HOW TO ASSESS CRISIS RISKS

DEVELOPING A NEW EARLY WARNING SYSTEM AT THE ASIAN DEVELOPMENT BANK

DECEMBER 2025

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Foreword

Economic crises remain a persistent threat even as Asia and the Pacific continues to demonstrate resilience to evolving challenges. The scars of economic crises are deep and change the trajectory of an economy's long-term growth. This can lead to sharp income declines due to lost jobs and wealth destruction amid falling asset prices, and stifle developing economies' ability to reach higher income levels, eradicate poverty, and support livelihoods.

Previous crisis episodes cast a long shadow of lost economic opportunity. A decade after the Asian financial crisis of 1997, for example, cumulative lost output for Indonesia, the Republic of Korea, Malaysia, and Thailand have been estimated to range between 8% and 14% of gross domestic product.

Recognizing the importance of early detection and timely policy responses, the Asian Development Bank (ADB) continues to strengthen its tools for crisis preparedness. This report, *How to Assess Crisis Risks: Developing a New Early Warning System at the Asian Development Bank*, introduces a cutting-edge methodology to predict crises, powered by state-of-the-art machine learning and a rich dataset of over 1,500 indicators, and representing a shift toward more adaptive forecasting. The early warning system integrates traditional macrofinancial metrics with emerging risks such as climate change and geopolitical tensions, and broadens the lens for assessing vulnerabilities. An intuitive companion dashboard to support ADB's internal country risk assessments delivers frequently updated forecasts, making insights accessible for policy dialogue with governments and development partners.

Early identification of financial and economic imbalances is critical for achieving development objectives in Asia and the Pacific. That is why building capacities for crisis detection and effective resolution remains core to ADB's mission. This new tool kit reflects ADB's commitment to continuously upgrade analytical frameworks for crisis preparedness, and to build regional capacities to reduce vulnerabilities that impede progress toward a more prosperous, inclusive, resilient, and sustainable region. Beyond technical capacities, ADB stands ready to support member economies in addressing economic vulnerabilities through innovative financing facilities, policy advice, and knowledge services.

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Abbreviations

ADB	Asian Development Bank
API	application programming interface
AUC	area-under-curve
AUROC	area under the receiver operating characteristic
CDS	credit default swap
COVID-19	coronavirus disease
DFM	dynamic factor model
EWS	early warning system
EWI	early warning indicator
FSI	financial stress index
GDP	gross domestic product
IMF	International Monetary Fund
LLM	large language model
MATR	Measure of Aggregate Trade Restrictions
ML	machine learning
NLP	natural language processing
RFE	Recursive Feature Elimination
ROC	receiver operating characteristic
SVM	support vector machine
US	United States

Executive Summary

The early detection of vulnerabilities leading to the buildup of economic crises is key to preserving growth and prosperity in Asia and the Pacific. This publication lays the conceptual groundwork for a new early warning system launched in September 2025 at ADB. Informed by a thorough review of state-of-the-art modeling approaches, we propose a new, machine-learning-based tool kit. The new tool kit predicts banking, currency, debt, and fiscal crises, with forecasting accuracy improvements by up to 23% to the legacy system. Relative to that legacy system, the tool kit draws on a significantly broader scope of predictor variables at mixed frequencies covering macroeconomic and financial data including international spillovers and asset price volatility, as well as new development challenges ranging from climate change to geopolitical tensions. We employ Shapley values and Shapley regressions to uncover the main determinants of the forecast, allowing identification of levers for preventive and mitigating actions, and to communicate actionable proposals to policymakers.

The analytical framework for crisis forecasting presented in this report is designed to be highly flexible, enabling the integration of additional indicators—such as those derived from text-based sources—and the incorporation of methodological advances in machine learning. The crisis chronologies used for calibrating projections are easily updatable, ensuring alignment with the evolving academic literature.

CHAPTER 1

Introduction

Recent economic and financial crises are a reminder that such events can have devastating impact on long-term growth and prosperity. Interest in identifying vulnerabilities and predicting financial stress has therefore surged. Sufficiently early detection of the buildup of stress gives mitigating measures a greater chance of dampening output losses or avoiding them altogether. Past approaches to predicting crises are challenged by overly adapting models to past observations (model overfitting), in part amplified by the selection of the economic and financial variables used to extract crisis signals.

Aggravated by only a few historical crisis observations available and generally hard-to-predict black swan-type events, the overfitting typically results in an unfavorable resolution of the trade-off between missed crises and false alarms. Given this, advances in machine learning (ML) offer a unique opportunity to improve upon the forecasting performance of past models. ML-based models are well suited to identify vulnerabilities in developing members of the Asian Development Bank (ADB), addressing their scarcity of relevant data and pronounced exposure to nontraditional economic risks like climate change and geopolitical tensions. This study develops a more flexible and comprehensive ML-based framework to predict crises. This new early warning system (EWS) significantly improves the forecasting performance of past models used at ADB.

All types of financial crises have huge economic and social costs (Kaminsky and Reinhart 1999; Hoggarth, Reis, and Saporta 2002; Reinhart and Rogoff 2009a, 2013; Laeven and Valencia 2020) as evidenced by rapid declines in output, employment, and asset prices, and accompanied by increases in government debt and inflation (Dell'Ariccia, Detragiache, and Rajan 2008; Reinhart and Rogoff 2009, 2013). Beyond the financial and economic impact, financial crises tend to have profound effects on the broader society, with examples spanning increased mortality rates (Cutler et al. 2002), reduced public spending on education and health care (Knowles, Pernia, and Racelis 1999), and a marked increase in poverty (Cruces and Wodon 2003; Suryahadi, Sumarto, and Pritchett 2003). Importantly, crises can lead to long-term economic depression, leading to a subsequent recession (Estrella and Mishkin 1996; Kaminsky and Reinhart 1999; Farmer 2012; Barro and Ursúa 2017). The output often does not fully recover from crisis-induced contractions. Thus, repeated crises can lead to permanent output losses, preventing income gaps between low- and high-income economies to close (Cerra and Saxena 2008). Therefore, an early detection of vulnerabilities possibly leading to crises is paramount to intervening with targeted policies to shore up economic resilience and prevent crises.

Crises are often thought of as unpredictable. For instance, senior policymakers took this position for the 2008 global financial crisis (Greenwood et al. 2022). Also, Gorton (2012) states that "crises are sudden, unpredictable events," a view also supported by earlier evidence showing that, while crises are often preceded by weak macroeconomic fundamentals, the predictability is low in light of an element of randomness (Kaminsky and Reinhart 1999; Chari and Kehoe 2003). The claim of non-predictability is rooted in two modeling challenges. First, and more specifically, crises are rare events making it hard to detect patterns and thus model crises. In turn, this can lead to model overfitting, causing often poor out-of-sample forecasting performance. Second, a trade-off between failing to detect crises, and false alarms needs to be managed well (Candelon, Dumitrescu, and Hurlin 2014; Aldasoro, Borio, and Drehmann 2018; Truong et al. 2022). On the one hand, the model needs to be sufficiently accurate so as not to miss crises (type I errors) or signal the crisis only when it is already too late to intervene. On the other hand, the model should not be calibrated too sensitive, leading to excessive false alarms (type II errors). The latter can be costly due to unnecessary policy responses and the buildup of crisis-fighting fatigue.[1] Third, it is difficult to aggregate relevant data into simple-to-use monitoring systems which remain sufficiently generalizable to be relied upon at any time, for every crisis, and in every economy. Fourth, relevant data are often scarce, especially in developing member economies. Fifth, model complexity often prevents distilling clear leading indicators to guide timely policy intervention. Finally, black-swan-type events (e.g., the coronavirus disease [COVID-19] pandemic) are by definition impossible to predict.

While predicting the future remains inherently difficult, recent advances in data science and data availability have eased the pressure on model design. Notably, the literature on forecasting techniques has grown rapidly, improving the accuracy of out-of-sample predictions by adopting state-of-the-art techniques, such as ML (Alessi and Detken 2018; Truong et al. 2022; Casabianca et al. 2022; Liu, Chen, and Wang 2022; Bluwstein et al. 2023). Second, historical records of crises have been collected, allowing new models to be calibrated on more past observations of crises than previously possible (Reinhart and Rogoff 2011; Laeven and Valencia 2013; Jordà, Schularick, and Taylor 2017; Dawood, Horsewood, and Strobel 2017; Laeven and Valencia 2020; Baron, Verner, and Xiong 2021; Moreno Badia et al. 2022). This report provides the context for EWS designs at ADB, outlines general principles, and explains the conceptual steps to construct a new EWS.

1.1 Revamping ADB's Early Warning System amid New Policy Challenges

The 1997 Asian financial crisis was among the worst financial crises of the 20th century for many Asian economies. Indonesia, the Republic of Korea, and Thailand were especially hard hit. Moreover, Asia was strongly exposed to spillovers of the 2008 global financial crisis. The financial distress and volatility were abetted and deepened through a combination of domestic and external factors, including weak internal financial systems, excessive debt, and fixed local exchange rates (Kaminsky and Reinhart 2001; Claessens and Kose 2013; Buckley et al. 2020). Globally, vulnerabilities to crises are on the rise: By 2019, public debt for the average economy stood at 43% of gross domestic product (GDP), up by 10 percentage points since 2008 (Ferrarini et al. 2023). Debt-fueled spending to address the COVID-19 pandemic increased debt levels. As of 2025, public debt to GDP in Asia has reached 47% on average. More recently, supply shocks from Russia's war in Ukraine, geopolitical fragmentation disrupting global supply chains, and aging societies have added to inflation pressures while lowering growth. Climate change and nature loss add to spending pressures, while technological innovations, notably in payment systems, may add to uncertainty. Financial markets' mispricing of such risks can upset financial stability across Asia (te Kaat, Raabe, and Tian, forthcoming). Finally, strong cross-border financial linkages can quickly amplify shocks through global network effects (Park et al. 2020; Rosenkranz and Melchor 2022; Chowdhury et al. 2019).

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[1] Models that raise alarms all the time will predict all crises, but are less useful and cost-effective (Kaminsky et al. 1998). Optimally calibrated models should effectively capture all crisis events while minimizing the occurrence of false alarms. However, given the potential for large long-term output losses, the cost of failing to signal a crisis is considered an order of magnitude higher than that of occasional incorrect alarms (Fuertes and Kalotychou 2007).

This is the context relevant to the aim of the revamped EWS, which is to produce forecasts that are more accurate than legacy systems. The new EWS expands to include a larger set of financial crises and a significantly increased set of explanatory variables. In turn, the new EWS strengthens macroeconomic stability in Asia and the Pacific, and regional policymakers' capacity to identify priorities to safeguard growth. While the new EWS equips policymakers with a better understanding of emerging vulnerabilities, and allows for a timely policy response, the design of appropriate macroeconomic, fiscal, and financial mitigating policies remains outside of the scope of the new forecasting model.

1.2 Crisis Forecasting at ADB: The Status Quo

ADB's legacy crisis forecasting framework was built in 2005 as a statistical tool kit along with a proprietary software, called VIEWS. The tool kit aimed at building regional capacity to detect emerging finance sector vulnerabilities and crises, and to inform the choice of mitigating policy actions. It relied on the signal approach of Zhuang (2005), based on the earlier works of Kaminsky and Reinhart (1999) and Goldstein, Kaminsky, and Reinhart (2000). Relative to the earlier literature, Zhuang (2005) innovated the modeling by (i) including leading indicators tailored to selected Asian economies, (ii) constructing six sector-specific composite indexes for crises prediction, and (iii) adopting a stochastic trend to proxy for the long-term equilibrium level of the real exchange rate. The VIEWS software was used to identify variables strongly associated with crisis episodes and to conduct scenario analyses (i.e., stress testing and forecasting). The framework's latest version covers currency and banking crises, and macroeconomic imbalances.[2] Details on the methodology and steps of the signal approach are discussed in Chapter 3. However, new sources of financial and economic vulnerabilities, as outlined earlier in this introduction, coupled with advances in modeling techniques, suggested a need to revamp ADB's new EWS.

1.3 Innovating ADB's Early Warning System: Machine Learning Models, Shapley Values, and Novel Variables

The new EWS relies on state-of-the-art ML models and innovates the legacy system along several dimensions. First, we augment past datasets by incorporating both standard EWS variables frequently used in the established literature on crisis forecasting such as macroeconomic, fiscal, and balance of payments indicators, and novel variables that reflect broader financial, economic, political, and demographic concepts—capturing new policy challenges not yet considered in established forecasting models. Second, beyond these standard data dimensions, we include cross-border financial linkages and international factors, acknowledging the importance of crisis

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[2] Currency crisis modeling relies on exchange market pressure index constructed as a weighted average of month-on-month percentage changes in the monthly bilateral nominal exchange rate, foreign reserves, and a short-term interest rate, with currency crisis episodes defined as months when the exchange market pressure index exceeds its sample mean by two to three standard deviations. Banking crisis episodes are predefined in VIEWS, with the timeline including events from 1970 to 2022, based on the analysis of Zhuang (2005) and internal ADB research, mostly relying on events-based approach and numerical indicators. Finally, macroeconomic imbalance crisis episodes are also predefined and constructed by considering a negative deviation (of 1.1 standard deviation) of (quarterly or annual) GDP per capita income from its long-term trend.

dynamics and the potential contagion across borders. Third, the ML approach allows us to build in flexibility to navigate nonlinearities, interactions, multicollinearity, and mixed frequencies. Finally, relative to the legacy system, we achieve a significant increase in forecast performance, as documented in Chapter 6. Moreover, running the model requires minimal manual intervention relative to the legacy framework, largely limited to updating some of the data feeding into the forecasting process. Producing forecasts, and the display of results on a dashboard, are fully automatized, allowing for quick, reliable, and transparent access.

The strength of ML models lies in capturing nonlinearities and incorporating information from a significantly expanded set of explanatory variables without specifying functional forms beforehand. The advantages of ML techniques become particularly valuable when forecasting crises in developing member economies, since they offer needed flexibility to manage sparse, unbalanced, and mixed-frequency datasets more effectively. However, the improvement in predictive accuracy and efficiency comes at the expense of model interpretability, as ML models obscure direct associations between outcome variables (crisis probability) and explanatory variables. As a remedy, we draw on so-called Shapley values, a concept recently adopted from game theory, and apply even more recently developed Shapley regressions to ensure that the ML model output remains interpretable, as elaborated in Chapter 5. This allows for a timely design of mitigating measures.

1.4 Early Warning System Design Steps

Next, we provide guidelines for designing effective EWSs. First, it is important to accurately identify the historical crisis chronology. In all the approaches used to classify a crisis, the resulting variable is either discrete, binary, or multinomial. This variable is then generally employed as the outcome variable of the predictive models in the EWS literature (Chapter 3) and used to train ML-based models in-sample (Goldstein, Kaminsky, and Reinhart 2000). Successfully identifying financial crisis episodes involves extending the analysis beyond the most recently recorded crises, encompassing a broader sample (Chapter 2). Second, EWSs require a set of explanatory variables to obtain the crisis prediction. The choice of the explanatory variables is usually guided by economic theory, and it differs according to the type of crisis to be predicted. However, as explained in Chapter 4, it is crucial to include a wide array of early warning indicators (Zhuang 2005; Lo Duca and Peltonen 2013; Truong et al. 2022). Third, the frequency of the data should be selected in line with the research endeavor. For instance, monthly data on several variables are available for fewer economies relative to annual data, and would result in a smaller sample. Conversely, monthly data provide more timely information. Finally, the accuracy of the out-of-sample model predictions is informative about the added value of specific explanatory variables to be included (Chapter 5).

CHAPTER 2

Crises Definitions and Dating

The early warning system (EWS) model performance crucially depends on proper identification of the crisis dates serving as model input. Hence, when building an EWS, the first step is to exactly date crises (Boyd et al. 2019; Baron, Verner, and Xiong 2021; Truong et al. 2022). Adopting wrong dates may either hide the relationship between a crisis event and other variables or generate spurious linkages between crises and these variables (Laeven and Valencia 2020). Records of crises, called chronologies, have expanded significantly.[3] A common approach to date crises is to use macroeconomic and financial data to construct EWS indicators, and denote a crisis as a period when these indicators exceed specific threshold values.[4] Values above the threshold signal upcoming distress and heightened probability of a crisis (Zhuang 2005; Truong et al. 2022). In the next sections, we review the literature on dating crises for each specific type of crisis: for banking, currency, sovereign debt, fiscal conditions, and their interactions, focusing on definitions and state-of-the-art chronologies.

2.1 Banking Crises

The 2008 global financial crisis sparked new interest in dating and predicting banking crises. Notable contributions came from Demirgüç-Kunt and Detragiache (1998), Reinhart and Rogoff (2009a), Schularick and Taylor (2012), Romer and Romer (2017), Laeven and Valencia (2013, 2020), Baron, Verner, and Xiong (2021), and Ahir et al. (2023). Most of these studies have taken different approaches to identifying and dating banking crises, encompassing mainly narrative approaches, policy interventions, quantitative research, or a mix of these.

The narrative approach looks at the narrative sources of events, such as bank runs, policy intervention, or equity declines. Pioneering works are Caprio and Klingebiel (1996); Bordo et al. (2001); Caprio and Klingebiel (2002); Reinhart and Rogoff (2009a, 2009b, 2011, 2013); Schularick and Taylor (2012); and Jordà, Schularick, and Taylor (2017). Authors from the International Monetary Fund (IMF) refined earlier banking crisis chronologies by expanding the criteria to identify substantial policy interventions and adopting quantitative variables (Laeven and Valencia 2013, 2020). The rationale of these studies, with hindsight of the "too big to fail" bank bailouts, was that policy interventions can mitigate bank losses and quantifying the depth of the crisis without them would be difficult. Therefore, a banking crisis is defined as an event meeting not one, but two conditions: (i) significant signs of financial distress in the banking system (e.g., significant bank runs, losses in the banking system, and/or bank liquidations), and (ii) significant policy intervention measures in response to significant losses in the banking system (Laeven and Valencia 2020). When banking sector losses or liquidations are severe, the first criterion is a

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[3] Some relevant studies include Laeven and Valencia 2013, Dawood, Horsewood, and Strobel 2017, Medas et al. 2018, Laeven and Valencia 2020, Baron, Verner, and Xiong 2021, Moreno Badia et al. 2022, and Ahir et al. 2023.

[4] Several approaches to construct such indicators have been proposed in the literature (Cardarelli et al. 2011; Lo Duca and Peltonen 2013; Truong et al. 2022), while Chapter 4 has more details on the main indicators adopted in the literature.

sufficient condition to date a banking crisis. The second criterion is also considered when it is not easy to quantify the degree of financial distress in a banking system. The first year when both criteria are met is considered the crisis start date. This approach ensures that crises are dated at the early signs of significant problems in the banking system. Furthermore, Laeven and Valencia (2020) update the comprehensive global database on banking crises put forward in Laeven and Valencia (2013). The update covers all crisis episodes during 1970–2017.

There are advantages and disadvantages of using these approaches separately (Romer and Romer 2017). Statistical measures are objective and capture variations in financial indicators across crisis episodes in real time but are typically limited to advanced economies and cover short time horizons. Hence, exclusive reliance on them may miss financial disruptions or misidentify crisis episodes. At the same time, one drawback of a focus on a narrative approach is that the source could be idiosyncratic or biased and might miss fundamentals shocks. For these reasons, the most broadly used financial crisis chronologies are based on historical analyses of events combined with statistical indicators (Caprio and Klingebiel 1996; Reinhart and Rogoff 2009a; Laeven and Valencia 2013, 2020; Baron, Verner, and Xiong 2021; Ahir et al. 2023).[5]

Table A1 in Appendix A reports several banking crisis episodes selected for some ADB regional members, taken from Ahir et al. (2023), and compares their index with other banking chronologies. We observe instances in which their index does not capture any financial stress episodes while other approaches do, and vice versa; this discrepancy is dependent on economy coverage, frequency, and time coverage across measures. Overall, several of the studies on dating banking crises note significant similarities with the crisis chronology by Laeven and Valencia (2013, 2020), when the sample overlaps. Given the comprehensive coverage of economies and historical sample period studied in this work, Laeven and Valencia (2020) can be considered among the best state-of-the-art banking crises chronologies available today.

2.2 Currency Crises

A currency crisis could occur for several reasons (Kaminsky 2006). They are often defined as episodes of significant currency depreciation (mostly against the United States [US] dollar), foreign reserve losses, or short-term interest rate hikes (Zhuang 2005). In practice, two methods have been used to date currency crises. The first considers month-on-month changes in exchange rates, foreign reserves, and interest rates in defining crises separately and adopting fixed and subjectively defined thresholds (Frankel and Rose 1996; Zhuang 2005). Many studies adopted this approach. For instance, Laeven and Valencia (2013, 2020) adopt the above criteria considering two thresholds for depreciation: (i) a year-on-year depreciation of at least 30%, and (ii) a depreciation of at least 10% extended from that in the year before, based on the official nominal bilateral exchange rates from the IMF. The second involves constructing an exchange market pressure index (Eichengreen et al. 1995; Kaminsky et al. 1998).[6] A crisis episode is considered to occur in a particular month if this index exceeds its sample mean by a certain number of standard deviations, the choice of which remains arbitrary.

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[5] Baron, Verner, and Xiong (2021) propose a refined chronology of banking crises by adopting a mixed narrative and quantitative approach. They collect (or partially hand-collect from historical newspapers) bank equity returns and back this up with information on banking panics and bank failures from narrative documentation, constructing a dataset of bank equity index returns for 46 advanced and emerging economies going back to 1870. Similarly, Ahir et al. (2023) introduce a new index that builds on Romer and Romer (2017), measuring the intensity of financial stress from the Economist Intelligence Unit word counts and extending the economy coverage to 110 economies, at quarterly frequency, over 1967–2018.

[6] The index was originally proposed by Eichengreen et al. (1995). It is a weighted average of month-on-month percentage changes in a bilateral nominal exchange rate, foreign reserves, and a short-term interest rate.

Other studies have adopted alternative approaches to dating crises (Zhang 2001), and a modified version of the Kaminsky et al. (1998) pressure index, adding more economies and variables (Edison 2003; Lestano and Jacobs 2004; Candelon, Dumitrescu, and Hurlin 2014). More recently, Goldberg and Krogstrup (2023) propose a new index that combines pressures observed in exchange rate adjustments with model-based estimates of incipient pressures that are masked by foreign exchange interventions and policy rate adjustments. However, crisis periods identified through these thresholds have to be cross-validated against the historical evidence of currency crises in each economy (Candelon, Dumitrescu, and Hurlin 2014; Lestano and Jacobs 2004).

