/paper/2017/hash/6449f44a102fde848669bdd9eb6b76fa-Abstract.html

Kim, C.-J., and C R. Nelson. 1999. *State-Space Models with Regime Switching: Classical and Gibbs-Sampling Approaches with Applications.* The MIT Press.

Kim, C.-J., C.R. Nelson, and R. Startz. 1998. “Testing for Mean Reversion in Heteroskedastic Data Based on Gibbs-Sampling-Augmented Randomization.” *Journal of Empirical Finance* 5 (2): 131–54.

Kim, H., W. Shi, and H.H. Kim. 2020. “Forecasting Financial Stress Indices in Korea: A Factor Model Approach.” *Empirical Economics* 59 (6): 2859–98.

Kliesen, K., and D.C. Smith. 2010. “Measuring Financial Market Stress.” Economic Synopses No. 2, Federal Reserve Bank of St. Louis, St. Louis, Missouri, United States, January 15. https://research.stlouisfed.org/publications/economic-synopses/2010/01/15/measuring-financial-market-stress/

Krishnamurthy, A. and T. Muir. 2024. “How Credit Cycles Across a Financial Crisis.” Working Paper No. 3579, Graduate School of Business, Stanford University, Stanford, California, United States, June 1. https://www.gsb.stanford.edu/faculty-research/working-papers/how-credit-cycles-across-financial-crisis

Laeven, L., and F. Valencia. 2020. “Systemic Banking Crises Database II.” *IMF Economic Review* 68: 307–361.

Lo, A.W. 2004. "The Adaptive Markets Hypothesis: Market Efficiency from an Evolutionary Perspective." *The Journal of Portfolio Management* 5 (30): 15–29.

Lo, A.W, H. Mamaysky, and J. Wang. 2000. “Foundations of Technical Analysis: Computational Algorithms, Statistical Inference, and Empirical Implementation.” *The Journal of Finance* 55 (4): 1705–1765.

Lo Duca, M., and T.A. Peltonen. 2013. “Assessing Systemic Risks and Predicting Systemic Events.” *Journal of Banking and Finance* 37: 2183–2195.

López-Salido, D., J. Stein, E. Zakrajšek. 2017. “Credit-Market Sentiment and the Business Cycle.” *The Quarterly Journal of Economics*, 132 (3): 1373–1426.

MacDonald, C., and V. Traclet. 2018. “The Framework for Risk Identification and Assessment.” Technical Report No.113, Bank of Canada, Ottawa, Canada, November.
https://www.bankofcanada.ca/2018/11/technical-report-113/

Marks, C., K. Kliesen, and M. McCracken. 2022. “The St. Louis Fed’s Financial Stress Index, Version 4.” The FRED Blog, St. Louis, Missouri, United States, November 10.
https://fredblog.stlouisfed.org/2022/11/the-st-louis-feds-financial-stress-index-version-4/

Menkhoff, L., and M. P. Taylor. 2007. “The Obstinate Passion of Foreign Exchange Professionals: Technical Analysis.” *Journal of Economic Literature* 45: 936–972.

Monin, P.. 2019. “The OFR Financial Stress Index.” *Risks* 7 (1): 1–21.
https://www.mdpi.com/2227-9091/7/1/25

Misina, Miroslav, and Greg Tkacz. 2009. “Credit, Asset Prices, and Financial Stress.” *International Journal of Central Banking* 5 (4): 95–122.
https://www.ijcb.org/journal/ijcb09q4a5.htm

Murphy, J. J. 1999. “Technical Analysis of the Financial Markets: A Comprehensive Guide to Trading Methods and Applications.” New York Institute of Finance, New York.

Neely, C.J., and P. A. Weller. 2012. “Technical Analysis in the Foreign Exchange Market.” In Handbook of Exchange Rates: 2012, edited by Jessica James, Ian W. Marsh, Lucio Sarno. Wiley Online Books, New Jersey, United States.

Nguyen, T., V. Castro, and J. Wood. 2022. “A New Comprehensive Database of Financial Crises: Identification, Frequency, and Duration.” *Economic Modelling* 108: 105770.

Panopoulou, E., and I. Souropanis. 2019. “The Role of Technical Indicators in Exchange Rate Forecasting.” *Journal of Empirical Finance* 53: 197–221.

Park, C.H., and S.H. Irwin. 2007. “What do We Know About the Profitability of Technical Analysis?” *Journal of Economic Surveys* 21 (4): 786–826.

Park, C.-Y., and R. Mercado. 2014. "Determinants of Financial Stress in Emerging Market Economies." *Journal of Banking and Finance* 45: 199–224.

Pattillo, C., A. Beerg, G. Milesi-Ferreti, and Eduardo Borenzstein. 2000. “Anticipating Balance of Payment Crises – the Role of Early Warning Systems.” Occasional Paper 186, International Monetary Fund, Washington, DC, January 24. https://www.elibrary.imf.org/display/book/9781557758286/9781557758286.xml

Poonpatpibul, C., A. Tan, S.L. Xinyi, and E. Choo. 2018. “Assessing Financial Stress in China, Japan, Korea, and ASEAN-5 Economies.” AMRO Working Paper WP/18-02, ASEAN+3 Macroeconomic Research Office, Singapore, October 5. https://amro-asia.org/assessing-financial-stress-in-china-japan-korea-and-asean-5-economies/

Ramyar, R. 2006. “Essays on Technical Analysis in Financial Markets.” Ph.D. Thesis, City University of London, London, United Kingdom, September. https://www.researchgate.net/publication/335146947_Essays_on_technical_analysis_in_financial_markets

Reinhart, C., and K. Rogoff. 2014. “Recovery from Financial Crises: Evidence from 100 Episodes.” *American Economic Review: Papers and Proceedings* 104 (5): 50–55.

Scott, G., M. Carr, and M. Cremonie. 2016. “Technical Analysis: Modern Perspectives.” CFA Institute Research Foundation, Virginia, United States, November 1. https://rpc.cfainstitute.org/en/research/foundation/2017/technical-analysis

Seabold, S., and J. Perktold. 2010. “Statsmodels: Econometric and Statistical Modeling with Python.” *Proceedings of the 9th Python in Science Conference.* http://conference.scipy.org.s3-website-us-east-1.amazonaws.com/proceedings/scipy2010/seabold.html

Shin, H. S. 2013. “Procyclicality and the Search for Early Warning Indicators.” Working Paper WP/13/258. International Monetary Fund, Washington, DC, December 20. https://www.imf.org/en/Publications/WP/Issues/2016/12/31/Procyclicality-and-the-Search-for-Early-Warning-Indicators-41160

Slingenberg, J.W. and J. de Haan. 2011. “Forecasting Financial Stress.” Working Paper No. 292, De Nederlandsche Bank, Amsterdam, April 17. https://www.dnb.nl/en/publications/research-publications/working-paper-2011/292-forecasting-financial-stress/.

Smith, D., N. Wang, Y. Wang, and E. Zychowicz. 2016. “Sentiment and the Effectiveness of Technical Analysis: Evidence from the Hedge Fund Industry.” *Journal of Financial and Quantitative Analysis* 51 (6): 1991–2013.

Sufi, A., and A. Taylor. 2022. “Chapter 7 - Financial Crises: A Survey.” *Handbook of International Economics* 6: 291–340.

Tan, A.. 2022. “Local Stress Index and Capital Flows at Risk in ASEAN-4 and Korea.” AMRO Working Paper WP/22-06, ASEAN+3 Macroeconomic Research Office, Singapore, December 20. https://amro-asia.org/local-stress-index-and-capital-flows-at-risk-in-asean-4-and-korea/

Urquhart, A., B. Gebka, and R. Hudson. 2015. “How Exactly Do Markets Adapt? Evidence from the Moving Average Rule in Three Developed Markets.” *Journal of International Financial Markets, Institutions and Money* 38: 127–147.

Vašíček, B., D. Žigraiová, M. Hoeberichts, R. Vermeulen, K. Šmídková, and J. de Haan. 2017. “Leading Indicators of Financial Stress: New Evidence. *Journal of Financial Stability* 28: 240 – 257.

Vermeulen, R., M. Hoeberichts, B. Vašíček, D. Žigraiová, K. Šmídková, and J.de Haan. 2015. “Financial Stress Indices and Financial Crises.” *Open Economies Review* 26: 383–406. https://link.springer.com/article/10.1007/s11079-015-9348-x

Wilder, J. Welles. 1978. “New Concepts in Technical Trading Systems.” Trend Research.

Zhang, J. 2013. *CCAR and Beyond*. Risk Books.

[This page is intentionally left blank]

Address: 10 Shenton Way, #15-08
MAS Building, Singapore 079117
Website: www.amro-asia.org
Tel: +65 6323 9844
Email: enquiry@amro-asia.org
**LinkedIn** | **Twitter** | **Facebook** | **YouTube**