2.3 Sovereign Debt Crises

During the 2008 global financial crisis, many governments chose to bail out failing banks, jeopardizing fiscal sustainability (Dawood, Horsewood, and Strobel 2017). This context revitalized the importance of constructing monitoring tool kits for sovereign debt turmoil. Monitoring largely elevated sovereign debt levels relative to pre-pandemic times has become a pressing in Asia and the Pacific (Ferrarini et al. 2023).[7] Manasse et al. (2003) propose an approach to date sovereign debt crises aiming to capture both actual and potential defaults on sovereign debt.[8] This classification has become a standard in the literature on forecasting sovereign debt crises, including Ciarlone and Trebeschi (2005), Fioramanti (2008), Manasse and Roubini (2009), and Dawood, Horsewood, and Strobel (2017).

Laeven and Valencia (2020) construct a database of historical debt crises dates. They date episodes of sovereign debt default and restructuring by relying on information mainly from Sturzenegger and Zettelmeyer (2007) and Cruces and Trebesch (2013), and also report from rating agencies and the media. Adopting this approach, they identify 79 episodes of sovereign debt crises during 1970-2017, 12 of which have taken place since 2007. The study by Laeven and Valencia (2020) is recognized as one of the most thorough chronologies of crises available, making it suitable as the main reference chronology in ADB's new EWS. Laeven and Valencia (2020) also provide an overview of the global coverage of the database covering banking, currency, and sovereign debt crises during 1970–2017, summing to 151 banking crises, 236 currency crises, and 79 sovereign crises.

2.4 Fiscal Crises

Finally, another important set of events includes fiscal crises. These typically entail a significant loss of annual output (Medas et al. 2018). Since the aftermath of the global financial crisis and the European sovereign debt crises of 2010, there is greater interest in how to detect and avoid fiscal crises (Hellwig 2021). However, the previous literature on different EWS for fiscal crises, in general, relies on relatively small samples of advanced and emerging

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[7] The growing importance of domestic debt markets has also sparked interest in the emerging literature on sovereign defaults under domestic law (Beers and de Leon-Manlagnit 2019; Erce et al. 2022).

[8] They define an economy to be in crisis either if it is rated by Standard & Poor's as being in default (i.e., is failing to meet its external obligations) or if it receives an IMF loan in excess of 100% of its quota as an extensive rescue package. Hence, the dependent variable, debt crisis assumes unity if any of the four following events occurs, and is zero otherwise: (i) accumulated interest and/or principal arrears exceed 5% of the outstanding debt, (ii) receiving a loan from the IMF in excess of 100% of the economy quota, (iii) cumulative credit obtained from the IMF increases above 200% of the quota, and (iv) engaging in a debt restructuring (buybacks or reductions) or rescheduling scheme that involves more than 20% of the outstanding debt.

market economies. Only a few studies include low-income economies (Cerovic et al. 2018), even as fiscal crises are found to be more frequent and associated with larger output losses in these economies (Gerling et al. 2017; Moreno Badia et al. 2022). Fiscal crises have been traditionally associated with sovereign debt crises triggered by external default episodes. While sovereign defaults represent one category of significant shocks that can lead to fiscal crises, they do not capture all fiscal crisis episodes. In fact, an economy may experience fiscal distress when large imbalances emerge between inflows (revenues and financing) and outflows (primary expenditures and debt service). These imbalances may lead to a fiscal crisis if the economy cannot adjust its fiscal position suffficiently and quickly (Gerling et al. 2017). Recent literature has started to model fiscal crises independent from defaults (Medas et al. 2018). Over time, the definition has extended to cover large-scale official financing, domestic public debt defaults, and higher inflation (Manasse et al. 2003; Reinhart and Rogoff 2009b, 2011; Erce et al. 2022). In general, the term fiscal crisis describes a period of heightened budgetary distress, resulting in the sovereign taking exceptional measures (Gerling et al. 2017; Hellwig 2021).

Recent studies produced chronologies of fiscal crises (Baldacci et al. 2011; Bruns and Poghosyan 2018; Medas et al. 2018; Moreno Badia et al. 2022).[9] By adopting the above criteria, Medas et al. (2018) expand the economy coverage to 188 economies, over 1970–2015, identifying 439 fiscal crises. Moreno Badia et al. (2022) update the IMF's dataset by Medas et al. (2018) during 1980–2018 by (i) expanding the coverage to sovereign debt yields, (ii) improving the information on domestic arrears, and (iii) checking the quality of data through IMF economy teams. The number of crises closely matches previous data from the IMF, identifying 384 crisis episodes for a sample of 188 economies over 1980–2018. This constitutes the most comprehensive and up-to-date studies of fiscal crises, and is thus used to train ADB's new ML-based EWS.

2.5 Twin Crises

In line with the Anna Karenina principle,[10] idiosyncratic factors tend to favor the buildup of vulnerabilities leading to crises. Still, crises tend to occur simultaneously.[11] Financial crises tend to begin with a private debt overhand, leading to banking crises, and eventually morphing into sovereign debt and/or fiscal crises as private losses are socialized. Laeven and Valencia (2020) document such twin crises. Figure A1 in Appendix A shows an example of crises interaction drawn from Laeven and Valencia (2020) during 1970–2017. Among twin crises, the currency–banking (31) and currency–debt (20) crisis pairs tend to be more common than the banking–debt (3) crisis pair. Triple crises (i.e., simultaneous banking, currency, and debt crises in a given economy) are less common (11) (Laeven and Valencia 2020).[12] Moreover, close to a fifth of fiscal crises happen at the same time as either a banking or currency crisis, and can coincide with both (Medas et al. 2018). The interaction between fiscal and banking crisis can lead to

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[9] The authors define a fiscal crisis as happening if any of the following four criteria is satisfied: (i) credit events associated with sovereign debt (e.g., defaults to private or official creditors, debt restructuring); (ii) exceptionally large official financing including any recourse to large-scale IMF or European Union financial support or financial arrangement with a fiscal adjustment objective and access above 100% of its IMF quota; (iii) implicit domestic public debt default which includes high inflation and the accumulation of domestic arrears proxied by other accounts payable; or (iv) loss of market confidence which captures any year with extreme market pressures (e.g., budgetary and economic distress). A year is considered to be a fiscal crisis year when at least one of the four criteria is met. For more information, details, and subcriteria, see Baldacci et al. (2011), Medas et al. (2018), and Moreno Badia et al. (2022).

[10] Success in complex systems requires avoiding multiple potential points of failure. It originates from the opening line of Leo Tolstoy's novel *Anna Karenina*: "All happy families are alike; each unhappy family is unhappy in its own way."

[11] The mid-2000s was unusual in terms of the low incidence of crises. Before the global financial crisis, banking crises had predominantly been a low- and middle-income economy phenomenon. However, the global financial crisis made it clear that financial crises are an equal threat for economies of any income level (Reinhart and Rogoff 2011).

[12] For more details on how to include such interactions within our framework, see Chapter 4, Section 4.2.

larger economic losses characterized by a deeper decline in growth than stand-alone crises (Laeven and Valencia 2013; Romer and Romer 2017). Moreno Badia et al. (2022) find that in about a third of cases there is an overlap between fiscal and currency crises, mostly in emerging markets or low-income economies. Finally, all types of crises tend to happen around the same time, not only within the same economy, but could also spread to others in "waves."[13] Especially, banking crises are rarely single-economy events, and spread across borders (e.g., across Latin America in the early 1980s; in Asia during the 1997 Asian financial crisis; and more recently, the 2008 global financial crisis).

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[13] Several earlier views tried to explain such waves. For instance, waves can be due to (i) the "fear of floating," that is, many emerging market economies have suffered financial crises due to soft pegs (Calvo and Reinhart 2002); (ii) the interactions between trade liberalization and financial liberalization (Martin and Rey 2006); or (iii) "booms gone bust" (Reinhart and Rogoff 2011; Schularick and Taylor 2012).

CHAPTER 3

Modeling the Early Warning System: A Literature Review

Significant advances have been made in improving crisis forecasting models. This chapter reviews the commonly adopted methods in the literature, contrasting their advantages and disadvantages.

3.1 Signal Approach

Seminal studies on forecasting financial crises relied on the signal approach (Kaminsky et al. 1998; Kaminsky and Reinhart 1999). The approach starts with a selection of indicators that are conjectured to predict crises. For each indicator, a specific threshold value is set based on a specific percentile of each indicator's sample distribution. If an indicator crosses this threshold, a signal is issued, suggesting that a crisis is likely to occur in the forecast time window. Leading indicators are converted into binary variables which take a value of 1 if the actual value of the leading indicator crosses the threshold (warning signal), or 0 if the actual value does not cross its threshold (no warning signal). For technical details on the mechanics, refer to Appendix B.1.

The signal approach is a nonparametric and simple method to use in different contexts (Kaminsky and Reinhart 1999). Its strengths lie in a straightforward assessment of indicators' predictive power, and its flexible use in several crisis prediction applications (Kaminsky et al. 1998; Goldstein, Kaminsky, and Reinhart 2000; Borio and Lowe 2002; Davis and Karim 2008; Baldacci et al. 2011; Savona and Vezzoli 2015; Cerovic et al. 2018). Despite its simplicity, flexibility, and ease to compute and interpret, the signal approach entails several drawbacks. The performance of the approach depends on the leading indicators chosen for each type of crises (Frankel and Saravelos 2012). Modeling the preferences governing the trade-off between false alarms and missing crises can be difficult. Choosing the "optimal" threshold that best balances both types of errors; that is, false alarms and missing crises can be challenging and discretional (Dawood, Horsewood, and Strobel 2017).

Moreover, although the economy may be vulnerable to an impending crisis, many of the indicators may not signal the possibility of distress, either jointly or in good time. A key reason lies in the ad hoc choice of the thresholds, which directly affects the distinction between crisis and noncrisis episodes (see Appendix B.1). Finally, this approach provides no statistical inference. ADB's legacy EWS incorporated in the VIEWS software relies on the signaling approach.

3.2 Discrete Choice Models

Discrete choice or limited dependent variable (logit/probit) models are frequently used. The most common form is a regression with the outcome variable being binary (crisis/noncrisis) and the probability that the event (crisis) occurs being estimated as a function of the factors adopted. From the estimated coefficients of the model, it is possible to retrieve the estimated probabilities of the crisis. An early study adopting this approach is Frankel and Rose (1996), who use a probit model to estimate the probability of currency crises using annual data. The first application of this methodology to banking crises is Demirgüç-Kunt and Detragiache (1998). The literature using this methodology to analyze sovereign debt crises includes Manasse et al. (2003), Fuertes and Kalotychou (2007), and Dawood, Horsewood, and Strobel (2017), and for financial crises comprises Davis and Karim (2008), Barrell et al. (2010), Gourinchas and Obstfeld (2012), Schularick and Taylor (2012), Duca and Peltonen (2013), and Caggiano et al. (2014). Discrete choice models are widely employed for their ease of estimation and interpretation. Moreover, their forecasting ability usually outperforms the signal approach (Berg and Pattillo 1999; Kumar et al. 2003; Fuertes and Kalotychou 2007).

Some disadvantages are that they heavily depend on data availability. Also, these early models do not consider that the chosen indicators could behave differently during tranquil times or postcrisis periods. For instance, the behavior of the indicator is affected both by the crisis itself and the policies undertaken to mitigate it. Combining observations of tranquil periods with those of postcrisis ones into a single (zero) group can lead to "postcrisis bias" (Bussiere and Fratzscher 2006). To overcome this bias, some studies adopted a multinomial logit where the crisis variable is modeled to reflect all three states—i.e., tranquil times, crisis, and after the crisis (Bussiere and Fratzscher 2006; Caggiano et al. 2014). Consequently, some "hybrid" methods combining approaches have been proposed (Fuertes and Kalotychou 2007; Schularick and Taylor 2012; Duca and Peltonen 2013; Savona and Vezzoli 2015), along with Markov switching models to analyze time series data in different regimes or states (Abiad 2003). Overall, discrete choice models are limited by data availability, crisis modeling, and, out-of-sample forecasting performance.

3.3 Dynamic Factor Models

Other advances in EWSs rely on dynamic factor models (DFMs) introduced by Forni et al. (2000) and Forni et al. (2005). In general, DFMs postulate that a small number of latent factors explain the common dynamics of a larger number of observed time series (Stock and Watson 2016). An important development in the literature on DFMs is also the popular mixed frequency generalization and mixed data sampling, or MIDAS, regression models (Bańbura and Modugno 2014).[14] Hence, DFMs are useful to combine information from rich but unbalanced mixed-frequency datasets. This approach is very flexible and allows the assimilation of newly available data, such as financial high-frequency data (Andreou et al. 2010, 2013). For instance, Truong et al. (2022) add data credit default swap into a DFM model, accounting for mixed-frequency data and external, domestic, and global factors applied to the Asian context.

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[14] MIDAS regressions represent a simple, parsimonious, and flexible class of time series models for handling mixed frequency data where the left-hand and right-hand variables of time series regressions can be sampled at different frequencies, i.e., a high-frequency predictor is converted into a set of low-frequency variables (Ghysels et al. 2005, 2006, 2007; Andreou et al. 2010; Pettenuzzo et al. 2016); and see Foroni and Marcellino (2013) for an exhaustive survey. Reverse Unrestricted (RU)-MIDAS regressions are adopted to forecast high-frequency variables using low-frequency variables (Foroni et al. 2018).

However, DFMs also come with limitations. One criticism is that the factors are estimated from extensive panel data and do not take full advantage of data hierarchy—for instance, ignoring economy-specific structures, heterogeneity between income levels, and nested relationships (e.g., indicators within economies over time) that may be crucial for interpretation (Wang et al. 2022). To overcome this problem, Truong et al. (2022) develop EWSs for financial crises with a focus on small open economies using DFMs with a multilevel factor structure applied to panel data. However, DFMs suffer limitations as overly simplified models, with the exact structure of factor interdependencies being chosen by prior knowledge rather than analytical detection, leading to potential model mis-specification (Wang et al. 2022), significant estimation bias, and poor model fit (Francis et al. 2017). In addition, DFMs rely heavily on the availability and quality of economic and financial data, and are based on assumptions about the underlying structure of the data. Also, they typically use lagged information to make predictions but do not consider contemporaneous shocks. Moreover, some DFMs can be computationally intensive, particularly when dealing with large datasets. Finally, in attempting to capture all potential sources of variation, DFMs can become overly complex, risking model overfitting and thus weak out-of-sample predictive performance (Stock and Watson 2016).

3.4 Machine Learning Approach

More recently, a large effort among academics and policymakers has seen the development of machine learning (ML) methods. ML can be defined as a subset of artificial intelligence in the field of computer science that draws on statistical techniques to give the model the ability to "learn" from the data without functional forms between variables being explicitly programmed (Samuel 1959).[15] In general, ML is a data-mining tool kit able to analyze complex datasets, fit multifaceted and flexible functional forms to the data, and find functions that perform well out of sample (Mullainathan and Spiess 2017). ML approaches have been growing fast and are applied extensively for predicting any type of financial crisis. Among several, Bluwstein et al. (2023), Samitas et al. (2020), and Tölö (2020) for financial crises; Duttagupta and Cashin (2011), Alessi and Detken (2018), and Wang et al. (2021) for banking crises; Manasse et al. (2003), Manasse and Roubini (2009), and Savona and Vezzoli (2015) for sovereign debt crises; Hellwig (2021) and Moreno Badia et al. (2022) for fiscal crises; and Lin et al. (2008) and Sevim et al. (2014) for currency crises.[16] More details on some of the most common ML approaches were reported in Appendix B.2.

The appeal of ML methods is that they overcome several well-known challenges in the literature on EWSs. First, they allow us to analyze complex and large datasets, circumventing the risk of model overfitting.[17] Second, ML approaches allow the inclusion of a large number of variables also taking into account crisis interactions, and even transformations of these variables and/or their lagged values, thus including predictors which could be redundant and highly correlated.[18] The more candidate predictors we add, the lower the risk that variable selection is biased

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[15] ML tasks are usually divided into two groups. The first is "supervised learning," in which the models are presented with example inputs and their desired outputs, given by a "teacher," where the goal is to learn a general rule that maps inputs to outputs. The second is the "unsupervised learning," where no labels are given to the learning algorithm, leaving the ML on its own to find structure in its input, or to discover hidden patterns in data (Athey 2018; Samitas et al. 2020). Other sub-families of approaches derived from these two main groups have also been developed (e.g., partial signal, multiple classes, continuous supervised approach).

[16] ML applications are well established in the finance literature, especially on asset pricing (Gu et al. 2020; Chen et al. 2023), or for a survey (Nagel 2021), forecasting stock market (Gogas et al. 2018; Ticknor 2013; Rather et al. 2015); and measuring contagion among financial time series (Zahedi and Rounaghi 2015; Göcken et al. 2016).

[17] Model underfitting and overfitting create a well-known trade-off for any predictive modeling exercise; however, ML algorithms try to optimally solve this trade-off, making them very appealing for crises predictions (Hellwig 2021).

[18] For instance, Hellwig (2021), predicting financial crises, simultaneously includes the same variable in current levels, lags, and changes over time at various frequencies, reaching 748 individual series.

by our own judgment. Third, the dynamics of financial crises are mostly complex, not well captured in linear models (Demirgüç-Kunt and Detragiache 1998; Hellwig 2021; Bluwstein et al. 2023). The clear advantage of ML approaches is their ability to learn nonlinearities and interactions directly from the data without pre-specification (Cesa-Bianchi et al. 2019; Goulet Coulombe et al. 2022; Bluwstein et al. 2023). In addition, the advancements of ML techniques pave the way for a recent strand of economic literature which leverages the power of large language models (LLMs) and natural language processing (NLP) for various applications, including economic time series forecasting (Carriero et al. 2024). Finally, the overall consensus in the ML literature is that most ML models outperform several other methods, including the signal approach, discrete choice models, and DFMs in out-of-sample predictions (Manasse and Roubini 2009; Sevim et al. 2014; Alessi and Detken 2018; Beutel et al. 2019; Tölö 2020; Fouliard et al. 2021; Hellwig 2021; Liu, Chen, and Wang 2022; Casabianca et al. 2022; Bluwstein et al. 2023).[19]

However, ML techniques can be typically complex and difficult to interpret, especially when interpreting the importance of explanatory variables (Bluwstein et al. 2023). This limitation makes ML models appear as "black box," obscuring insights for policymakers on which actions to take to avert crises. For the same reason, economic mechanisms underpinning the prediction cannot be easily inferred, although none of the statistical techniques to forecast crises can prove causality.

To overcome these difficulties in interpretation and classification of important variables, several authors recently started to augment ML methods with Shapley values (Liu, Chen, and Wang 2022; Buckmann et al. 2022; Chan-Lau et al. 2023; Bluwstein et al. 2023; Casabianca et al. 2022). Use of Shapley values for ML models interpretation is borrowed from the cooperative game theory literature (Shapley 1953; Strumbelj and Kononenko 2010). In that literature, Shapley values are used to calculate the payoff distribution across a group of players, whereas in the context of crisis prediction, they can be used to calculate the marginal contribution from including different predictors in the models. This allows crisis probability to be decomposed into the sum of contributions from each predictor (Shapley values) (Bluwstein et al. 2023). Augmenting the ML output with Shapley values allows us to identify which variables are driving the model prediction, to quantify their marginal contribution and the direction of the effect on the crisis probability.

Shapley values are superior to other importance measures given the set of appealing analytical properties thanks to their origin in game theory (Lundberg et al. 2020; Bluwstein et al. 2023), especially local accuracy and consistency. The first assumes that the sum of Shapley values across all variables equals the difference between the model's prediction for a specific variable and the average prediction; the second assumes that the importance of the variables' rankings is preserved when comparing models or subsets of variables. In other words, Shapley values guarantee consistency; that is, a consistent measure of variable importance preserves the relative importance between variables across situations where such a ranking is imposed (Buckmann et al. 2022). In other words, relative importance does not measure importance for individual predictions and cannot be used to identify functional relationships learned by the models, which are important for nonlinear models (Bluwstein et al. 2023). In addition, the Shapley value framework is model agnostic and can be applied to any ML model (Bluwstein et al. 2023; Buckmann et al. 2022). Finally, the adoption of Shapley values allows for testing the statistical significance of the predictors within each model, and to identify the key economic drivers of our models and test them statistically (Bluwstein et al. 2023; Buckmann et al. 2022). Overall, Shapley values allow us to unpack the relationship and thus the economic reasoning behind the explanatory variables entering the ML, and estimated crisis probabilities instead of accepting the "black box" of ML models (Bluwstein et al. 2023). More details on the computation of the Shapley values follow in Chapter 5, Section 5.4.

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[19] One exception is Beutel et al. (2019) who show that a variety of ML approaches are typically outperformed by the logit approach in recursive out-of-sample evaluations.

Finally, another advantage of Shapley values is that it is possible to test the statistical significance of the predictors and to identify the key drivers (e.g., coefficients interpretation, statistical inference) (Buckmann et al. 2022; Bluwstein et al. 2023). The tool kits which allow us to conduct such tests are Shapley regressions (Joseph 2019). This regression framework transforms the complex form of predictors in the ML model into a simple form that can be used to reflect the statistical significance of the predictors, and in making statistical inference of the coefficients. Chapter 5, Section 5.5 and Appendix D.1 describe Shapley regressions and coefficients in detail.

CHAPTER 4

Standard and Novel Early Warning Indicators

Several of the approaches mentioned in Chapter 3, heavily depend on the choice of explanatory variables. Machine learning (ML) techniques are better suited to handle a large number of variables to timely detect crises. They can also draw on a large set of variables and their transformations without concern about multicollinearity, overfitting, and handling of mixed frequencies. However, previous early warning system (EWS) models have predominantly relied on a limited set of ad hoc selected variables. Relying solely on standard variables may not adequately capture emerging risks or lend itself to forecasting a broader spectrum of crises. Thus, an expanded set of variables is required to cover increasingly relevant, primarily non-economic and emerging risks, all while still enhancing out-of-sample forecasting. In this chapter, we briefly review the standard variables and then portray the novel variables that could be included in the new EWS. A detailed list of the proposed variables is in Appendix C.

4.1 Standard Early Warning Indicators

Several variables have become standard in the literature on forecasting crises. The selection of variables typically depends on the methodology, the crisis type, the region or economies of interest, and the sample period. Variables are often categorized into (i) economy specific and (ii) global (Caggiano et al. 2014; Dawood, Horsewood, and Strobel 2017; Aldasoro, Borio, and Drehmann 2018; Laeven and Valencia 2020; Moreno Badia et al. 2022; Truong et al. 2022). In the first group, data covers macroeconomic fundamentals, banks and household behavior, foreign exchange and international capital movements, equity and debt markets, external debt exposure, and the external sector. The second group comprises variables tracking, for instance, the US and global financial conditions, global macroeconomic variables like commodities and energy, the global stock market, investor sentiment, and global credit. We discuss some of the most common early warning indicators for specific crises in Appendix C, and present a comprehensive list of standard variables, with their main data sources and its references (see Table C1). The details and definitions of the variables, and our calculations, are based on related literature. We refer to Ali Abbas et al. (2011), Hellwig (2021), Mbaye et al. (2018), Medas et al. (2018), and Moreno Badia et al. (2022) for debt and fiscal variables; Aldasoro, Borio, and Drehmann (2018), Caggiano et al. (2014), and Truong et al. (2022) for banking variables; and Dawood, Horsewood, and Strobel (2017) for sovereign debt and credit markets. Some of the variables and indicators we adopt are comprehensively listed in the online appendixes of Hellwig (2021) and Moreno Badia et al. (2022).

4.2 Novel Early Warning Indicators

New and emerging risks to macrofinancial stability, as well as the big data capacities of ML models, require forecasting models to account for an expanded set of variables. We go beyond traditionally covered macroeconomic indicators and include a wide range of additional factors, discussed in the following sections. A detailed list of all the novel variables covered in ADB's new EWS is reported in Appendix C, Table C2.

Crisis History and Interaction Variables

The data-lead ML approach to forecasting allows the inclusion of many more time series, including on other economies' past crises of the same and different type, such as those captured by variables like the number of economies currently in crisis and the time passed since the last crisis, both in the economy in question and in others. Following Medas et al. (2018) and Hellwig (2021), we model this history through dummy variables. Including these interactions is crucial for accounting for contagion, time dependence, and twin-crisis dynamics (as discussed in Chapter 2, Section 2.5). These variables help reflect that crises often spread across economies and regions, as well as recur over time, helping the model to anticipate systemic regional or global vulnerabilities and spillovers.

Climate Change and Physical-Hazard-Driven Disasters

Climate change has profound repercussions for economic growth through the various channels, as discussed in Batten (2018) and Bansal et al. (2019), and may jeopardize financial stability through sudden realizations of climate risks (for more details, see the discussion by the Financial Stability Board 2020). Notably, developing economies are particularly exposed to climate risks, entailing large financing needs for mitigation and adaptation. A wide range of variables in our model covers climate risks such as global disaster data from CRED's EM-DAT; economies' ranks based on the human and economic impacts of extreme weather events; the gain scores and readiness indexes from the Notre Dame Global Adaptation Initiative and the IMF; various climate scores from Bloomberg covering carbon transition, power sector transition, and climate policy; and several climate attention indexes (see Table C2 in Appendix C for further details and sources).

Political Risk

The relation between economy-specific political risk and financial outcomes is well studied, especially for developing economies (Chan and Wei 1996; Diamonte et al. 1996; Lehkonen and Heimonen 2015; Gozgor 2018). We include several variables to gauge political risk in our model, spanning several elements, such as polity score, governance indicators, election indexes, and political stability scores collected from various sources.

Geopolitical Fragmentation

We also include variables accounting for geopolitical risk, such as the geopolitical risk index by Caldara and Iacoviello (2022). Moreover, Aiyar et al. (2023) introduced the term *geoeconomic fragmentation* to describe a policy-driven reversal of global economic integration due to national strategic considerations taking precedence (e.g., national security, drive for self-reliance, emphasizing domestic economic policy objectives). This paradigm shift has profound implications for global financial stability, cross-border investments, international payment systems, and asset prices (Aiyar et al. 2023; Campos et al. 2023; IMF 2025). For instance, geoeconomic fragmentation affects ADB's developing members through heightened volatility in commodity trade (Alvarez et al. 2023). New restrictions on commodities trade can cause large price volatility for many commodities, directly affecting trade balances and inflation in commodity-importing economies. To include trade restrictions in our model, we use a new Measure of Aggregate Trade Restrictions (MATR) developed by Estefanía-Flores et al. (2022).[20] The index strongly correlates with other measures of trade (e.g., Trade Restrictions Index by the World Bank), but provides a longer time series and broader economy coverage.

Global Financial Factors

We include variables measuring external threats to domestic macrofinancial stability. First, we include the Vulnerability Index by Dabla-Norris and Gündüz (2014) to assess vulnerabilities to growth declines. Second, the US monetary policy shocks are well documented to induce co-movements in international financial variables affecting the *global financial cycle* (Miranda-Agrippino and Rey 2020).[21] In fact, the US dollar is an important funding currency for financial intermediaries and a large portion of portfolios worldwide. Asia's global financial integration and US dollar dependence amplify capital flow volatility in Asia and the Pacific, making the region prone to spillovers from the US financial system (ADB 2024). Specifically, we include the global factor proposed by Miranda-Agrippino and Rey (2020), explaining 20% of the variance in the global financial cycle capturing international asset prices and capital flows. Figure C1 in Appendix C illustrates this factor over time. Third, and closely related, recent work by Adler et al. (2024) provides a new dataset of foreign exchange intervention covering a large number of economies since 2000 at monthly and quarterly frequencies. Estimates account for a wide range of central bank operations, including both spot and derivative transactions, improving upon traditional proxies based on changes in reserves.

Economic and Policy Uncertainty

A broad literature on financial markets, growth, and sovereign risk highlights the importance of uncertainty (Bloom 2009; Jurado et al. 2015; Danielsson et al. 2018; Ferńandez-Villaverde et al. 2011; Ludvigson et al. 2021; Baruník et al. 2024). The main channel for uncertainty to affect economic outcomes is by inducing firms to postpone or cancel planned investments, financial institutions to lend more cautiously, and consumption to fall due to reduced consumer sentiment. The literature determines uncertainty in two broad ways: First, a text-to-data approach is applied to newspaper articles seeking for uncertainty-related search terms, then cast into indexes measuring uncertainty for various subcategories such as uncertainty in economic, monetary, trade, and climate policies. Baker, Bloom, and Davis (2016) constitute the seminal work on a series of news-based policy uncertainty measures, starting with the Economic and Policy Uncertainty Index.[22] One of its most recent variants constructed by Ahir, Bloom, and Furceri (2022) constitutes a World Uncertainty Index using textual analysis from economy reports from the Economist Intelligence Unit. Its strengths are a wide geographic coverage of 143 economies, starting in

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[20] Using data from the IMF's Annual Report on Exchange Arrangements and Exchange Restrictions. MATR measures how restrictive official government policy is towards the international flow of goods and service, and spans over the last 70 years and includes up to 157 economies. It covers tariffs, nontariff barriers, and restrictions on requiring, obtaining, and using foreign exchange for current transactions. MATR is related to five different policy dimensions: (i) exchange measures; (ii) arrangements for payments and receipts; (iii) imports and imports payments; (iv) exports and exports proceeds; and (v) payment and proceeds from invisible transfers and current transfers.

[21] See also Avdjiev et al. (2019) and Avdjiev et al. (2019) for studies documenting the role of the US dollar itself as an important global factor, and the triangular relationship between (1) the strength of the US dollar, (2) cross- border bank flows and (3) real investment; suggesting that a stronger US dollar has real macroeconomic and trade effects.

[22] From the Baker, Bloom, and Davis (2016) website, other indexes measuring several risks can be extracted (e.g., Energy Uncertainty Index). For others, see Table C2 in Appendix C.

1952, coupled with cross-economy comparability due to the Economist Intelligence Unit reports as single source of information. The index captures uncertainty related to economic and political events, both near-term and long-term risks. Second, uncertainty in economic and financial variables is measured through their volatility (Bloom 2009; Jurado et al. 2015; Ludvigson et al. 2021).

Financial Stress Index

Financial stress indexes (FSIs) have been commonly used to monitor financial crisis risk (Cardarelli et al. 2011; Lo Duca and Peltonen 2013; Truong et al. 2022). Several approaches to construct FSI have been proposed in the literature, spanning different economic regions, variables included, and methodologies. In general, FSI is constructed as a variance-weighted average of variables summarized in subindexes. The latter are specific to various financial market segments such as banking, debt, equity, and foreign exchange. Illing and Liu (2006) were one of the first to compute FSI for Canada; many other studies followed—for instance, Hakkio et al. (2009) for the US, Cardarelli et al. (2011) for 17 economies, Hollo et al. (2012) for the euro area, and Park and Mercado Jr. (2014) introduced an FSI for Asia and the Pacific (ADB's FSI). FSIs are usually computed at a higher frequency (e.g., daily, monthly), and thus require access to financial market data providers. Poor financial market data coverage of emerging and developing economies historically meant that FSIs could only be made available for advanced economies. Advancements in analytics have overcome this limitation. For instance, recent work by Ahir et al. (2023) uses a text-to-data approach to construct FSIs for 110 economies at quarterly frequency for 1967–2018. Figure C2 in Appendix C illustrates this particular FSI. Additional measures of financial stress are proxied by the CBOE VVIX index, as well as by measures of aggregate, upside, and downside volatility computed following Barndorff-Nielsen, Kinnebrock, and Shephard (2008); Feunou, Jahan-Parvar, and Okou (2018); Kilic and Shaliastovich (2019); and Bevilacqua, Morelli, and Tunaru (2019).

International Spillovers and Network Effects

A broad literature discusses the salience of international spillovers and networks (Diebold and Yılmaz 2014; Alter and Beyer 2014; Gertler and Karadi 2015; Minoiu et al. 2015; Passari and Rey 2015; Constantin et al. 2018; Miranda-Agrippino and Rey 2020; Baruník et al. 2022, 2024). Several studies investigated the rapidly changing interconnectedness of Asian financial markets within the global markets, especially amid the Asian financial crisis and the global financial crisis, in shaping such networks (Chowdhury et al. 2019; Park et al. 2020; Rosenkranz and Melchor 2022; Khan et al. 2023). These works emphasize an intensification of the interconnectedness of the Asian economies among themselves and among other global economies over the past 2 decades.

Figures C3 and C4 (Appendix C) illustrate examples of total spillovers and net spillovers index from a study by Khan et al. (2023) applied to the Asian context. The total spillover index captures the overall level of risk or volatility transmitted across the entire system, in this case, across the Asian region. The net spillover index measures each economy's role in the system by measuring whether it is a transmitter or receiver of shocks and volatility. The latter is an economy-specific measure that can provide more information on crisis risk at the individual economy level, and accounts for economies' heterogeneous importance as source and amplifier of international spillovers. An intensification of spillovers or network linkages indicates stronger interconnections between economies, which can, in turn, facilitate the transmission of shocks across borders. This increased interconnectedness raises the likelihood of systemic disruptions and the risk of financial crises. The new EWS draws on such measures to account for economies' interconnectedness. We construct spillover measures using financial variables (e.g., stock returns, volatility, exchange rates, credit default swaps) following Diebold and Yılmaz (2014) and Baruník et al. (2022). Spillover measures for different asset classes capture a broader spectrum of network spillover risk in our model, covering equity, foreign exchange, and sovereign debt markets.

CHAPTER 5

New Early Warning System Workflow Implementation

This chapter illustrates the main steps in the workflow for ADB's new early warning system (EWS). The suggested steps comprise data and model selections, producing out-of-sample forecasts, computing Shapley values for predictors, and finally assigning economic significance through Shapley regressions.

5.1 Data Selection

Data selection is a challenging step in the construction of any EWS. Some studies in forecasting literature recommend selecting an ad hoc small set of predictors based on prior knowledge (Armstrong et al. 2015; Buckmann et al. 2022; Bluwstein et al. 2023). However, the small set of variables may lead to forecasting underperformance. Other studies forecast with large sets of variables (Medeiros et al. 2021). This often makes it hard to associate predictors with forecasts. Another common approach to increase the predictive power is to calibrate the model on common factors representing key information contained in the input variables (Stock and Watson 2002). However, such factors conceal the underlying variables summarized into the factors, impeding causal associations between predictors and forecasts.

Recent studies in machine learning (ML) are agnostic about the form in which variables are included in the model (e.g., *levels, first diff, lags*) (Hellwig 2021; Moreno Badia et al. 2022). While many of these predictors are likely highly correlated and thus potentially redundant, the ML approach can cope with such collinearity. This reduces the selection bias previously introduced through ad hoc choices of the presumably correct variable form. In practice, the ML employs Recursive Feature Elimination (RFE) to select the variables with the highest predictive power. For this, the algorithm iteratively estimates the ML model, drops the least important variables, and re-estimates the model until (cross-validated) forecast performance stops improving (Hellwig 2021; Moreno Badia et al. 2022).[23] This dimensionality reduction also reduces computational power needs and thus speeds up estimations while improving the ability to interpret results. The RFE applies the same ML algorithm for both the feature selection process and the out-of-sample forecast. However, during the RFE, the model is iteratively trained and evaluated on different subsets of variables, with the least important ones progressively removed based on their contribution to the model's forecast performance. The final model for the out-of-sample forecast is then built using the selected subset of variables, balancing a limited number of predictors with the highest possible performance.

A few data challenges need to be discussed in more detail. First, small samples can lead to overfitting. Hellwig (2021) proposes an approach to enhance or preserve the sample size by pooling economies with heterogeneous features into appropriately delimited larger samples instead of estimating separate models for different economies.

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[23] Specifically, for the EWS implementation, a random forest model for RFE is employed, but other classifiers can also be defined for performing the RFE (Hellwig 2021). The full method is described in Breiman (2001).

For instance, observations can be pooled by the economy's income level. Second, forecasts can be constrained by missing data. To this end, Hellwig (2021) proposes imputation to avoid the loss of observations and obtain greater accuracy. However, imputations come with a trade-off. While imputations fill in missing observations and thus increase the sample size for improved forecasts, the filled-in values can also add noise, reducing in-sample fit and leading to biased forecasts (Hellwig 2021). See also Thomas and Rajabi (2021) for a survey of imputation techniques.

5.2 Model Selection

Empirical evidence suggests that some ML models work better for specific prediction problems (Fernández-Delgado et al. 2014). Choosing the appropriate model ex ante, however, is not straightforward as a function of data characteristics. This is why the studies tend to apply several models to the same problem, then comparing forecasting performance among the models and against a benchmark model as established by prior literature (Fouliard et al. 2021; Liu, Chen, and Wang 2022; Bluwstein et al. 2023).[24] The performance metric to compare the models can be, for instance, the trade-off between type I and II errors when predicting a binary (crisis) variable (Buckmann et al. 2022). Following Buckmann et al. (2022) and Liu, Chen, and Wang (2022), the new EWS pursues this multi-model approach, comparing, for example, random forest, decision tree, and artificial neural network models, with details on these models given in Appendix B.

5.3 Out-of-Sample Prediction and Model Evaluation

Having filtered for the variables and model(s) likely to yield high predictive power, the workflow proceeds to predict the probability of financial crises out of sample. This requires choosing an in-sample training period and out-of-sample forecasting horizons. These periods are subsequently cross-validated.[25]

Next, the out-of-sample predicting performance of different models is evaluated in order to select the best and discard the worst-performing models. To do so, many studies compare the models' forecast accuracy. The area-under-curve (AUC) value is a common evaluation index, based on the receiver operating characteristic (ROC) curve (Fouliard et al. 2021; Hellwig 2021; Liu, Chen, and Wang 2022; Bluwstein et al. 2023). The ROC curve describes the performance of a binary prediction model as a function of the proportion of crises correctly predicted and incorrectly predicted (false alarms). The ideal model should achieve a high true positive rate (close to 1) and a low false positive rate (close to 0). Ranking models by AUC allows for choosing the best-performing ones. Table 5.1 provides an example of ranking models by AUC from the Liu, Chen, and Wang (2022) paper. For instance, among the ML models, random forests, neural networks, and support vector machines were particularly successful, with the out-of-sample predictive accuracy stable above 80% across crises predicted.

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[24] For instance, Fouliard et al. (2021) combine several predictive models, including regression and decision trees, to forecast financial crises in seven economies between 1985 and 2018. Liu, Chen, and Wang (2022) develop EWS for financial crises based on the logit model and a battery of ML methods, finding that the out-of-sample performance of the ML models, especially the random forest, gradient boosting decision tree, and ensemble models, outperform the logit model. Bluwstein et al. (2023) develop a range of models to predict financial crises by applying various ML algorithms on 17 economies during 1970–2016, finding that ML models mostly outperform logit in the out-of-sample prediction of crises.

[25] Cross-validation entails randomly dividing the available data into k groups, known as folds, equal in size. A model is calibrated using the data in k − 1 groups (the training set) and evaluated in the remaining group (the test set). Several recent studies use this validation technique (Holopainen and Sarlin 2017; Hellwig 2021; Bluwstein et al. 2023).

Table 5.1: Out-of-Sample Predictive Area-Under-Curve Values of Machine Learning Models

	Financial Crisis	Currency Crisis	Banking Crisis	Debt Crisis
k-NN	0.8585	0.8073	0.8301	0.8589
SVM	0.8502	0.8699	0.8810	0.8782
ANN	0.8154	0.8149	0.7277	0.6732
Decision Tree	0.7026	0.7959	0.6695	0.6282
AdaBoost	0.8367	0.8470	0.8534	0.8581
RF	0.9013	0.9020	0.9015	0.9207
GBDT	0.9009	0.9162	0.9003	0.9073

ANN = artificial neutral network, GBDT = gradient boosting decision tree, NN = neutral network, RF = random forest, SVM = support vector machine.

Note: This table shows the out-of-sample predictive area-under-curve values across the adopted machine earning models across different crisis types predicted from Liu, Chen, and Wang (2022).

Source: Liu, Chen, and Wang (2022).

5.4 Computing Shapley Values

Next, we elaborate on the computation of Shapley values referred to earlier. Shapley values indicate predictors' contribution to the crisis forecast, and are thus informative about the relative economic importance of variables. Shapley values also serve to check for forecast consistency across different ML models, complementing comparisons on forecast accuracy. The greater the alignment among models regarding the use of predictive variables, the higher the confidence the modeler can have in the chosen models' ability to forecast crises. Shapley values play a pivotal role in providing such an indication about model robustness and reliability (Liu, Chen, and Wang 2022; Bluwstein et al. 2023).

The concept of Shapley values applied here is derived from game theory. There, Shapley values gauge the marginal contribution of a player in a coalition of players to the overall payoff. The Shapley value represents the mean of the marginal contribution of a player across varying coalitions. For the EWS, the player corresponds to the predictor variables and their combinations used in various models. Thus, Shapley values are calculated by traversing all possible combinations of variables in the model, then calculating the mean of the marginal contribution of each variable.[26] To achieve stability, Shapley values are averaged across *n* cross-validation iterations, weighting by the number of permutations in groups of variables (Bluwstein et al. 2023). This process will aid interpretability by computing economy-time specific Shapley values over several randomly varying indicator combinations in a similar procedure to the k-fold cross-validation. From these values, the final mean absolute Shapley values for each indicator are computed.

Figure 5.1 illustrates the use of Shapley values for financial crisis predictions from Bluwstein et al. (2023). The figure shows the mean Shapley values of variables across different ML models. The yield curve slope and credit growth (both domestic and global) seem to be the most important variables in explaining the crisis forecast in the specific setting described in Bluwstein et al. (2023).

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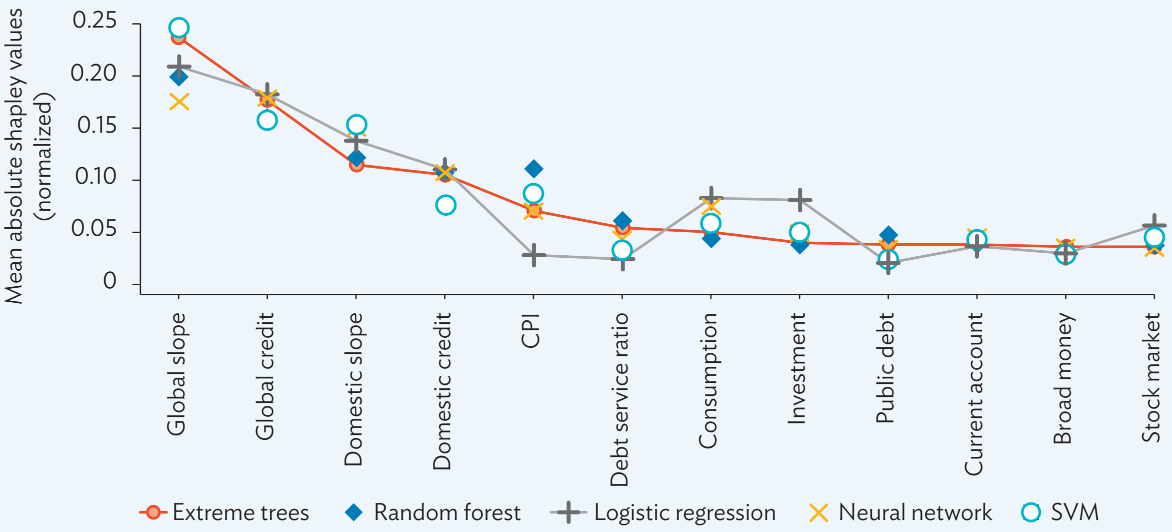
[26] In practice, Shapley values are computed by using the *shap* Python package (Lundberg and Lee 2017; Bluwstein et al. 2023).

Figure 5.1: Mean Absolute Shapley Values



CPI = consumer price index, SVM = support vector machine.

Note: This figure shows an example of mean absolute Shapley values of individual variables across different models.

Source: Bluwstein et al. (2023).

5.5 Shapley Regressions

Shapley values by themselves do not indicate how reliably the variables predict the outcome, as high Shapley values do not imply statistical significance. The final step in the workflow is thus to apply hypothesis testing through Shapley regressions (Buckmann et al. 2022; Bluwstein et al. 2023; Joseph 2019). Shapley regressions determine the statistical significance of the predictors in the ML models by regressing the crisis indicator *y* on the Shapley values of individual predictors using a logistic regression. That is, the probability of predicting a crisis is given by:

$$Y_{n\times 1} = \text{Logit}(\Phi(X_{n\times m})\hat{\beta}) + \hat{\varepsilon}$$

where $Y_{n x 1}$ is the crisis indicator, and $X_{n x m}$ are the Shapley values, where *n* is the number of observations and *m* is the number of predictors. This regression transforms the complex form of predictors in the ML model into a simple form that can be used to reflect the statistical significance of the predictors as expressed by the coefficient $\hat{\beta}$. As higher Shapley values imply greater importance of a variable to the crisis probability, the coefficient estimate should be positive.[27] If the coefficients are negative or statistically insignificant, it means that the predictor has no significant effect on crisis prediction (Liu, Chen, and Wang 2022). Appendix D provides further details on Shapley regressions and coefficients.

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[27] This is why a one-sided hypothesis test applies (Bluwstein et al. 2023).

In Table 5.2, we report an example of Shapley regression from the Bluwstein et al. (2023) study. The sign of the coefficients in the first column is taken from a separate logistic regression, not from the Shapley regression result. We observe that, consistent with Figure 5.1, global and domestic credit and yield curve slope obtain the highest coefficients and lowest p-values. Changes in investment and stock market indexes are also significant ($p < 0.05$), implying that even though they present small coefficients in terms of predictive shares, their values are significantly aligned with the crisis indicator.

Overall, by adopting Shapley values and regressions, the ML model output becomes easily interpretable, similar to common regression coefficients. This leads to meaningful and interpretable insights for decision-makers similar to standard ordinary least squares regressions.

Table 5.2: Shapley Regressions

	Direction	Share	Coefficient (SE)	p-value
Global slope	-	0.24	0.56(0.17)	0.00
Global credit	+	0.18	0.33(0.08)	0.00
Domestic slope	-	0.12	0.36(0.12)	0.00
Domestic credit	+	0.11	0.32(0.09)	0.00
CPI	+	0.07	0.31(0.11)	0.00
Debt service ratio	+	0.05	0.05(0.10)	0.31
Consumption	-	0.05	0.23(0.08)	0.00
Investment	+	0.04	0.19(0.09)	0.02
Public debt	+	0.04	-0.04(0.14)	1.00
Current account	-	0.04	0.01(0.07)	0.46
Broad money	-	0.04	-0.10(0.13)	1.00
Stock market	-	0.04	0.18(0.09)	0.03

CPI = consumer price index, SE = standard error.

Note: This table presents the direction of alignment between predictor and crisis outcome (sign of logistic regression), coefficients and standard errors, p-values against the null hypothesis (positive coefficients only), and predictive share of variables listed in Bluwstein et al. (2023).

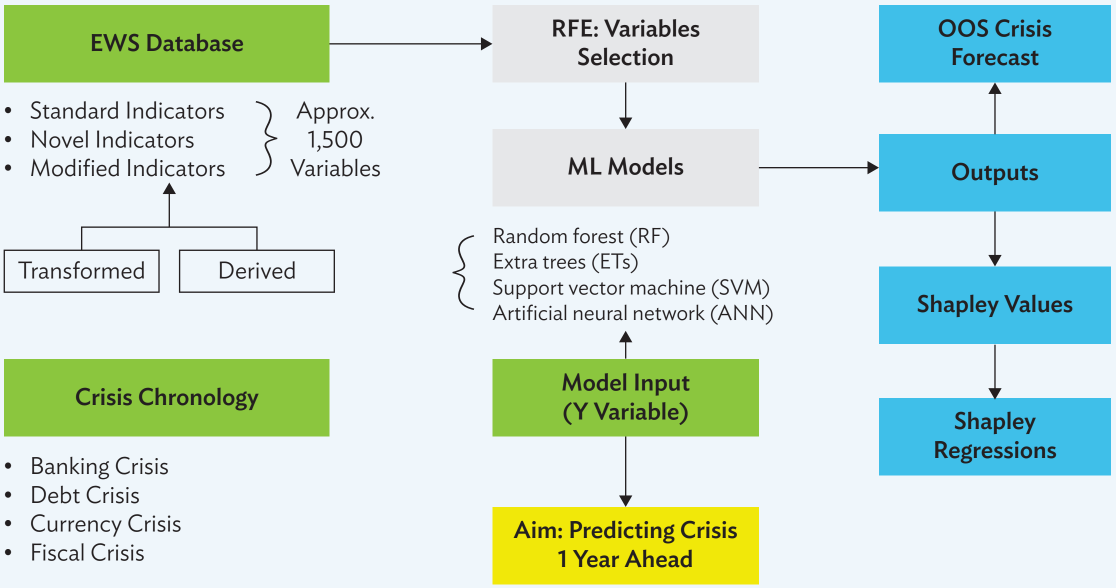
Source: Bluwstein et al. (2023).

CHAPTER 6

Early Warning System at ADB: Workflow and Preliminary Results

This chapter presents the workflow for ADB's new early warning system (EWS) and illustrates the forecasting framework's application with a case study. Figure 6.1 summarizes the key steps, spanning from data and crisis chronology loading to machine learning (ML) model implementation and output generation.

Figure 6.1: Early Warning System Workflow



EWS = early warning system, ML = machine learning, OOS = out of sample, RFE = Recursive Feature Elimination.

Note: This diagram illustrates the EWS workflow.

Source: Asian Development Bank.

6.1 Processing of Data Variables

Standard and novel variables: The EWS database is composed of both standard and novel variables as discussed in Chapter 4. The variables are collected from several sources, and incorporated through application programming interfaces (APIs) or spreadsheets. Where possible, data are collected from APIs such as the IMF and World Bank. APIs allow for automatic updating, speeding up data updates and reducing the margin of human error for routine data updates. Where data are not available from APIs, it is loaded from spreadsheets containing data collected at annual, quarterly, monthly, and daily frequencies, depending on availability. Standard and novel variables account for about 400 variables in total (see also Chapter 4, and Tables C1 and C2 in Appendix C).

Data imputation: ML models require some input data to be present for all variables in the model. Within an economy, where data are unavailable for a particular date, it is imputed with data from an earlier date within a certain range. For instance, if the range is set to three periods and a value for an economy's gross domestic product (GDP) in January 2015 was not available, it will be replaced with the chronologically closest monthly GDP value available in the past 3 months before the missing date. Similarly, in the cross section, missing data are filled in with the column median across economies within the same income group. Variables with too little data available (e.g., less than 5% of observations within an economy) may be excluded from the training dataset (see also Chapter 5).

Variable transformations: In addition, previous research (Hellwig 2021) suggests that crisis forecasting performance can be improved by training models on simple transforms of variables such as averages, growth rates, lags, or logs, in comparison to the basic level. We therefore allow the same variable to be included in a single model with several transforms, on average four per variable. While in many cases the desired variable is directly available from the data provider (e.g., GDP per capita), in other cases, the variables must be calculated based on several others (e.g., the spread between long-term and short-term interest rates requires data on interest rates at both time horizons).

Derived variables: Moreover, following previous studies (Moreno Badia et al. 2022; Truong et al. 2022), we also include volatility, spillovers, and contagion measures as special cases of derived variables. Volatility is constructed as the sum of the asset's squared returns, and aggregated at a monthly (annual) frequency if daily (monthly) assets are considered (Schwert, 1989). Volatility measures are constructed for global stock price indexes, inflation, credit default swap (CDS), sovereign bonds, exchange rates, and portfolio capital flows. In addition, for financial assets, we decompose measures of volatility into their downside and upside components as used in Barndorff-Nielsen, Kinnebrock, and Shephard (2008); Feunou, Jahan-Parvar, and Okou (2018); Kilic and Shaliastovich (2019); and Bevilacqua, Morelli, and Tunaru (2019). Spillovers measures are computed by following the seminal work by Diebold and Yılmaz (2014), and for selected financial assets, downside and upside spillovers measures are also computed (Baruník et al. 2022). Spillover measures are computed for global stock market returns and volatility, CDS volatility, exchange rates, and sovereign bonds (see Chapter 4 and Appendix C, Table C1 for details). After transformations and derivations, the approximately 400 raw variables from the dataset translate into about 1,500 variables as input to predict crises, as summarized in Table 6.1.

Table 6.1: Summary of Variables in the Database

Category	Description	# of Time Series
Raw indicators	Directly available from the data provider	400, of which 250 standard and 150 novel
Transformed variables	Simple transformations (e.g., averages, growth rates, lags, logs) (Hellwig 2021).	approximately 1,050
Derived variables	Computed values (e.g., spreads, volatility, spillovers).	approximately 50

Source: Asian Development Bank.

Crisis chronology: Next, we require a crisis chronology for ML training, as highlighted in Chapter 2. The chronology lists the starting month of banking, currency, and debt crises, and the start and end years of fiscal crises.[28] There is a mixture of constant, annual, quarterly, monthly, and daily data stored in the database. The model excludes postcrisis data for economies currently experiencing or recently emerging from a crisis of the same type that the model is intended to predict. This is justified on the basis that the values of variables may be anomalous. We follow Bluwstein et al. (2023) in choosing to exclude data from 2 years after the crisis ended, although this parameter remains a flexible choice.

Recursive Feature Elimination: This step serves to evaluate which variable should be included in the model. The EWS uses RFE techniques to determine which variables should be retained. Both data availability and the marginal additional predictive power of that data are decisive for variable selection. As discussed in Chapter 5, this step is fundamental for excluding irrelevant or highly correlated variables, reducing overfitting and improving prediction accuracy, reducing the number of variables in the model as well as computation time, and aiding the estimation of Shapley values.[29]

6.2 Machine Learning Model Outputs

Model performance evaluation: Most variables are at annual frequency. Thus, we focus on annual models producing predictions 1 year ahead. The core metrics for performance evaluation of ML models applied to binary classification problems are the area under the receiver operating characteristic (AUROC) and the precision-recall curve. The AUROC serves as a comparator metric between models, with a higher area under the curve indicating a more favorable trade-off between false alarms (false positive rate) and missed crises (false negative rate). Similarly, a larger area under the precision-recall curve indicates higher model performance. Precision refers to the proportion of true positive results among all positive results predicted. Recall is the proportion of true positive results among all actual positive results. The threshold for the crisis probability estimate to be interpreted as a crisis prediction is to be selected manually based on the desired trade-off between a false alarm and missed crises. The curves presented in Figures 6.2 and 6.3 summarize the trade-off between false negatives and false positive rates (precision-recall) for each ML model and two crisis types. A high (low) threshold implies low (high) false positives but high (low) false negatives.

Random forest and extra trees present the highest AUROC for debt crises and banking crises (Figures 6.2 and 6.3). The model denoted as *manual logit* presents the results obtained under a logit (non-ML) model based on the legacy EWS as programmed in VIEWS. This model incorporates relative to the ML models few and ad hoc selected variables. Notably, the legacy EWS shows the worst forecasting performance, with all ML models achieving a higher AUROC. For the list of variables adopted in the manual logit, see Appendix D.2. On average, from these examples, the predictive power of the best ML model increases by up to 23% (measured by AUROC) compared to the legacy EWS.

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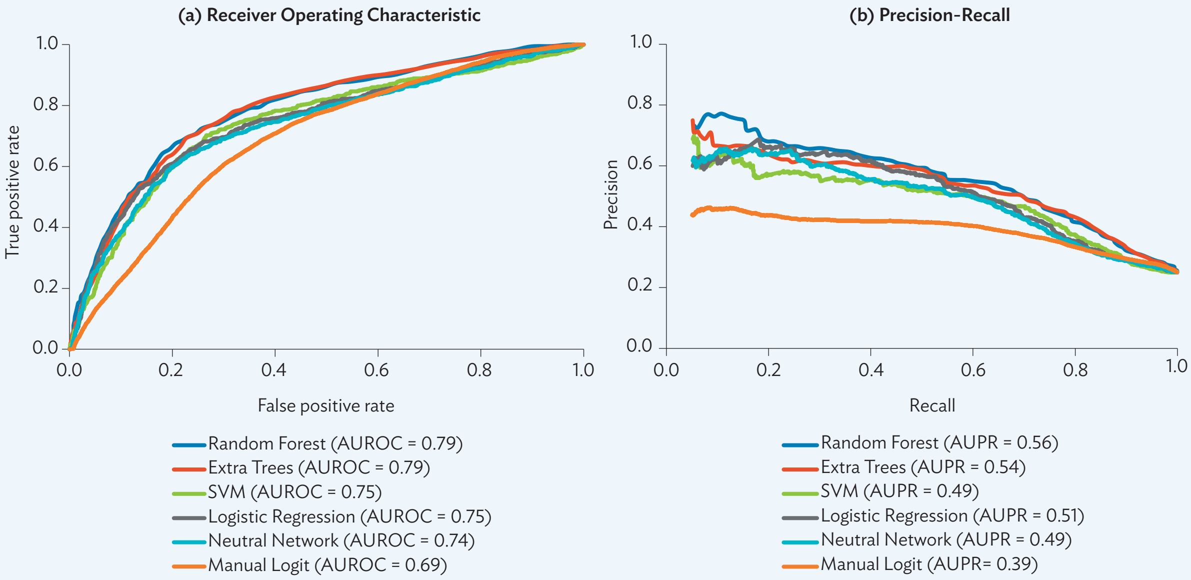
[28] This is not a limitation for making predictions, but only for training data.

[29] To avoid information leakage and ensure evaluation results are not biased, variable selection is performed on a subset of the dataset separate from that used for evaluation. For more technical information on the data assembly and RFE steps, please refer to Chapter 5 and the EWS Technical Manual.

Figure 6.2: AUROC and AUPR Curve, Debt Crises



(a) Receiver Operating Characteristic

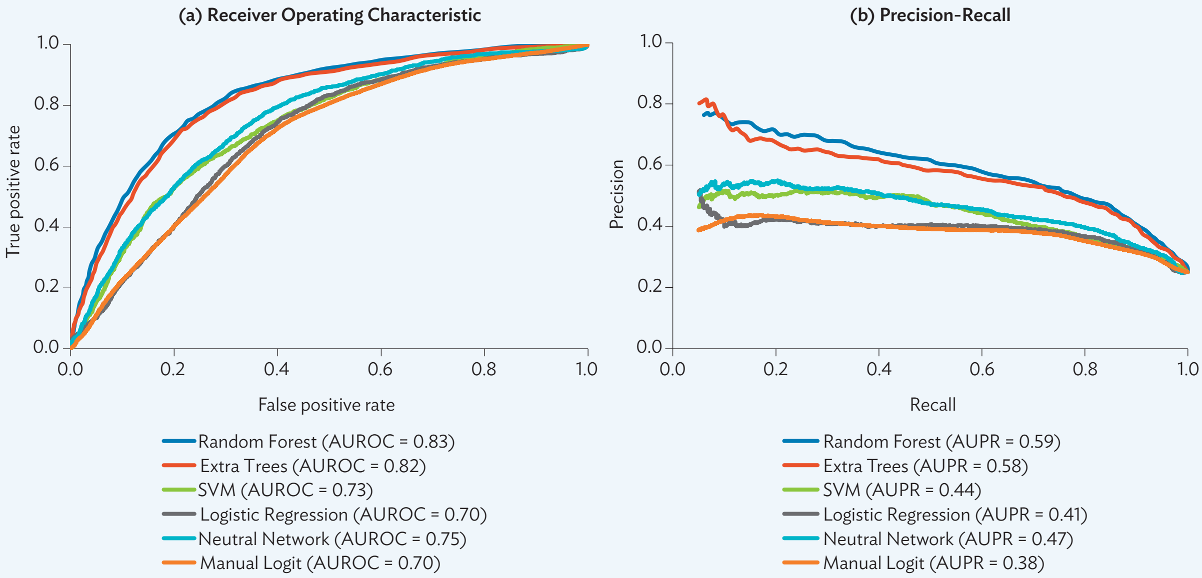
(b) Precision-Recall

AUPR = area under precision-recall curve, AUROC = area under the receiver operating characteristic, SVM = support vector machine.

Note: Receiver operating characteristics and precision-recall curves for debt crises, 15 variables.

Source: ADB calculations using data from new Early Warning System database.

Figure 6.3: AUROC and AUPR Curve, Banking Crises



(a) Receiver Operating Characteristic

(b) Precision-Recall

AUPR = area under precision-recall curve, AUROC = area under the receiver operating characteristic, SVM = support vector machine.

Note: Receiver operating characteristic and precision-recall curves for banking crises, 15 variables.

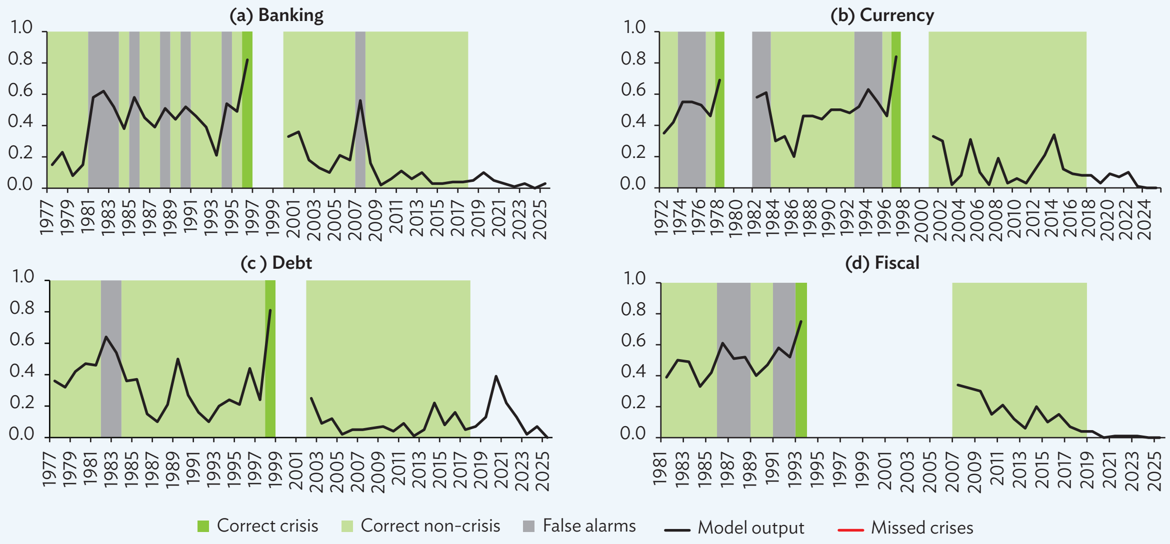
Source: ADB calculations using data from new Early Warning System database.

6.3 Crisis Forecasting Sample

In-sample and out-of-sample crisis forecast: Next, Figure 6.4 shows an example of in-sample and out-of-sample crisis forecasting for Indonesia for all types of crises, using a random forest model. “Out of sample” refers to the forecast period beyond the end of the crisis chronology—i.e., after 2017. This threshold will be updated frequently within the EWS framework, as crisis chronologies are being updated. The prediction is performed until the end of 2024. We observe that the model performs well, successfully detecting all crises identified in the chronology and no crises missed. However, in this case, the chosen threshold (0.5) leads to the model generating some false alarms.[30] Figure 6.4 illustrates that the model successfully predicts Indonesia’s 1996 banking crisis, with the crisis probability exceeding 80% surpassing the 50% threshold and classifying Indonesia as experiencing a crisis. In 2007, the model assigns a crisis probability of nearly 60%. However, despite this coinciding with the onset of the global financial crisis, the underlying crisis chronology does not classify the period as banking crisis for Indonesia; and so the result is a false alarm. Finally, in the out-of-sample post-2017 period, the model does not predict any crises for Indonesia across all four crisis types. The highest predicted probability (40%) was for a debt crisis in 2020, but that remains below the 50% crisis threshold.

The blank areas in the within-sample forecast (until the end of 2017) in Figure 6.4 represent the 2 years following a documented crisis. We exclude these periods from the forecast as the economy is likely still in crisis or recovering, and thus outside the model’s predictive scope. For fiscal crises, these non-forecast periods are longer, reflecting the typically extended duration of such crises (Moreno Badia et al. 2022).

Figure 6.4: Forecasting Crises–Indonesia



Notes:

1. This figure shows crisis probabilities estimated for Indonesia for four crisis types, in sample and out of sample.
2. The model does not flag missed crises for Indonesia for the period studied.

Source: ADB calculations using data from new Early Warning System database.

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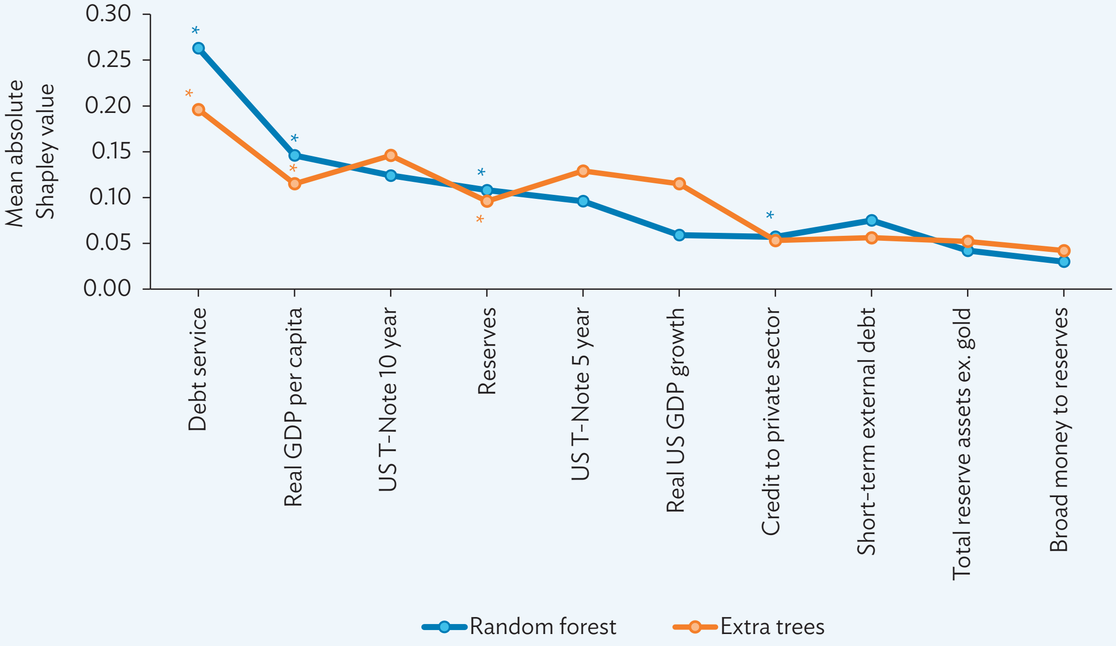
[30] As discussed earlier, we do not require an ex-ante choice of crisis threshold. The threshold depends on the trade-off between false positives (false alarms) and false negatives (missed crises).

6.4 Results of Shapley Regressions

Shapley values: Having obtained estimates for crisis probabilities in the forecast period, we are interested in what factors contribute most to the forecast, allowing policymakers to take mitigating actions. To unpack the forecast, we compute Shapley values and run Shapley regressions, as first discussed in Chapter 3, Section 3.4. Shapley values can be computed for each variable and for individual economies, as well as averaged across economies. Figures 6.5 and 6.6 present the mean absolute Shapley values of the 10 most important variables contributing to the forecast of debt and banking crises in Indonesia for the two best-performing ML models (random forests and extra trees). Mean absolute Shapley values refer to the average importance of a variable obtained from computing economy-time specific Shapley values over several randomly varying indicator combinations (see also Chapter 5, Section 5.4). We find that debt service, real GDP per capita, and reserves are the primary drivers of a debt crisis forecast, while real US GDP growth, total debt, and inflation are key contributors to a banking crisis forecast.

Figure 6.5: Mean Absolute Shapley Values, Debt Crises

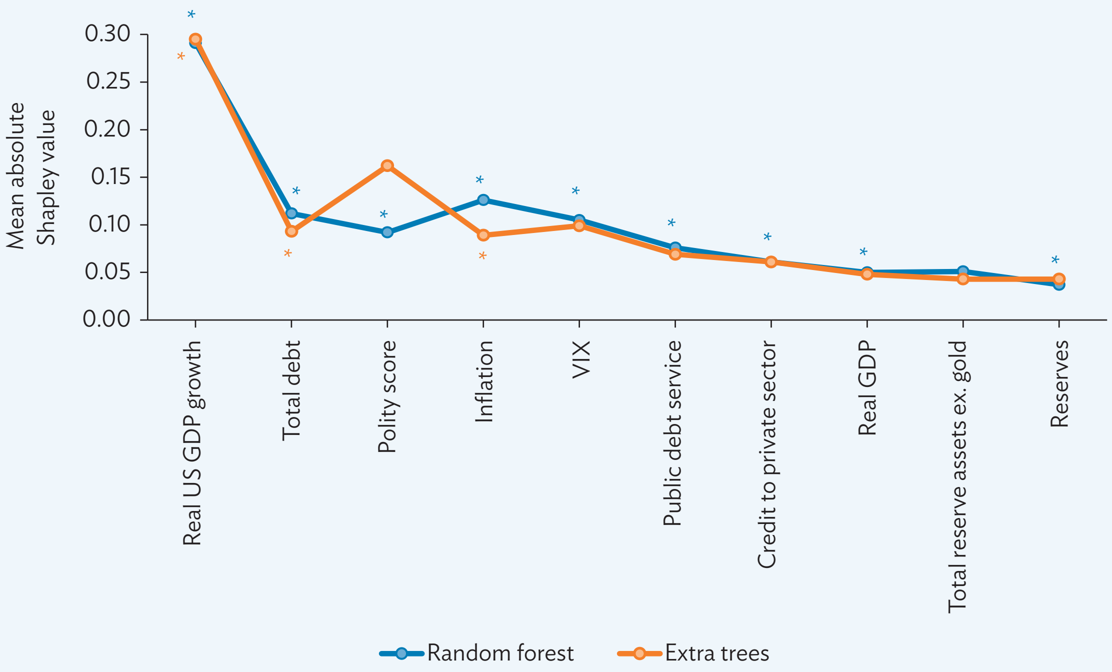


GDP = gross domestic product, US = United States.

Note: Mean absolute Shapley values for debt crises, 10 variables. Asterisks denote statistical significance ($p < 0.05$) in associated Shapley regressions.

Source: ADB calculations using data from new Early Warning System database.

Figure 6.6: Mean Absolute Shapley Values, Banking Crises



GDP = gross domestic product, US = United States, VIX = volatility index.

Note: Mean absolute Shapley values for banking crises, 10 variables. Asterisks denote statistical significance ($p < 0.05$) in associated Shapley regressions.

Source: ADB calculations using data from new Early Warning System database.

Shapley regressions: We access the statistical significance of Shapley values using Shapley regressions. The coefficients of Shapley regressions measure the effect of a change in Shapley values on the crisis prediction. The coefficient sign, however, does not indicate the sign of the association between predictors and crisis probability because Shapley values absorb the sign of the relation. Higher coefficient values should reflect an increase in the predicted probability of crisis (Liu, Chen, and Wang 2022), and variables with higher Shapley shares tend to have lower p-values as the model relies more on important variables (Buckmann et al. 2022; and see Chapter 5, Section 5.5 for more details). We apply this concept to the crisis forecasts obtained for Indonesia. The asterisks in Figures 6.5 and 6.6 indicate statistical significance of the Shapley values at the 5% level. For example, for the debt crisis adopting a random forest model, debt service contributes 26.3% to the prediction of debt crises. Tables D1 and D2 in Appendix D report the exact coefficients estimates and p-values associated with these figures.

Conclusion

Methodological advances in forecasting techniques, the emergence of new sources of risks and vulnerabilities, and the need to broaden the scope of crisis types warrant an update of ADB's statistical tool kit to forecast crises. This paper scans the literature for state-of-the-art methodologies and predictor variables, and it proposes a new early warning system (EWS) using machine learning (ML) models enhanced with novel variables covering new development challenges. The new EWS draws on latest methods to unpack the ML output for policymakers, which allows forecasts to be translated into mitigating actions.

The new EWS innovates the legacy system along several dimensions. First, ML models are well suited to incorporate a much broader scope of variables at various frequencies all at once. Importantly, ML models consider latent interactions and nonlinearities without this being explicitly programmed. This yields significant improvements in the forecast performance, notably for economies with typically less data coverage. Second, leveraging the flexibility of ML methods, we include a wide range of novel variables—beyond traditional macroeconomic variables and including financial stress, global factors, geopolitical and climate risks, and international spillovers. Third, we employ Shapley values and regressions to open the "black box" of ML-derived forecasts. This allows assignment of an economic importance to each predictor variable and, in turn, to identify policy levers to take preventive and mitigating policy measures.

APPENDIX A
Financial Crises

Table A1: Financial Crisis Dates–Financial Stress Index Versus Other Measures

Source	ADFPQ2023	LV2020	RR2017	RR2009	CK2003	DKD2005	ST2012	BEKM2001	BVX2021
Economy coverage:	110	165	24	81	93	94	14	56	46
Frequency:	quarterly	annual	semi-annual	annual	annual	annual	annual	annual	annual
Time coverage:	1967-2018	1970-2017	1967-2017	1800-2014	late 1970s-1999	1980-2002	1870-2008	1880-1998	1870-2016
Australia	1977Q3	0	0	0	0	-	0	0	0
Australia	1990Q4–1993Q1	0	0	1989–1992	1989–1992	-	1989	1989	1989
Australia	2008Q1–2009Q1	0	2008:1–2009:1	0	-	-	0	-	2008
PRC	1993Q3–1993Q4	0	-	0	0	-	-	0	-
PRC	1998Q1–2001Q4	1998	-	1997–1999	1998	-	-	0	-
PRC	2008Q4	0	-	-	-	-	-	-	-
Hong Kong, China	1983Q4–1986Q4	0	-	1982–1986	1982–1986	-	-	1982	1982
Hong Kong, China	1992Q2–1993Q3	0	-	0	0	-	-	0	0
Hong Kong, China	1997Q4–2000Q3	0	-	1998	1998	-	-	0	1998
Hong Kong, China	2008Q4–2010Q4	0	-	0	-	-	-	-	0
India	1991Q1–1998Q4	1993	-	1993–1998	1993–1999	1991–1994	-	1994	1991
India	2008Q4–2009Q1	0	-	0	-	-	-	-	0
India	2016Q1–2016Q4	0	-	0	-	-	-	-	-
Indonesia	1967Q4	-	-	0	-	-	-	0	0
Indonesia	1984Q4–1988Q4	0	-	0	-	0	-	0	0

continued on next page

Table A1 *continued*

Source	ADFPQ2023	LV2020	RR2017	RR2009	CK2003	DKD2005	ST2012	BEKM2001	BVX2021
Indonesia	1993Q1–1994Q3	0	-	1992–1994	1994	1992–1995	-	1992	1992
Indonesia	1997Q4–2003Q3	1997–2001	-	1997–2002	1997–1999	1997–2002	-	1997	1997
Indonesia	2008Q4–2009Q3	0	-	0	-	-	-	-	0
Japan	1990Q1–2004Q2	1997–2001	1990:2–2005:1	1992–2001	1990 s	1992–2002	1992	1992	1991
Japan	2008Q3–2010Q1	0	2008:2–2010:1	0	-	-	0	-	2008
ROK	1997Q2–2000Q4	1997–1998	1997:1–2005:1	1997–2000	1997–1999	1997–2002	-	1997	1997
ROK	2009Q1–2009Q3	0	2008:2–2012:2	-	-	-	-	-	0
Lao PDR	0	0	-	-	Early 1990 s	-	-	-	-
Lao PDR	1998Q2–1998Q3	0	-	-	0	-	-	-	-
Lao PDR	2009Q2	0	-	-	-	-	-	-	-
Malaysia	1979Q1	0	-	0	0	-	-	0	0
Malaysia	1984Q1–1989Q1	0	-	1985–1988	1985–1988	1985–1988	-	1985	1985
Malaysia	1997Q4–2000Q2	1997–1999	-	1997–2001	1997–1999	1997–2001	-	1998	1997
Nepal	0	0	-	-	1988	1988–1991	-	-	-
Nepal	0	0	-	-	0	0	-	-	-
New Zealand	1987Q4–1991Q1	0	0	1987–1990	1987–1990	-	-	1987	1987
New Zealand	2007Q4–2009Q3	0	2007:2–2012 :1	0	-	-	-	-	2007
Pakistan	1971Q2	0	-	-	-	-	-	0	-
Pakistan	2008Q4–2010Q3	0	-	-	-	-	-	-	-
Pakistan	2012Q2–2013Q2	0	-	-	-	-	-	-	-
Philippines	1981Q3–1987Q4	1983–1986	-	1981–1987	1981–1987	1981–1987	-	1981	1981
Philippines	1997Q4–2003Q3	1997–2001	-	1997–2001	1998–1999	1998–2002	-	1998	1997
Philippines	2009Q2	0	-	0	-	-	-	-	0
Singapore	0	0	-	1982	1982	-	-	1982	1982
Singapore	1985Q4–1986Q2	0	-	0	0	-	-	0	0
Singapore	2008Q4	0	-	0	-	-	-	-	0

continued on next page

Table A1 *continued*

Source	ADFPQ2023	LV2020	RR2017	RR2009	CK2003	DKD2005	ST2012	BEKM2001	BVX2021
Sri Lanka	1985Q2	0	-	-	0	0	-	-	-
Sri Lanka	0	1989–1991	-	1989–1993	1989–1993	1989–1993	-	1989	-
Sri Lanka	1998Q4	0	-	0	0	0	-	0	-
Taipei,China	1983Q4–1984Q2	-	-	1983–1984	1983–1984	0	-	1983	-
Taipei,China	1993Q3	-	-	0	0	0	-	0	0
Taipei,China	1995Q4–1996Q1	-	-	1995	1995	0	-	1995	1995
Taipei,China	0	-	-	1997–1998	1997–1998	1997–1998	-	0	1997
Taipei,China	1999Q1–2003Q3	-	-	0	0	0	-	-	0
Taipei,China	2008Q4–2009Q2	-	-	0	-	-	-	-	0
Thailand	1981Q3–1991Q3	1983	-	1983–1987	1983–1987	1983–1987	-	1983	1983
Thailand	1996Q2–2001Q3	1997–2000	-	1996–2000	1997–1999	1997–2002	-	1997	1996
Thailand	2008Q3–2009Q3	0	-	0	-	-	-	-	0
Viet Nam	1995Q4	0	-	-	0	-	-	-	-
Viet Nam	1997Q2–2000Q3	1997	-	-	1997–1999	-	-	-	-
Viet Nam	2008Q4–2009Q1	0	-	-	-	-	-	-	-
Viet Nam	2014Q1–2014Q4	0	-	-	-	-	-	-	-

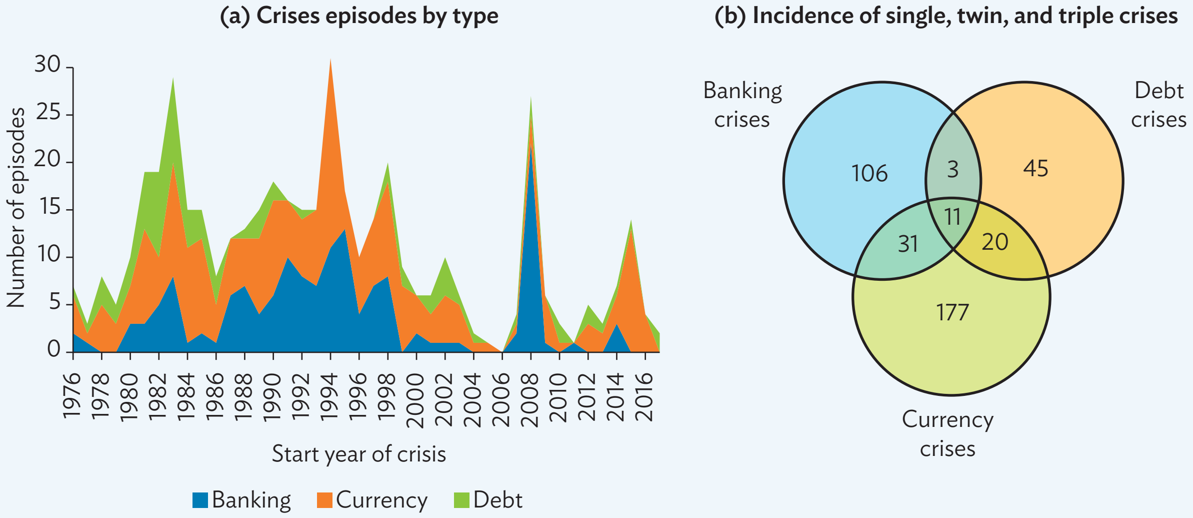
PRC = People's Republic of China, ROK = Republic of Korea, Lao PDR = Lao People's Democratic Republic, Q = quarter.

Notes: "0" indicates no crisis; "-" indicates that it is not within the economy and/or time coverage of the respective study. Each column refers to data gathered through the different sources listed below:

- ADFPQ2023 is based on the new financial stress indicator indicator by Ahir et al. (2023);
- LV2020 column is based on Tables 1 and 2 of Laeven and Valencia (2020);
- RR2017 is based on Table 2 of the Online Annex of Romer and Romer (2017);
- RR2009 is based on the online reference of banking crisis of Reinhart and Rogoff (2009a);
- CK2002 is based on pages 32 to 48 of Caprio and Klingebiel (2002);
- DKD2005 column is based on Table 2 of Demirgüç-Kunt and Detragiache (2005);
- ST2012 is based on Table A1 of the web Annex of Schularick and Taylor (2012);
- BEKM2001 is based on Annex A of Bordo et al. (2001); and
- BVX is based on Annex Table 2 of Baron, Verner, and Xiong (2021).

Source: ADB compilation based on Ahir et al. (2023); Baron, Verner, and Xiong (2021); Bordo et al. (2001); (2001); Caprio and Klingebiel (2002); Demirgüç-Kunt and Detragiache (2005); Laeven and Valencia (2020); Reinhart and Rogoff (2009a); Romer and Romer (2017); and Schularick and Taylor (2012).

Figure A1: Crises Interactions



(a) Crises episodes by type

(b) Incidence of single, twin, and triple crises

Notes: This figure shows examples of crises interactions, in (a) the time series of crisis episodes by type (banking, currency, debt), and in (b) the incidence of single, twin, and triple crises.

Source: Laeven and Valencia (2020).

APPENDIX B

Review of Early Warning System Approaches

B.1 Signal Approach

In the signal approach, variables are chosen ad hoc as leading indicators of crises, although the selection is guided by theory. A threshold value for each variable has to be chosen as well, with the threshold indicating that a crisis is likely to happen in the near future. Hence, a selected indicator signals a crisis when it exceeds a particular threshold or cutoff, calculated as a specific percentile of each indicator's sample distribution. After determining the threshold, leading indicators can be converted into binary variables. These take a value of 1 if the actual value of the leading indicator crosses the threshold (warning signal), or 0 if the actual value does not cross its threshold (no warning signal). By comparing these signals to the actual crisis episodes, four cases emerge (Zhuang 2005; Dawood, Horsewood, and Strobel 2017) and are shown in Table B1. Outcomes *A* and *D* reflect "good" signals of crisis and tranquil periods, while outcome *C* depicts the failure to predict an actual crisis (i.e., "missed crisis"), and outcome *B* denotes a "false alarm" as the warning signal was not followed by a crisis within the specified crisis window.

Table B1: Contingency Table for Crisis Prediction Model

	A crisis follows	No crisis follows
Signal	A	B
Not signal	C	D

Source: Dawood, Horsewood, and Strobel (2017) and Zhuang (2005).

Clearly, choosing a low (high) cutoff probability increases the probability of false alarms (missed crises). Fuertes and Kalotychou (2007) argue that false alarms are less important to policymakers than missed crises, since the preemptive policies are less costly than the significant economic and social losses from unanticipated crises. Conversely, Savona and Vezzoli (2015) warn against the costs associated with false alarms, as they tend to trigger negative market sentiments and affect international reputation. Also, a signal issued "too early" (i.e., outside the crisis window) is also counted as a false alarm. To assess and validate the predictive power of the models considered, a common tool kit adopted is the in-sample noise-to-signal ratio (NSR), which is defined as the ratio of bad to good signals.

$$NSR = \frac{P(B|B \cup D)}{P(A|A \cup C)}$$

Specifically, it is the ratio between (i) the ratio of the number of crises incorrectly predicted to all noncrisis episodes (false positive rate) and (ii) the ratio of the number of crises correctly predicted to all crisis episodes (true positive rate). The lower the NSR, the better the ability to predict a crisis.[1] The EWS for each economy is built as the weighted sum of the individual indicators, forming a composite index, where the weights are given by the inverse of the NSR to account for forecasting accuracy (Kaminsky and Reinhart 1999).

B.2 Machine Learning Approaches: Details

This section provides a high level, nontechnical description of the most popular machine learning (ML) approaches, their advantages and disadvantages according to the selected application, and some references applying these methods to crisis predictions.

Decision trees. A decision tree successively splits the data into subsets by testing a single predictor at each node. All observations are then divided into two child nodes, one for which the test in the node is true and one for which it is false. This process is recursively repeated in the respective child nodes. Each test is determined by iterating through all predictors and possible split points choosing the one that best separates the observations of the positive and negative class in that node, with positive classes denoting crises, and negative classes noncrises. Nodes that are not split further make predictions according to the class of the observations that fall into the node during training (Bluwstein et al. 2023). However, the bigger a tree grows, the less likely it will be to generalize very well to out-of-sample data. Big trees tend to fit well to the specific observations of a data sample and therefore often perform substantially worse on a new set of observations drawn from the same population—i.e., overfitting. Decision trees are transparent models: it is easy to understand and explain their decisions. However, they often have limited predictive power compared to more complex methods such as random forests, especially when the dataset is small.[2]

Random forests. A random forest is a collection of many, often hundreds, of decision trees. By averaging the predictions of the trees, random forest usually suffer less from overfitting than any individual tree Breiman (2001). To ensure that trees are sufficiently different from each other, the random forest algorithm uses two techniques. First, each tree is trained on a different subset of the data, which is drawn with replacement from all observations. Second, the algorithm does not choose the best of all possible splits but randomly samples *m* candidates from the *k* predictors, optimizes the split for each of them and then chooses the best split from this subset (Bluwstein et al. 2023). The split optimization is typically governed by impurity reduction criteria, and continues until a stopping rule is met, such as a minimum number of observations in a node or a maximum tree depth. In a forest, each individual tree predicts either the positive or negative class for an observation. The mean prediction across all trees gives an estimate of the probability that an instance belongs to the positive class. Random forest often performs substantially better than individual decision trees and many other ML algorithms (Fernández-Delgado

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[1] Another approach to date crises is to combine extreme financial distress and significant policy intervention, as a tool kit to try to minimize false alarm types of errors, as well as to rely less on the choice of the indicator's threshold. Seminal studies adopting this approach are Laeven and Valencia (2013, 2020).

[2] Alessi and Detken (2018) and Liu, Chen, and Wang (2022) adopt decision trees which bootstraps and aggregates a multitude of trees, to predict banking crises in the European Union and the United Kingdom, using quarterly data from 1970 to 2013. Other studies adopting decision trees in relation to financial crises are Ghosh and Ghosh (2003) and Frankel and Wei (2004) for currency crises, Manasse and Roubini (2009) and Savona and Vezzoli (2015) for sovereign debt crises, Duttagupta and Cashin (2011) for banking crises, and Joy et al. (2017) use them to predict banking and currency crises in 36 advanced economies between 1970 and 2010. Some studies adopted gradient boosting decision trees for predicting crises (Ng 2014; Carmona et al. 2019; Bluwstein et al. 2023).

et al. 2014). Random forest can be memory-intensive, especially when allowed to grow many large trees on a large dataset. Further, random forest can deal well with high-dimensional data and a limited number of observations. Compared to other methods, they also deal well with extreme values and correlated variables (Buckmann et al. 2022; Liu, Chen, and Wang 2022).[3]

Extremely randomized trees. Extremely randomized trees "are similar to random forests but tend to produce predictions that are more continuous as a function of the predictors. They achieve that by creating more diverse trees. The method differs in two aspects from random forests. First, each tree is trained on the complete training data and not on a resampled subset of the data. Second, the splitting process in each tree is more random. For each of the candidate *m* predictors that are randomly sampled, a split is not optimized but made completely at random across the range of the values of the indicator. Of these random splits, the best one is used in the tree" (Bluwstein et al. 2023, pages 19–20).

Artificial neural networks. Artificial neural networks have "achieved success in classification problems and applications to very large datasets. A neural network consists of an input layer that represents the values of the predictors, at least one hidden layer, and an output layer. The inputs are passed from one layer to the next and are finally integrated as a prediction in the output layer. Without a hidden layer, a neural network is a linear function of the input layer, such as a linear regression. Starting with the first hidden layer, each node computes a weighted sum of all its inputs from the previous layer, transforms the sum using an activation function (e.g., a logistic function), and passes its output to the next layer. Given a dataset with k predictors and a network with a single hidden layer containing m nodes, $k \times m$ weights are needed to fully wire the input layer to the hidden layer, and m weights are needed to connect the hidden layer with the output layer, which contains only a single node in a binary classification task. A neural network has hyperparameters that control the structure of the model such as the number of hidden layers, the number of nodes in each layer, and the activation function. The high number of parameters and hyperparameters, and a network's sensitivity to these, makes learning in a predictive network challenging, especially when the available data are small" (Bluwstein et al. 2023, pages 20–21). Averaging the predictions of several models that are trained on different samples drawn with replacement from the training set reduces overfitting (Liu et al. 2022). However, artificial neural networks can be both computation and data intensive (Buckmann et al. 2022, page 456).[4]

Support vector machines. A support vector machine (SVM) is similar to a logistic regression as it relies on a linear function of the inputs. However, unlike logistic regression, SVMs can handle more complex, nonlinear patterns by using a technique called a kernel. Kernels allow the SVM to transform the data into a higher-dimensional space where the groups become more easily separable (Ferńandez-Delgado et al. 2014; Bluwstein et al. 2023). An SVM has costs when the dataset is large; however, an SVM only has a few relevant hyperparameters and often performs well without tuning the hyperparameters at all (Buckmann et al. 2022; Liu, Chen, and Wang 2022).

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[3] For instance, Duttagupta and Cashin (2011) apply random forest, specifically a Binary Classification Tree model to analyze banking crises in 50 emerging market and developing economies during 1990–2005.

[4] For instance, Rodriguez and Rodriguez (2006) and Fioramanti (2008) use artificial neutral networks to predict sovereign debt crises. Tölö (2020) shows that recurrent neural networks yield better early warning models than both ordinary neural networks and logistic regression. Sevim et al. (2014) compare artificial neutral networks and decision trees to a logit model to develop an early warning system to predict currency crises in Türkiye between January 1992 and December 2011.

B.3 Large Language Models

A recent strand of economic literature related to ML leverages the power of large language models (LLMs) and natural language processing (NLP) for various applications, including economic time series forecasting (Carriero et al. 2024). NLP encompasses various techniques for machine analysis of human language, while LLMs specialize in generating and understanding text with high coherence and context awareness. NLP provides structural and semantic understanding, whereas LLMs leverage vast datasets and transformer models to generate contextually appropriate text. Their ability to capture linguistic nuances, contextual dependencies, and semantic meaning has made LLMs widely recognized for human-like text generation, and widespread for several applications.

For instance, Chen et al. (2022) feed news text data from the Thomson Reuters Real-Time News Feed in different languages into pretrained LLMs—BERT, RoBERTa, and OPT—and use the resulting sentiment scores to predict firm-level daily returns. Bybee (2023) feeds a historical sample of news articles from *The Wall Street Journal* into an LLM to predict various financial and macroeconomic quantities, which they then aggregate into a time series of monthly and quarterly expectations compared to existing survey forecasts. Kim et al. (2024) feed standardized and anonymous financial statements to GPT4 and instruct the model to analyze them to determine the direction of future earnings, finding that LLMs outperform financial analysts in their ability to predict earnings changes. Faria-e Castro and Leibovici (2024) look at time series LLMs focusing only on one target variable (inflation). Carriero et al. (2024) investigate how LLMs perform in a broader predicting macroeconomic time series forecasting exercise, providing valuable insights into their strengths and limitations. Studies also adopted language models to leverage and decipher communication such as central bank speeches and the US Federal Reserve meetings (Gambacorta et al. 2024; Gorodnichenko et al. 2023; Hansen et al. 2018).

Gorodnichenko et al. (2023) develop a deep learning model to detect emotions embedded in press conferences after the Federal Reserve Open Market Committee meetings and their impact on financial markets. Hansen et al. (2018) adopt computational linguistics algorithms to study changes in communication patterns. This strand of literature is in its early stages, with strengths and limitations of LLMs in economic forecasting still unclear. Thus, our EWS framework does not currently incorporate NLP techniques, but it is designed to flexibly accommodate them in the future.

APPENDIX C

Standard and Novel Early Warning Indicators

C.1 Standard Early Warning Indicators

Banking crises early warning indicator: The economy-specific early warning indicator (EWI) for banking crises can be grouped in five main areas—(i) Macroeconomic fundamentals: current account balance as a share of gross domestic product (GDP), external debt-to-gross national income, public debt as a ratio of GDP, inflation, and so on; (ii) Banking variables: credit-to-GDP, bank credit-to-bank deposits, economy-wide debt service ratios, credit growth, banks returns' volatility, and so on; (iii) Household sector: growth of the real house price index, household credit-to-GDP gap; (iv) Foreign exchange: the foreign exchange market pressure index, degree of openness of an economy, international debt; and (v) Equity and debt market: returns, volatility, sovereign debt spreads, 5-year sovereign credit default swaps (Laeven and Valencia 2013; Caggiano et al. 2014; Aldasoro, Borio, and Drehmann 2018; Laeven and Valencia 2020; Greenwood et al. 2022; Truong et al. 2022). Among the main global factors, there are 10-year United States (US) Treasury rate, composite energy price index, global macroeconomic variables for largest regions, global stock market conditions (e.g., the VIX, S&P 500, TED), global credit growth, and so on (Laeven and Valencia 2020; Truong et al. 2022).

Currency crises early warning indicator: The main economy-specific EWI for currency crises can be divided into two groups: (i) Domestic finance sector: domestic credit over GDP, the growth rate of domestic credit over GDP, real interest rate, real exchange rate overvaluation; and (ii) External sector: the growth rate of international reserves, the growth rate of imports and exports, and ratio of M2 to foreign reserves—all over 1-year time frames. Kaminsky et al. (1998) and Candelon, Dumitrescu, and Hurlin (2014) have more details about the variables and measures. Among global EWI for currency crises, some indicators could consider the effect of international capital flow pressures.

Sovereign debt crises early warning indicator: The main adopted indicators can be classified into four groups: (i) Debt exposure: total debt gross external debt as percentage of GDP, International Monetary Fund (IMF) credit loans from IMF as percentage of GDP, global interest rate; (ii) External sector: foreign exchange reserves as percentage of GDP, trade openness, export growth, current account balance, foreign direct investments; (iii) Domestic macroeconomic conditions: real GDP annual growth, real effective exchange rate, inflation rate, M2 reserve ratio, national saving ratio, government expenditures; and (iv) Banking sector: domestic credit, bank assets, government bank loans. For more details on these variables please refer to Fuertes and Kalotychou (2007), Manasse and Roubini (2009), and Dawood, Horsewood, and Strobel (2017).

Fiscal crises early warning indicator: Finally, according to Moreno Badia et al. (2022), the most common predictors in the literature for fiscal crises, based on a survey of 42 empirical papers between 1970 and 2019, can be grouped as follows: (i) Debt: external debt, debt service, public debt, fiscal balance, private debt; (ii) Foreign exchange: FX reserves, current account, exchange rate, exports, imports; (iii) Macro: GDP, GDP per capita, short-term debt, inflation; (iv) Domestic: political variables, default history, banking crisis history; and (v) Global: US variables, commodity prices.

Table C1 provides a comprehensive list of the most commonly adopted standard variables.

Table C1: Data Description and Sources, Standard Variables

Description	Sources/References	Frequency
Economy Category Variables		
Dummy: Monetary union member	IMF WEO	Constant
Dummy: Island economy	Wikipedia	Constant
Dummy: Landlocked economy	Wikipedia	Constant
Dummy: Small state	IMF WEO; WB WDI; Moreno Badia et al. (2022)	Constant
Dummy: Fragile state	WB WDI	Constant
Dummy: Commodity exporter	IMF WEO	Constant
Current Account		
Current account balance (% of GDP)	WB WDI	Annual
Current account balance (% of GDP)	CEIC Data Company	Quarterly
Export of goods and services (% of GDP)	WB WDI	Annual
Export of goods and services (% of GDP)	CEIC Data Company	Quarterly
Import of goods and services (% of GDP)	WB WDI	Annual
Import of goods and services (% of GDP)	CEIC Data Company	Annual
Personal remittances (% of GDP)	WB WDI; WB staff estimates based on IMF balance of payments data	Annual
Current account	IMF WEO	Annual
Current account	IMF WEO	Quarterly
Net foreign direct investment (% of GDP)	CEIC Data Company	Annual
Net foreign direct investment (% of GDP)	CEIC Data Company	Annual
Other investment, net (loans, deposits, insurance, pensions, trade credits, SDR, percent of GDP)	IMF BOP; IMF IFS	Annual, Quarterly
Direct Investment, Assets	IMF BOP; Koepke and Paetzold (2020)	Quarterly
Direct Investment, Liabilities	IMF BOP	Quarterly
Other Investment, Assets	IMF BOP	Quarterly
Other Investment, Liabilities	IMF BOP	Quarterly
Capital Account		
Capital flows	IMF BOP	Monthly
Capital flows	OECD	Monthly
Portfolio Fund Inflow, Total Equity Flow	EPFR	Daily
Portfolio Fund Inflow, Total Bond Flow	EPFR	Daily
Portfolio Fund Inflow, Total Flow	EPFR	Daily
External Sector Variables		
Portfolio investment, net	CEIC Data Company	Annual
Portfolio investment, net	WB WDI	Annual
Portfolio investment, net	CEIC Data Company	Monthly

continued on next page

Table C1 *continued*

Description	Sources/References	Frequency
Portfolio investment, net	CEIC Data Company	Quarterly
Percent change in terms of trade (of goods and services) Index	Haver Analytics; Oxford Economics	Annual
External gross financing needs	Authors calculations based on data from IMF WEO; WDI	Annual
Value of oil exports, percent of GDP	OPEC	Annual
External assets in percent of GDP	IMF WEO; Lane and Milesi-Ferretti (2007 2017)	Annual
Net open FX position (assets) in percent of GDP	IMF IFS Caggiano et al. (2014)	Quarterly
Terms of trade index	Haver Analytics (Oxford Economics); Truong et al. (2022)	Annual
Capital account openness–index	Chinn-Ito index (KAOPEN) Chinn and Ito (2006)	Annual
Capital account openness–normalized	Chinn-Ito index (KAOPEN) Chinn and Ito (2006)	Annual
Trade openness (ratio of exports + imports to GDP)	WB WDI; Dawood, Horsewood, and Strobel (2017)	Annual
Trade openness (ratio of exports + imports to GDP)	Haver Analytics (IMF DOTS); Dawood, Horsewood, and Strobel (2017)	Quarterly
Volume of imports of goods and services (percentage change)	Haver Analytics (IMF)	Quarterly
Volume of exports of good and services (percentage change)	Haver Analytics (IMF)	Quarterly
Portfolio Investment, Assets	IMF BOP	Quarterly
Portfolio Investment, Liabilities	IMF BOP	Quarterly
FX Reserves		
Percent change in total reserve assets, excluding gold ($)	WB WDI	Annual
Reserves, in months of imports	WB WDI	Annual
Exchange Rate		
Annual percentage change of average $ exchange rate	IMF IFS	Annual
Annual percentage change of end-of-period $ exchange rate	IMF IFS	Annual
Openness (10-year average of exports + imports of goods and services / GDP)	WB WDI	Annual
Openness (10-year average of exports + imports of goods and services / GDP)	Haver Analytics (IMF)	Quarterly
Nominal Effective Exchange Rate (y-o-y, %)	BIS	Monthly
Nominal Effective Exchange Rate	BIS	Monthly
Real Effective Exchange Rate (y-o-y, %)	BIS	Monthly
Real Effective Exchange Rate	BIS	Monthly
Price level ratio of PPP conversion factor (GDP) to market exchange rate	WB WDI	Annual

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Table C1 *continued*

Description	Sources/References	Frequency
Log of PPP-based real exchange rate	WB ICP	Annual
RER overvaluation	WB WDI	Annual
Price level ratio of PPP conversion factor (GDP) to market exchange rate	WB WDI	Annual
Price level index (World = 100)	WB ICP	Annual
Fiscal Variables		
General government expenditures (% of GDP)	IMF Public Finances in Modern History; Medas et al. (2018); Ali Abbas et al. (2011)	Annual
General government primary expenditures (% of GDP)	IMF Public Finances in Modern History; Medas et al. (2018); Ali Abbas et al. (2011)	Annual
Overall balance (% of GDP)	IMF Fiscal Monitor; Medas et al. (2018); Ali Abbas et al. (2011)	Annual
General government primary balance, percent of GDP	IMF Fiscal Monitor; Medas et al. (2018); Ali Abbas et al. (2011)	Annual
General government revenues in percent of GDP	IMF Public Finances in Modern History; Medas et al. (2018); Ali Abbas et al. (2011)	Annual
Stock-and-flow adjustments to public debt	Authors calculations based on data from CEIC Data Company; Moreno Badia et al. (2022); Medas et al. (2018)	Annual
Institutions / Elections		
Revised Combined Polity Score (single regime score, from 1 (full democracy) to -1 (full autocracy))	CSP	Annual
Checks and balances index	DPI	Annual
Checks and balances index	DPI	Annual
Bureaucracy Quality	PRS; WB WGI	Annual
Corruption	PRS	Annual
Years remaining in current chief executive's term	DPI	Annual
Legislative election held dummy variable	DPI	Annual
Executive election held dummy variable	DPI	Annual
Political Stability and Absence of Violence/ Terrorism: Estimate	WB WGI	Annual
Regulatory Quality: Estimate	WB WGI	Annual
Demographics		
Population ages 15–64, total	WB WDI	Annual
Percent change of population ages 15–64, total	WB WDI	Annual
Urban population (% of total)	WB WDI	Annual
Age Dependency Ratio, % of working-age population	WB WDI	Annual
Population density (people per sq. km of land area)	WB WDI	Annual
Log of population (relative to US)	CEIC Data Company (UN Population)	Annual

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Table C1 *continued*

Description	Sources/References	Frequency
Natural Resources		
Dummy: fuel exporter	UN DESA, based on data from UNCTAD	Constant
Mineral rent (% of GDP)	WB WDI	Annual
Oil rent (% of GDP)	WB WDI	Annual
Total natural resources rent (% of GDP)	WB WDI	Annual
Agriculture, forestry, and fishing (% of GDP)	WB WDI	Annual
Cost of physical-hazard-driven disasters, (% of GDP)	Authors calculations based on data from CRED's EM-DAT and CEIC Data Company	Annual
Cost of physical-hazard-driven disasters, adjusted (% of GDP)	Authors calculations based on data from CRED's EM-DAT and CEIC Data Company	Annual
Private Debt Variables		
(One-sided) credit gap—general government debt (% of GDP)	IMF GDD; Mbaye et al. (2018)	Annual
(One-sided) credit gap—household debt (% of GDP)	IMF GDD; Mbaye et al. (2018)	Annual
(One-sided) credit gap—nonfinancial corporations debt (% of GDP)	IMF GDD; Mbaye et al. (2018)	Annual
Total Debt, loans and securities, (% of GDP)	IMF GDD; Mbaye et al. (2018)	Annual
10-year average credit gap	IMF GDD; Mbaye et al. (2018)	Annual
Domestic credit to private sector by banks (% of GDP)	WB WDI	Annual
External debt stocks, private non-guaranteed, percent of GDP	WB WDI	Annual
WDI Broad Money, % of GDP	WB WDI	Annual
Household debt (% of GDP)	IMF GDD	Annual
General government debt (% of GDP)	IMF GDD	Annual
Nonfinancial corporations debt (% of GDP)	IMF GDD	Annual
Public Debt Variables		
Public debt (% of GDP)[a]	IMF WEO; Mbaye et al. (2018)	Annual
Public debt in percent of general government revenue[b]	Authors calculations based on data from IMF GDD and Haver Analytics	Annual
Public external debt (% of GDP)[c]	IMF GDD; Arslanalp and Tsuda (2014)	Annual
Public external debt (% of GDP) - Central government debt securities market, fixed rate	BIS DSS; Arslanalp and Tsuda (2014)	Annual
Public external debt (% of GDP) - International Debt Securities (National Issuers)	BIS IDS; Arslanalp and Tsuda (2014)	Annual
Public external debt (% of GDP) - International Debt Securities (Resident Issuers)	BIS IDS	Annual
Public external debt, percent of exports	Haver Analytics (Oxford Economics); Arslanalp and Tsuda (2014)	Annual
Public external debt, percent of exports	Haver Analytics (Oxford Economics); Arslanalp and Tsuda (2014)	Quarterly

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Table C1 *continued*

Description	Sources/References	Frequency
General government short-term external debt (% of GDP)	Authors calculations based on data from CEIC Data Company (World Bank) and Haver Analytics (IMF)	Quarterly
General government short-term external debt in percent of reserves	Authors calculations based on data from Haver Analytics and WB WDI	Annual
External and Total Debt		
Short-term external debt (% of GDP)	CEIC Data Company	Annual
Short-term external debt to reserves	WB WDI	Annual
Total external debt (% of GDP)	WB WDI; Lane and Milesi-Ferretti (2007 2017)	Annual
Total external debt in percent of export	WB WDI; Lane and Milesi-Ferretti (2007 2017)	Quarterly
Total debt (public plus private debt) (% of GDP)	Authors calculations based on data from IMF GDD; Mbaye et al. (2018)	Annual
Total reserves (% of total external debt)	WB WDI	Annual
Central government debt, total (% of GDP)	WB WDI	Annual
Debt Service		
General government interest expenses (% of GDP)	IMF WEO; Medas et al. (2018) Ali Abbas et al. (2011)	Annual
Amortization of external public debt (% of GDP)	Haver Analytics (Oxford Economics)	
Amortization of external public debt in percent of reserves: Ext. Debt Service Pmt, Interest Payments on SDR allocations, 0 to 3 mo, All instruments, $	WB QEDS	Annual
Amortization of external public debt in percent of reserves: Ext. Debt Service Pmt, Interest Payments on SDR allocations, 3 to 6 mo, All instruments, $	WB QEDS	Quarterly
Amortization of external public debt in percent of reserves: Ext. Debt Service Pmt, Interest Payments on SDR allocations, 12 to 18 mo, All instruments, $	WB QEDS	Quarterly
Amortization of external public debt in percent of reserves: Ext. Debt Service Pmt, Public and Publicly Guar. Private Sector Ext. Debt, 0 to 3 mo., All instruments, Prin. and Int., $	WB QEDS	Quarterly
Amortization of external public debt in percent of reserves: Ext. Debt Service Pmt, Public and Publicly Guar. Private Sector Ext. Debt, 12 to 18 mo., All instruments, Prin. and Int., $	WB QEDS	Quarterly
Amortization of external public debt in percent of reserves: Ext. Debt Service Pmt, Public and Publicly Guar. Private Sector Ext. Debt, 18 to 24 mo., All instruments, Prin. and Int., $	WB QEDS	Quarterly

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Table C1 *continued*

Description	Sources/References	Frequency
Amortization of external public debt in percent of reserves: Ext. Debt Service Pmt, Public and Publicly Guar. Private Sector Ext. Debt, 3 to 6 mo., All instruments, Interest, $	WB QEDS	Quarterly
Amortization of external public debt in percent of reserves: Ext. Debt Service Pmt, Public Sector Ext. Debt, 0 to 3 mo., All instruments, Prin. and Int., $	WB QEDS	Quarterly
Amortization of external public debt in percent of reserves: Ext. Debt Service Pmt, Public Sector Ext. Debt, 12 to 18 mo., All instruments, Prin. and Int., $	WB QEDS	Quarterly
Amortization of external public debt in percent of reserves: Ext. Debt Service Pmt, Public Sector Ext. Debt, 18 to 24 mo., All instruments, Prin. and Int., $	WB QEDS	Quarterly
Amortization of external public debt in percent of reserves: Ext. Debt Service Pmt, Public Sector Ext. Debt, 3 to 6 mo., All instruments, Prin. and Int., $	WB QEDS	Quarterly
Public debt service to revenue, in percent	Authors calculations based on data from WB WDI	Annual
Public debt service to export, in percent	WB WDI	Annual
Debt service on total external debt, percent of GDP	Authors calculations based on data from WB WDI	Annual
Debt service on total external debt, percent of exports	Authors calculations based on data from WB WDI and Haver Analytics (Oxford Economics)	Annual
Debt service on total external debt, percent of reserves	Authors calculations based on data from WB WDI	Annual
Global lending interest rate	WB WDI; Dawood, Horsewood, and Strobel (2017)	Annual
Foreign Aid and Debt Exposure		
Net official development assistance (% of GDP)	WB WDI	Annual
IMF loans as % of GDP	Authors calculations based on data from IMF and Haver Analytics; Dawood, Horsewood, and Strobel (2017)	Monthly
Real Sector Variables/Economic Activity		
Log (real GDP per capita) (in PPP dollars), relative to US	Authors calculations based on data from WB WDI	Annual
Percent change of real GDP per capita	WB WDI	Annual
Percent change of real GDP–annual	WB WDI	Annual
Percent change of real GDP–quarterly	Authors calculations based on data from IMF IFS	Quarterly

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Table C1 *continued*

Description	Sources/References	Frequency
Percent change of real GDP, deviation from 5-year average	Authors calculations based on data from WB WDI; Medas et al. (2018)	Annual
Percent change of nominal GDP	Authors calculations based on data from IMF IFS	Quarterly
Percent change of period average consumer price index	IMF WEO	Annual
Percent change of end-of-period consumer price index	IMF WEO	Annual
Log of nominal GDP in $, relative to US	Authors calculations based on data from CEIC Data Company	Annual
Standard deviation of real GDP growth	Authors calculations based on data from WB WDI; Moreno Badia et al. (2022)	Annual
Industrial production index–total index	IMF IFS; official national sources	Monthly
Industrial production index–total index	CEIC Data Company	Quarterly
Industrial production index–manufacturing sector	IMF IFS; official national sources	Monthly
Industrial production index–iron	IMF IFS; official national sources; WB WDI	Monthly
Industrial production index–construction materials	IMF IFS; official national sources; WB WDI	Monthly
Retail Sales Growth	ARIC ADB	Monthly
Vehicle sales	CEIC Data Company; official national sources; Truong et al. (2022)	Annual, Monthly
Manufacturing new orders	CEIC Data Company; official national sources; Truong et al. (2022)	Annual, Monthly
Capacity utilization	Haver Analytics (official national sources); Truong et al. (2022)	Quarterly
Inventory index	IMF IFS; Truong et al. (2022)	Annual
Business confidence index	OECD;Truong et al. (2022)	Monthly
Consumer confidence index	OECD; Truong et al. (2022)	Monthly
Industrial/ Manufacturing Production Growth Rate (y-o-y, %)	IMF IFS	Quarterly
Gross domestic savings (current $)	WB WDI	Annual
Gross domestic savings (percent of GDP)	WB WDI	Annual
Inflation		
Standard deviation of inflation	Authors calculations based on data from CEIC Data Company; Moreno Badia et al. (2022)	Annual
Headline inflation rate (y-o-y, %)	CEIC Data Company	Monthly
Banking		
Credit-to-GDP growth (BIS)	Authors calculations based on data from BIS and CEIC Data Company; Caggiano et al. (2014)	Quarterly
Credit-to-GDP growth, Private credit by deposit money banks to GDP (%)	WB GFD Caggiano et al. (2014)	Annual
Credit-to-GDP growth, Credit to government and state-owned enterprises to GDP (%)	WB GFD Caggiano et al. (2014)	Annual
Credit-to-GDP gaps (actual trend)	BIS; Aldasoro, Borio, and Drehmann (2018)	Quarterly

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Table C1 *continued*

Description	Sources/References	Frequency
Credit-to-GDP trend (HP filter)	BIS; Aldasoro, Borio, and Drehmann (2018)	Quarterly
Credit-to-GDP ratios (actual data)	BIS; Aldasoro, Borio, and Drehmann (2018)	Quarterly
Debt service ratio: Nonfinance corporations	BIS; Aldasoro, Borio, and Drehmann (2018)	Quarterly
Debt service ratio: Private nonfinance sector	BIS; Aldasoro, Borio, and Drehmann (2018)	Quarterly
Debt service ratio: Households and NPISHs	BIS; Aldasoro, Borio, and Drehmann (2018)	Quarterly
Property price gaps—Real Residential Property Price Index	BIS; Aldasoro, Borio, and Drehmann (2018)	Quarterly
Cross-border claims to GDP	Authors calculations based on data from BIS and CEIC Data Company; Aldasoro, Borio, and Drehmann (2018)	Quarterly
Foreign currency debt to GDP: Debt securities held by nonresidents	Authors calculations based on data from WB JEDH; Aldasoro, Borio, and Drehmann (2018)	Quarterly
Foreign currency debt to GDP: Intl debt securities all maturities	Authors calculations based on data from WB JEDH; Aldasoro, Borio, and Drehmann (2018)	Quarterly
Household credit-to-GDP gap	BIS; Aldasoro, Borio, and Drehmann (2018)	Quarterly
Leverage ratiod	Authors calculations based on data from Haver Analytics	Monthly
Liquidity ratio	Authors calculations based on data from Haver Analytics	Monthly
Money market interest rate	IMF IFS; Truong et al. (2022)	Monthly
Prime rate interest rate	IMF IFS; Truong et al. (2022)	Monthly
Commercial banks time deposit rate	WB WDI; Truong et al. (2022)	Annual
Interbank interest rate (overnight)	Haver Analytics (official national sources); Truong et al. (2022)	Daily
Interbank interest rate (1 month)	Haver Analytics (official national sources); Truong et al. (2022)	Monthly
Interbank interest rate (6 month)	Haver Analytics (official national sources); Truong et al. (2022)	Semestral
Interbank interest rate (1 year)	Haver Analytics (official national sources); Truong et al. (2022)	Annual
Treasury yield 3 months	Haver Analytics (official national sources); Truong et al. (2022)	Monthly
Treasury yield 10 years (daily)	Haver Analytics (official national sources); Truong et al. (2022)	Daily
Treasury yield 10 years (monthly)	Haver Analytics (official national sources); Truong et al. (2022)	Monthly
Bank credit to private sector: Domestic credit to private sector	WB WDI; Truong et al. (2022)	Annual
Bank loans to consumers—Haver Analytics	Haver Analytics (official national sources); Truong et al. (2022)	Monthly
Bank loans to consumers—Credit to nonfinance sector (BIS)	BIS	Quarterly
Credit to nonfinancial corporations (% GDP)	BIS; Truong et al. (2022)	Quarterly

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Table C1 *continued*

Description	Sources/References	Frequency
Credit to nonfinancial corporations (in $ billions)	BIS; Truong et al. (2022)	Quarterly
Deposit lending interest rate differential	IMF IFS; Truong et al. (2022)	Monthly
TERM spread (1- year and 3-month Treasury yield differential)	Haver Analytics (official national sources); Truong et al. (2022)	Monthly
Private Credit by Deposit Money Banks & Other Financial Instruments to GDP (%) growth rate	Haver Analytics (World Bank)	Annual
Domestic Credit to Government/State-Owned Enterprises to GDP (%) growth rate	Haver Analytics (World Bank)	Annual
Private nonfinancial credit-to-GDP gap	Haver Analytics (BIS)	Quarterly
Credit to nonfinance sector from all sectors (Market Value, as % of GDP)	Haver Analytics (BIS)	Quarterly
Total credit-to-GDP	Authors calculations based on data from Haver Analytics (BIS) and CEIC Data Company	Quarterly
Monetary and Financial Sector		
Broad Money Growth (%)	WB WDI	Annual
Broad Money to Reserves (%)	WB WDI	Annual
Claims on the Private Sector (y-o-y, %)	ARIC ADB	Monthly
Policy Rate, end of period (% per annum)	IMF IFS	Monthly
Size (Ratio of M2 to GDP)	Authors calculations based on data from CEIC Data Company	Monthly
Money supply M1 to GDP ratio	CEIC Data Company;Truong et al. (2022)	Annual
Money supply M2 multiplier (ratio of M2 to M0)	Haver Analytics (official national sources);Truong et al. (2022)	Monthly
Residential property price index	BIS; Truong et al. (2022)	Quarterly
Real house price index (y-o-y %)	BIS; Casabianca et al. (2022)	Quarterly
TED spread, 3 months (local treasury yield and US treasury yield differential)	CEIC Data Company; Truong et al. (2022)	Daily
TED spread, 10 years (local treasury yield and US treasury yield differential)	CEIC Data Company; Truong et al. (2022)	Monthly
Equity and Financial Markets		
Composite Stock Price Index (monthly average, local index)	CEIC Data Company	Monthly
Stock Price Index (daily price, local index)	Haver Analytics (official national sources)	Daily
Equity market capitalization to GDP	WB WDI; Truong et al. (2022)	Annual
Credit default swap 5 years, sovereign	Bloomberg Truong et al. (2022)	Daily
Global Variables		
Percent change of crude oil price (corresponding period, previous year)	Haver Analytics (WB)	Monthly
Percent change of nonfuel commodity price index, change previous year	Haver Analytics (IMF); Medas et al. (2018)	Monthly
Percent change of nonfuel commodity price index, change previous period	Haver Analytics (IMF); Medas et al. (2018)	Monthly

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Table C1 *continued*

Description	Sources/References	Frequency
Percent change of global food price index, change previous year	Haver Analytics (IMF); Medas et al. (2018)	Monthly
Percent change of global food price index, change previous period	Haver Analytics (IMF); Medas et al. (2018)	Monthly
Percent change of energy price index, change previous year	Haver Analytics (IMF); Medas et al. (2018)	Monthly
Percent change of energy price index, change previous period	Haver Analytics (IMF); Medas et al. (2018)	Monthly
US T-Bill rate, Percent	Haver Analytics (Federal Reserve Board)	Daily
US industrial production index	FRED	Monthly
Percent change of US CPI, period average	Haver Analytics	Monthly
Global Variables		
Percent change of US CPI, end of period	IMF	Monthly
Real US GDP growth	Haver Analytics	Quarterly
Standard deviation of US real GDP growth	Authors calculations based on data from Haver Analytics; Moreno Badia et al. (2022)	Quarterly
VIX, period average	Haver Analytics	Monthly
VIX, period end	Haver Analytics	Monthly
S&P index, period average	Haver Analytics (S&P)	Monthly
S&P index, period end	Haver Analytics (S&P)	Monthly
Percent change of VIX, period average	Authors calculations based on data from Haver Analytics	Monthly
Percent change of VIX, period end	Authors calculations based on data from Haver Analytics	Monthly
Percent change of S&P index, period average	Authors calculations based on data from Haver Analytics (S&P)	Monthly
Percent change of S&P index, period end	Authors calculations based on data from Haver Analytics (S&P)	Monthly
US T-Note 5-year rate Percent, Period Average	Haver Analytics (Federal Reserve Board)	Monthly
US T-Note 10-year rate Percent, Period Average	Haver Analytics (Federal Reserve Board)	Monthly
US T-Note 5-year rate Percent, End of Period	Haver Analytics (Federal Reserve Board)	Monthly
US T-Note 10-year rate Percent, End of Period	Haver Analytics (Federal Reserve Board)	Monthly
World real GDP growth, in percent	IMF WEO	Annual
US TED spread	FRED	Daily
US Credit default swap index	Bloomberg	Daily
US Credit default swap 5 years–sovereign	Bloomberg	Daily
Dow Jones	Haver Analytics (Wall Street Journal)	Daily
NASDAQ Composite	Haver Analytics (Wall Street Journal)	Daily
NYSE Composite	Haver Analytics (Wall Street Journal)	Daily
Russell 2000	Haver Analytics (Russell)	Daily

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Table C1 *continued*

Description	Sources/References	Frequency
Euro Area S&P Index	Haver Analytics (S&P)	Daily
Derived: Volatility		
Volatility of Real Effective Exchange Rate	Authors calculations based on data from BIS; Moreno Badia et al. (2022)	Annual
Volatility of real GDP growth	Authors calculations based on data from IMF IFS	Quarterly
Volatility of inflation	Authors calculations based on data from IMF WEO	Annual
Volatility of stock Price Index (daily price, local index)	Authors calculations based on data from Haver Analytics (official national sources)	Daily
Volatility of stock Price Index (daily price, local index, upside)	Authors calculations based on data from Haver Analytics (official national sources)	Daily
Volatility of stock Price Index (daily price, local index, downside)	Authors calculations based on data from Haver Analytics (official national sources)	Daily
Volatility of US real GDP growth	Authors calculations based on data from Haver Analytics (official national sources)	Quarterly
Volatility of S&P index	Authors calculations based on data from Haver Analytics (S&P)	Daily
Volatility of S&P index (upside)	Authors calculations based on data from Haver Analytics (S&P)	Daily
Volatility of S&P index (downside)	Authors calculations based on data from Haver Analytics (S&P)	Daily
Volatility of US credit default swap index	Authors calculations based on data from Bloomberg	Daily
Volatility of US credit default swap 5 years–sovereign	Authors calculations based on data from Bloomberg	Daily
Volatility of CDS	Authors calculations based on data from Bloomberg; Truong et al. (2022)	Daily
Sovereign bond markets volatility	Authors calculations based on data from Haver Analytics; Truong et al. (2022)	Daily
Portfolio Fund Inflow volatility, Total Equity Flow	Authors calculations based on data from EPFR	Daily
Portfolio Fund Inflow volatility, Total Bond Flow	Authors calculations based on data from EPFR	Daily
Portfolio Fund Inflow volatility, Total Flow	Authors calculations based on data from EPFR	Daily
Derived: Spillovers		
Global stock market volatility spillover–total	Authors calculations based on data from Diebold and Yilmaz (2015)	Daily
Global stock market volatility spillover—net	Authors calculations based on data from Diebold and Yilmaz (2015)	Daily
CDS market volatility spillover—total	Authors calculations based on data from Diebold and Yilmaz (2015)	Daily
CDS market volatility spillover—net	Authors calculations based on data from Diebold and Yilmaz (2015)	Daily

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Table C1 *continued*

Description	Sources/References	Frequency
Foreign exchange markets volatility spillover—total	Authors calculations based on data from Diebold and Yilmaz (2015)	Daily
Foreign exchange markets volatility spillover— net	Authors calculations based on data from Diebold and Yilmaz (2015)	Daily
Sovereign bond markets volatility spillover—total	Authors calculations based on data from Diebold and Yilmaz (2015)	Daily
Sovereign bond markets volatility spillover—net	Authors calculations based on data from Diebold and Yilmaz (2015)	Daily
Global stock market returns spillover–total (computed in EWS)	Authors calculations based on data from Haver Analytics (official national sources)	Daily
Global stock market returns spillover—net (computed in EWS)	Authors calculations based on data from Haver Analytics (official national sources)	Daily
Global stock market volatility spillover–total (computed in EWS)	Authors calculations based on data from Haver Analytics (official national sources)	Daily
Global stock market volatility spillover—net (computed in EWS)	Authors calculations based on data from Haver Analytics (official national sources)	Daily
Global stock market volatility spillover—total, upside (computed in EWS)	Authors calculations based on data from Haver Analytics (official national sources)	Daily
Global stock market volatility spillover—net, upside (computed in EWS)	Authors calculations based on data from Haver Analytics (official national sources)	Daily
Global stock market volatility spillover—total, downside (computed in EWS)	Authors calculations based on data from Haver Analytics (official national sources)	Daily
Global stock market volatility spillover—net, downside (computed in EWS)	Authors calculations based on data from Haver Analytics (official national sources)	Daily
CDS market volatility spillover—total (computed in EWS)	Authors calculations based on data from Bloomberg; Truong et al. (2022)	Daily
CDS market volatility spillover—net (computed in EWS)	Authors calculations based on data from Bloomberg; Truong et al. (2022)	Daily
Global stock market volatility spillover—net	Authors calculations based on data from Diebold and Yilmaz (2015)	Daily
CDS market volatility spillover—total (computed in EWS)	Authors calculations based on data from Bloomberg; Truong et al. (2022)	Daily
CDS market volatility spillover—net (computed in EWS)	Authors calculations based on data from Bloomberg; Truong et al. (2022)	Daily
Foreign exchange markets volatility spillover—total (computed in EWS)	Authors calculations based on data from BIS; Moreno Badia et al. (2022)	Annual
Foreign exchange markets volatility spillover—net (computed in EWS)	Authors calculations based on data from BIS; Moreno Badia et al. (2022)	Annual
Sovereign bond markets volatility spillover—total (computed in EWS)	Authors calculations based on data from Haver Analytics; Truong et al. (2022)	Daily
Sovereign bond markets volatility spillover—net (computed in EWS)	Authors calculations based on data from Haver Analytics; Truong et al. (2022)	Daily
Capital flows volatility spillover—total (computed in EWS)	Authors calculations based on data from EPFR	Daily

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Table C1 *continued*

Description	Sources/References	Frequency
Capital flows volatility spillover—net (computed in EWS)	Authors calculations based on data from EPFR	Daily
Global stock market returns spillover—upside, net (computed in EWS)	Authors calculations based on data from Haver Analytics (official national sources)	Daily
Global stock market returns spillover—upside, total (computed in EWS)	Authors calculations based on data from Haver Analytics (official national sources)	Daily
Global stock market returns spillover—downside, net (computed in EWS)	Authors calculations based on data from Haver Analytics (official national sources)	Daily
Global stock market returns spillover—downside, total (computed in EWS)	Authors calculations based on data from Haver Analytics (official national sources)	Daily

ARIC ADB = Asia Regional Integration Center; BIS = Bank for International Settlements; BOP = balance of payments; CDS = credit default swap; CPD = WB Commodity Price Data; CRED's EM-DAT = CRED's EM-DAT The International Disaster Database; CSP = Centre for Systemic Peace; DPI = The Database of Political Institutions; EPFR = Emerging Portfolio Fund Research; EWS = early warning system; FRED = Federal Reserve Economic Data at St. Louis Fed; FX = foreign exchange; GDD = Global Debt Database; GDP = gross domestic product; GFD = Global Financial Development; ICP = International Comparison Program; IFS = International Financial Statistics; IMF = International Monetary Fund; IDS = international debt securities; JEDH = Joint External Debt Hub; OECD = Organisation for Economic Co-operation and Development; OPEC = Organization of the Petroleum Exporting Countries; PCP = IMF Primary Commodity Prices; PRS = PRS Group; QEDS = Quarterly External Debt Statistics; S&P = S&P Global Ratings; UN DESA = United Nations Department of Economic and Social Affairs; UNCTAD = United Nations Conference on Trade and Development; VIX = volatility index; WB = World Bank; WDI = World Development Indicators; WEO = World Economic Outlook; WGI = Worldwide Governance Indicators.

Notes: This table reports the standard variables used in the new EWS. The first column of the table reports the variable name and short description. The second column reports the variables main source and the relevant references to studies which adopted these variables. Some of the indicators are described as follows:

i. Public debt includes total debt liabilities of the government with domestic and foreign creditors. In compiling public debt series for each economy, we look at the different perimeters of government (nonfinancial public sector, general government, and central government) for which the Global Debt Database reports data, choosing the debt category for which the time series is the longest. In many cases, particularly, among low-income economies, this results in a narrow definition of debt (central government) but ensures the consistency of the series across time. In contrast, previous studies have often used a hybrid approach to compile debt statistics, switching debt concepts depending on availability which may have yielded longer but inconsistent time series (Mbaye et al. 2018).

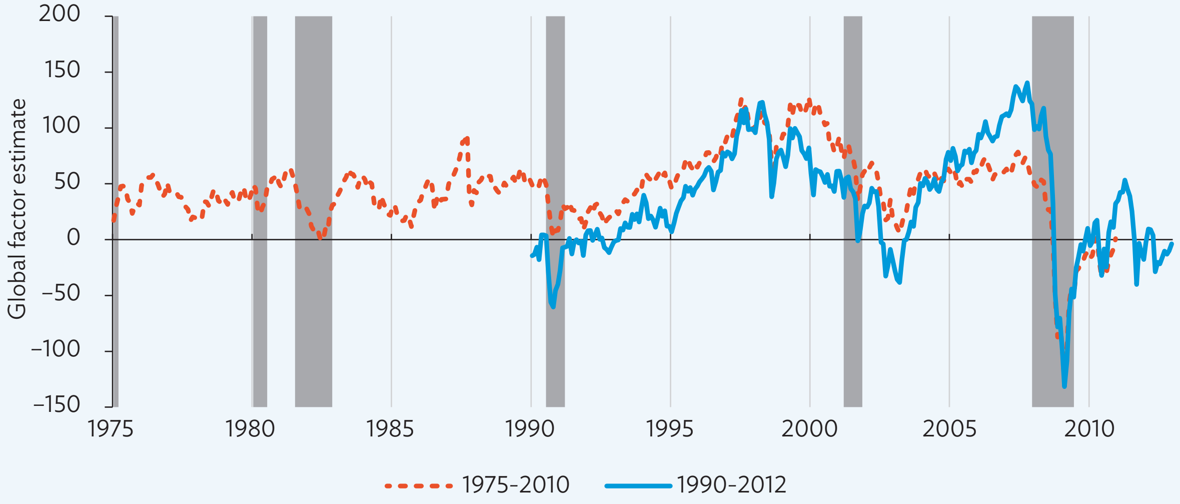
ii. Public external debt is defined in terms of the residency of holder. It includes general government debt and debt guaranteed by the government and, as such, it may have a wider sectoral coverage than our measure of total public debt.

iii. Leverage ratio is defined as the ratio of banking system capital to assets. Aggregate data are used to determine capital and liquidity ratios. The resulting ratios are essentially the average ratios of the system (Caggiano et al. 2014).

Source: ADB compilation.

C.2 Novel Early Warning Indicators

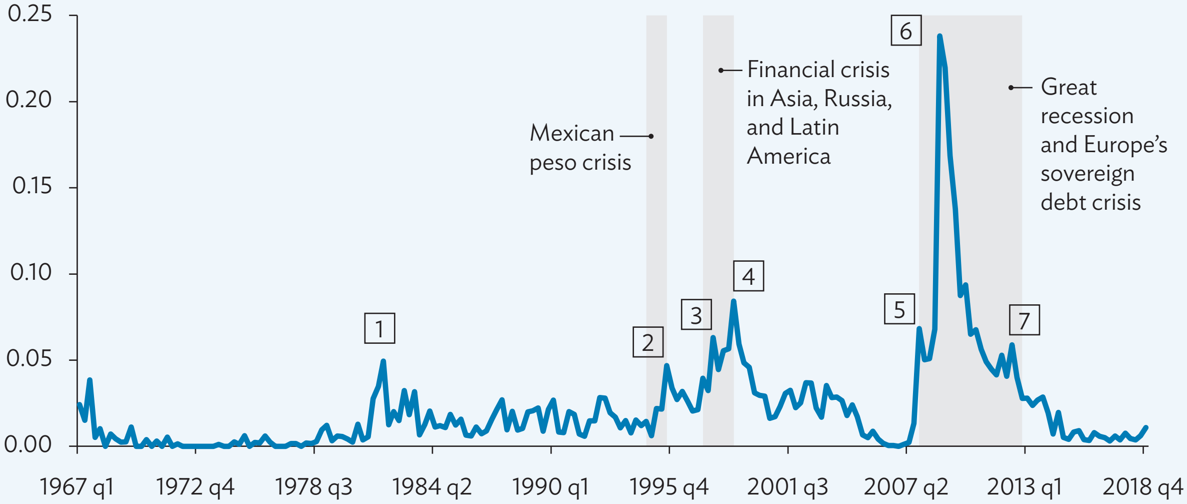
Figure C1: Global Factor Timeline



Notes: This figure plots the estimates of the Miranda-Agrippino and Rey (2020) global factor for a 1975–2010 sample (dotted line), and shorter sample 1990–2012 (solid line). Shaded areas denote recessions as dated by the National Bureau of Economic Research.

Source: Miranda-Agrippino and Rey (2020).

Figure C2: Financial Stress Index Timeline

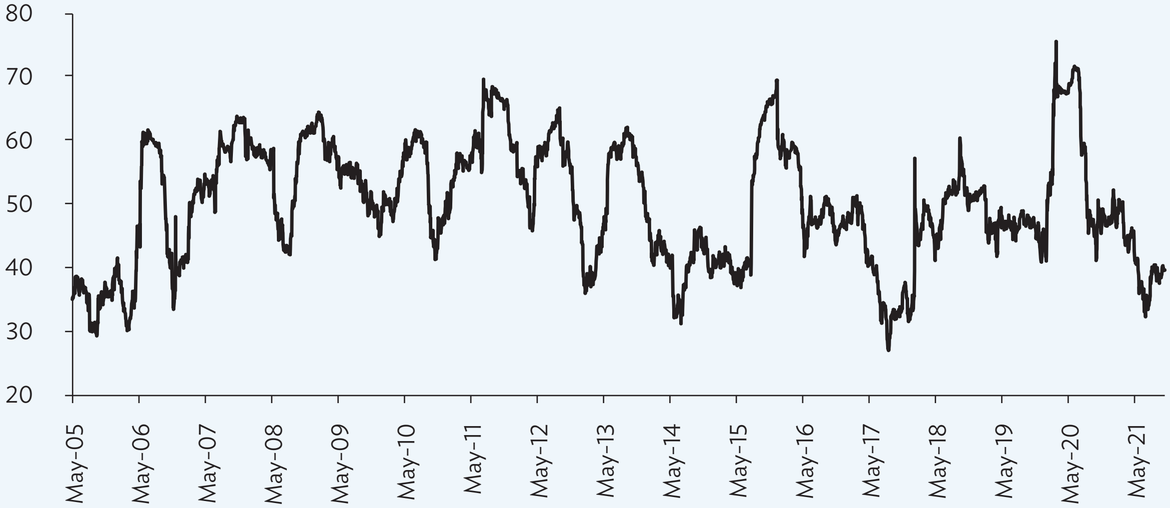


q1 = first quarter, q2 = second quarter, q3 = third quarter, q4 = fourth quarter.

Notes: This figure plots the time series of the financial stress index computed in Ahir et al. (2023), from 1967 to 2018.

Source: Ahir et al. (2023).

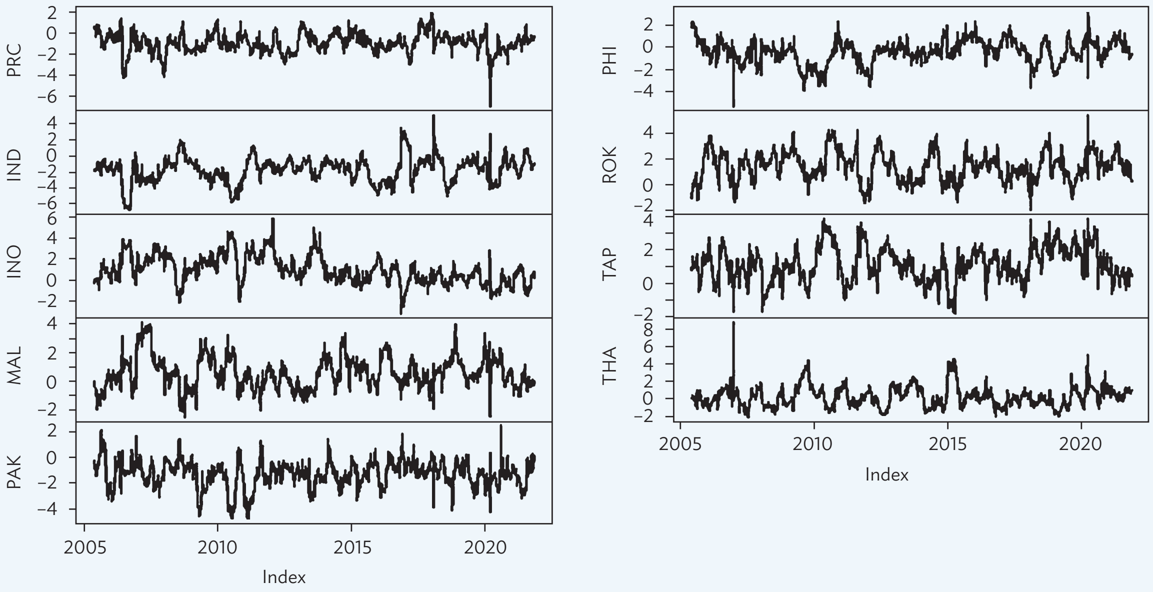
Figure C3: Total Spillovers Index



Notes: This figure shows the total spillovers index from 2005 to 2021, from Khan et al. (2023), for the following economies: the People's Republic of China; India; Indonesia; the Republic of Korea; Malaysia; Pakistan; the Philippines; Taipei,China; and Thailand.

Source: Khan et al. (2023).

Figure C4: Net Spillovers Indexes



PRC = People's Republic of China; IND = India; INO = Indonesia; ROK = the Republic of Korea; MAL = Malaysia; PAK = Pakistan; PHI = Philippines; TAP = Taipei,China; THA = Thailand.

Notes: This figure shows net spillovers indexes from 2005 to 2021, from Khan et al. (2023) for the following economies: the People's Republic of China; India; Indonesia; the Republic of Korea; Malaysia; Pakistan; the Philippines; Taipei,China; and Thailand.

Source: Khan et al. (2023).

Table C2: Data Description and Sources, Novel Variables

Description	Sources/References	Frequency
Crisis History And Interaction Variables		
Contagion: number of economies with fiscal crisis start	Fiscal crisis chronology (Medas et al. 2018; Moreno Badia et al. 2022)	
All economies (t; t-1)		Annual
Advanced and Emerging Economies (t; t-1)		Annual
Emerging and Low Income Economies (t; t-1)		Annual
Advanced Economies (t; t-1)		Annual
Emerging Economies (t; t-1)		Annual
Low-Income Economies (t; t-1)		Annual
Contagion: number of economies with banking crisis start	Banking crisis chronology (Laeven and Valencia 2020)	
All economies (t; t-1)		Monthly
Advanced and Emerging Economies (t; t-1)		Monthly
Emerging and Low-Income Economies (t; t-1)		Monthly
Advanced Economies (t; t-1)		Monthly
Emerging Economies (t; t-1)		Monthly
Low-Income Economies (t; t-1)		Monthly
Contagion: number of economies with sovereign debt crisis start	Sovereign debt crisis chronology (Laeven and Valencia 2020)	
All economies (t; t-1)		Monthly
Advanced and Emerging Economies (t; t-1)		Monthly
Emerging and Low-Income Economies (t; t-1)		Monthly
Advanced Economies (t; t-1)		Monthly
Emerging Economies (t; t-1)		Monthly
Low-Income Economies (t; t-1)		Monthly
Contagion: number of economies with currency crisis start	Currency crisis chronology (Laeven and Valencia 2020)	
All economies (t; t-1)		Monthly
Advanced and Emerging Economies (t; t-1)		Monthly
Emerging and Low-Income Economies (t; t-1)		Monthly
Advanced Economies (t; t-1)		Monthly
Emerging Economies (t; t-1)		Monthly
Low-Income Economies (t; t-1)		Monthly
Contagion: number of economies currently in fiscal crisis	Fiscal crisis chronology (Medas et al. 2018; Moreno Badia et al. 2022)	
All economies (t)		Annual
Advanced and Emerging Economies (t)		Annual
Emerging and Low-Income Economies (t)		Annual
Advanced Economies (t)		Annual
Emerging Economies (t)		Annual

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Table C2 *continued*

Description	Sources/References	Frequency
Low-Income Economies (t)		Annual
Contagion: number of economies currently in banking crisis	Banking crisis chronology (Laeven and Valencia 2020)	
All economies (t)		Monthly
Advanced and Emerging Economies (t)		Monthly
Emerging and Low-Income Economies (t)		Monthly
Advanced Economies (t)		Monthly
Emerging Economies (t)		Monthly
Low-Income Economies (t)		Monthly
Contagion: number of economies currently in sovereign debt crisis	Sovereign debt crisis chronology (Laeven and Valencia 2020)	
All economies (t)		Monthly
Advanced and Emerging Economies (t)		Monthly
Emerging and Low-Income Economies (t)		Monthly
Advanced Economies (t)		Monthly
Emerging Economies (t)		Monthly
Low-Income Economies (t)		Monthly
Contagion: number of economies currently in currency crisis	Currency crisis chronology (Laeven and Valencia 2020)	
All economies (t)		Monthly
Advanced and Emerging Economies (t)		Monthly
Emerging and Low-Income Economies (t)		Monthly
Advanced Economies (t)		Monthly
Emerging Economies (t)		Monthly
Low-Income Economies (t)		Monthly
Years passed since last fiscal crisis	Fiscal crisis chronology (Medas et al. 2018; Moreno Badia et al. 2022)	
Years passed since last banking crisis	Banking crisis chronology (Laeven and Valencia 2020)	
Years passed since last sovereign debt crisis	Sovereign debt crisis chronology Laeven and Valencia (2020)	
Years passed since last currency crisis	Currency crisis chronology (Laeven and Valencia 2020)	
Dummy: Fiscal crisis start (t; t-1)	Fiscal crisis chronology (Medas et al. 2018; Moreno Badia et al. 2022)	Annual
Dummy: Banking crisis start (t; t-1)	Banking crisis chronology (Laeven and Valencia 2020)	Monthly
Dummy: Sovereign debt crisis start (t; t-1)	Sovereign debt crisis chronology (Laeven and Valencia 2020)	Monthly
Dummy: Currency crisis start (t; t-1)	Currency crisis chronology Laeven and Valencia (2020)	Monthly
Contagion: number of economies with fiscal crisis start	Fiscal crisis chronology (Medas et al. 2018; Moreno Badia et al. 2022)	Annual
Contagion: number of economies with banking crisis start	Banking crisis chronology (Laeven and Valencia 2020)	Monthly
Contagion: number of economies with sovereign debt crisis start	Sovereign debt crisis chronology Laeven and Valencia (2020)	Monthly

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Table C2 *continued*

Description	Sources/References	Frequency
Contagion: number of economies with currency crisis start	Currency crisis chronology Laeven and Valencia (2020)	Monthly
Climate Change and Physical-Hazard-Driven Disasters		
Economic and human impact variables	CRED's EM-DAT (International disaster database)	Annual
Reconstruction Costs ($'000)	CRED's EM-DAT (International disaster database)	Annual
Reconstruction Costs, Adjusted ($'000)	CRED's EM-DAT (International disaster database)	Annual
Insured Damage ($'000)	CRED's EM-DAT (International disaster database)	Annual
Insured Damage, Adjusted ($'000)	CRED's EM-DAT (International disaster database)	Annual
Total Damage ($'000)	CRED's EM-DAT (International disaster database)	Annual
Total Damage, Adjusted ($'000)	CRED's EM-DAT (International disaster database)	Annual
Total Deaths (including reported deaths and missing people)	CRED's EM-DAT (International disaster database)	Annual
No. Injured	CRED's EM-DAT (International disaster database)	Annual
No. Affected	CRED's EM-DAT (International disaster database)	Annual
No. Homeless	CRED's EM-DAT (International disaster database)	Annual
Total Affected (No. Injured, No. Affected, and No. Homeless)	CRED's EM-DAT (International disaster database)	Annual
Climate risk index	Resource Watch	Annual
IMF climate change indicator	IMF Macroeconomic Climate Indicators	Annual
JRC climate change risk index	JRC INFORM Climate Change	Annual
Readiness index	ND-GAIN index	Annual
Net readiness index	ND-GAIN index	Annual
Bloomberg government climate scores–BBG climate scores	Bloomberg	Quarterly
Bloomberg government climate scores–climate policy scores	Bloomberg	Quarterly
Sentometrics US Media Climate Change Index	Sentometrics Research	Monthly
Climate Attention Index	International Climate News	Daily
Climate Attention Index: Economic	ND-GAIN index	Annual
Climate Attention Index: Governance	ND-GAIN index	Annual
Climate Attention Index: Social	ND-GAIN index	Annual
Climate Attention Index: Gain	ND-GAIN index	Annual
Climate Attention Index: Net gain	ND-GAIN index	Annual
Economy Political Variables		
Voice and Accountability–Estimated	World Bank WGI	Annual
Political Stability and Absence of Violence/ Terrorism–Estimated	World Bank WGI	Annual
Government Effectiveness–Estimated	World Bank WGI	Annual
Regulatory Quality–Estimated	World Bank WGI	Annual
Rule of Law–Estimated	World Bank WGI	Annual
Control of Corruption–Estimated	World Bank WGI	Annual
Voice and Accountability–Rank	World Bank WGI	Annual

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Table C2 *continued*

Description	Sources/References	Frequency
Political Stability and Absence of Violence/ Terrorism–Rank	World Bank WGI	Annual
Government Effectiveness–Rank	World Bank WGI	Annual
Regulatory Quality–Rank	World Bank WGI	Annual
Rule of Law–Rank	World Bank WGI	Annual
Control of Corruption–Rank	World Bank WGI	Annual
Economist Intelligence Unit political risk score	Economist Intelligence Unit	Monthly
Political risk index	CountryData Online by PRS Group	Annual
Global Factors, Vulnerabilities, and Geopolitical Risk		
Geopolitical risk index	Haver Analytics; GPR Caldara and Iacoviello (2022)	Monthly
Vulnerability Index	Haver Analytics; Dabla-Norris and Gündüz (2014)	Annual
US global factor	Miranda-Agrippino and Rey (2020)	Monthly
Foreign exchange intervention in $ millions	Adler et al. (2024)	Quarterly
Foreign exchange intervention (% GDP)	Adler et al. (2024)	Quarterly
Foreign exchange intervention in $ millions	Adler et al. (2024)	Monthly
Foreign exchange intervention (% GDP)	Adler et al. (2024)	Monthly
Geopolitical Fragmentation		
Aggregate trade restrictions index	Measure of Aggregate Trade Restrictions Estefanía-Flores et al. (2022)	Annual
Trade restrictiveness index	World Bank	Annual
Financial Stress		
ADB FSI	ADB's FSI; Park and Mercado Jr. (2014)	Monthly
IMF FSI	IMF; Ahir et al. (2023)	Quarterly
IMF FSI–Regulatory Capital to Risk-Weighted Assets, Percent	IMF; Ahir et al. (2023)	Quarterly
IMF FSI–Nonperforming Loans to Total Gross Loans, Percent	IMF; Ahir et al. (2023)	Quarterly
IMF FSI–Return on Assets, Percent	IMF; Ahir et al. (2023)	Quarterly
IMF FSI–Return on Equity, Percent	IMF; Ahir et al. (2023)	Quarterly
Global Uncertainty Measures		
EPU indexes (economy specific)	EPU website (Baker, Bloom, and Davis 2016)	Monthly
EPU indexes (all categories)	EPU website (Baker, Bloom, and Davis 2016)	Monthly
Monetary policy	EPU website (Baker, Bloom, and Davis 2016)	Monthly
Fiscal Policy	EPU website (Baker, Bloom, and Davis 2016)	Monthly
Taxes	EPU website (Baker, Bloom, and Davis 2016)	Monthly
Government Spending	EPU website (Baker, Bloom, and Davis 2016)	Monthly
Health care	EPU website (Baker, Bloom, and Davis 2016)	Monthly
National security	EPU website (Baker, Bloom, and Davis 2016)	Monthly
Entitlement programs	EPU website (Baker, Bloom, and Davis 2016)	Monthly
Regulation	EPU website (Baker, Bloom, and Davis 2016)	Monthly
Financial Regulation	EPU website (Baker, Bloom, and Davis 2016)	Monthly
Trade policy	EPU website (Baker, Bloom, and Davis 2016)	Monthly

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Table C2 *continued*

Description	Sources/References	Frequency
Sovereign debt, currency crises	EPU website (Baker, Bloom, and Davis 2016)	Monthly
US monetary policy uncertainty	EPU website (Baker, Bloom, and Davis 2016)	Monthly
Japan monetary policy uncertainty	EPU website (Arbatli Saxegaard et al. 2022)	Monthly
Energy uncertainty index (economy specific)	EPU website (Dang et al. 2023)	Monthly
Energy uncertainty index (global)	EPU website (Dang et al. 2023)	Monthly
Immigration-related index	EPU website (Baker, Bloom, and Davis 2016)	Quarterly
Inter-Korean geopolitical risk index	EPU website (Jung, Lee, and Lee 2021)	Monthly
Oil price uncertainty index	EPU website (Abiad and Qureshi 2023)	Monthly
World Uncertainty Index	WUI (Ahir, Bloom, and Furceri 2022)	Monthly
VVIX Index	Cboe website	Daily
Trade Restrictions		
Average tariff rate	World Bank WDI	Annual

ADB = Asian Development Bank; CBOE VVIX = Chicago Board Options Exchange volatility of volatility index; CRED'S EM-DAT = Centre for Research on the Epidemiology of Disasters Emergency Events Database; EUI = energy uncertainty index; EPU = economic policy uncertainty; FSI = financial stress index; GDP = gross domestic product; GPR = geopolitical risk; IMF = International Monetary Fund; JRC = Joint Research Centre; MPU = monetary policy uncertainty; ND-GAIN = Notre Dame Global Adaptation Initiative; OPU = oil price uncertainty; WUI = World Uncertainty Index; US = United States; WDI = World Development Indicators; WGI = Worldwide Governance Indicators.

Notes: This table reports the novel variables used in the new early warning system. The first column of the table reports the variable name and short description. The second column reports the variables main sources and the relevant references to studies which adopted these variables or make them available from their websites. Crisis chronologies for the construction of the dummy/ordered variables related to the crisis history and interaction variables category can be collected from the authors' websites or online appendixes of their papers (Medas et al. 2018; Laeven and Valencia 2020; Moreno Badia et al. 2022). To provide further clarity, the selected indicators are described as follows:

i. The Climate Risk Index ranks economies based on the human and economic impacts of extreme weather events.

ii. IMF Climate Change indicator modifies the original ND-GAIN score by substituting one sub-pillar of readiness component with a new composite index.

iii. The INFORM Climate Change Risk Index is an enhancement of the INFORM Risk Index, incorporating climate and socioeconomic projections. It offers quantified estimates of the future risk of humanitarian crises and disasters due to climate change.

iv. Readiness Index assesses an economy's ability to leverage investments and convert them into adaptation actions. ND-GAIN assesses overall readiness through three components: economic readiness, governance readiness, and social readiness.

v. Net readiness index refers to the change or difference in an economy's readiness score over time.

vi. Bloomberg government climate scores aggregate three pillars: carbon transition, power sector transition, and climate policy. This indicator primarily focuses on gauging transition risks.

vii. Bloomberg climate policy scores, a component of Bloomberg government climate score, comprises the BloombergNEF (BNEF) climatescope power policy score, green bond issuance, and net zero legislation.

viii. Gain refers to the ND-GAIN Index.

ix. Net gain is the ND-GAIN score adjusted for GDP.

x. ADB's FSI is a composite index that measures the degree of financial stress in Asia, covering the four major financial markets: the banking sector, the foreign exchange market, the equity market, and the debt market.

Source: ADB compilation.

APPENDIX D

Early Warning System Workflow—Additional Details and Results

D.1 Shapley Regressions

The nonlinear and unobservable function of the predictor variables is transformed via Shapley values into a linear, parametric space, turning the estimation of p-values for hypothesis testing into a simple (common) regression (see Chapter 3 and Chapter 5). The coefficients ($\hat{\beta}$) measure the alignment between the predicted probabilities of crises and actual crises. The coefficients ($\hat{\beta}$) are expected to be positive because Shapley values absorb the sign of a relation, such that higher values should reflect an increase in the predicted probability of crisis. More specifically, the coefficients represent the effects of the Shapley values for a one standard deviation change of Shapley values on the predicted log-odds of crisis ($\log \frac{\hat{y}}{1-\hat{y}}$). At the extreme, values close to 1 indicate perfect convergence of the learning process. This implies that the model accurately captures the effect of a variable on the crisis prediction outcome. In contrast, values larger than 1 suggest that the model underestimates the variable's impact on crisis prediction. The opposite for values smaller than 1, and the significance decreases as the β_k approaches zero. In other words, Shapley regressions help in evaluating how well the model has learned the underlying relationships between the selected variables and the predicted outcome (Buckmann et al. 2022). In general, variables with higher Shapley shares tend to have lower p-values as the model relies more on important variables (Buckmann et al. 2022). Moreover, Driscoll-Kraay standard errors are commonly adopted to account for uncertainty from sample splitting (Bluwstein et al. 2023).[1]

D.2. Manual Logit: Variables List

- Exports
- Imports
- Current Account Balance
- Trade Openness
- Real Effecting Exchange Rate
- Short-Term External Debt
- Total Reserves
- Size
- Foreign Currency Debt
- Commercial Bank Deposit Rate
- Bank Loans to Consumers

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[1] See Joseph (2019), Buckmann et al. (2022), and Bluwstein et al. (2023) for theory of inference and convergence of Shapley regressions.

- Debt Service Ratio
- Deposit Lending Interest Rate
- Money Market Interest Rate
- Prime Rate Interest Rate
- Money Supply M1
- Money Supply M2
- Nonfinancial Corporation Debt
- Domestic Credit to Private Sector
- Industrial Production Index
- Stock Price Index
- Overall Balance
- General Government Primary Balance
- General Government Expenditures
- General Government Revenues
- Crude oil price
- US GDP
- US T-note 5-year Rate

Table D1: Debt Crises Shapley Regressions

Panel A: Random Forest Model				
	Shapley Value	Coefficient	Standard Error	*p*-value
Public debt service	0.263	1.491	0.450	0.001*
Real GDP per capita	0.146	1.387	0.473	0.003*
US T-Note 10 year	0.124	0.695	0.717	0.169
Reserves	0.108	0.899	0.437	0.023*
US T-Note 5 year	0.096	0.567	0.725	0.219
Short-term external debt	0.075	0.545	0.410	0.095
Real US GDP growth	0.059	0.742	0.459	0.056
Credit to private sector	0.057	0.774	0.395	0.028*
Total reserve assets ex. gold	0.042	0.489	0.378	0.101
Broad money to reserves	0.030	0.550	0.454	0.116
Panel B: Extra Tree Model				
	Shapley Value	Coefficient	Standard Error	*p*-value
Public debt service	0.196	1.389	0.546	0.007*
US T-Note 10 year	0.146	0.677	1.263	0.297
US T-Note 5 year	0.129	0.508	1.310	0.350
Real US GDP growth	0.115	1.112	0.719	0.064
Real GDP per capita	0.115	1.129	0.597	0.032*
Reserves	0.096	1.031	0.594	0.045*
Short-term external debt	0.056	0.570	0.636	0.187
Credit to private sector	0.053	0.804	0.626	0.103
Total reserve assets ex. gold	0.052	0.529	0.569	0.178
Broad money to reserves	0.042	0.049	0.614	0.468

GDP = gross domestic product, US = United States

Notes: Results of the Shapley regressions for debt crisis are presented using 10 indicators. The models adopted are Random Forest (Panel A) and Extra Tree (Panel B). An asterisk next to p-value indicates that the corresponding coefficient is statistical significance at the 5% level.

Source: ADB calculations using data from ADB's new Early Warning System database.

Table D2: Banking Crises Shapley Regressions

Panel A: Random Forest Model				
	Shapley Value	Coefficient	Standard Error	p-value
Real US GDP growth	0.291	1.364	0.336	0.000*
Inflation	0.126	0.700	0.279	0.008*
Total debt	0.112	0.799	0.315	0.007*
VIX	0.105	1.098	0.457	0.010*
Polity score	0.092	0.701	0.340	0.022*
Public debt service	0.076	0.698	0.286	0.009*
Credit to private sector	0.061	0.504	0.282	0.040*
Total reserve assets ex. gold	0.051	0.440	0.275	0.058
Real GDP	0.050	0.627	0.310	0.024*
Reserves	0.037	0.477	0.273	0.044*
Panel B: Extra Tree Model				
	Shapley Value	Coefficient	Standard Error	p-value
Real US GDP growth	0.295	1.553	0.420	0.000*
Polity score	0.162	0.605	0.443	0.089
VIX	0.099	0.710	0.504	0.083
Total debt	0.093	0.814	0.436	0.034*
Inflation	0.089	0.761	0.413	0.036*
Public debt service	0.069	0.663	0.414	0.058
Credit to private sector	0.061	0.420	0.373	0.133
Real GDP	0.048	0.459	0.465	0.165
Reserves	0.043	0.377	0.402	0.177
Total reserve assets ex. gold	0.043	0.223	0.372	0.276

GDP = gross domestic product, US = United States, VIX = volatility index.

Notes: Results of the Shapley regressions for banking crisis are presented adopting 10 indicators. The models adopted are Random Forest (Panel A) and Extra Tree (Panel B). An asterisk next to p-value indicates that the corresponding coefficient is statistical significance at the 5% level.

Source: ADB calculations using data from ADB's new Early Warning System database.

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How to Assess Crisis Risks
Developing a New Early Warning System at the Asian Development Bank

Early detection of economic vulnerabilities is vital for sustaining inclusive and resilient growth in Asia and the Pacific. This report presents a new early warning system to predict crises, powered by state-of-the-art machine learning and a rich dataset of over 1,500 indicators. Representing a shift toward more adaptive forecasting, the early warning system integrates traditional macrofinancial metrics with emerging risks, and broadens the lens for assessing vulnerabilities. An intuitive companion dashboard delivers frequently updated forecasts, making insights accessible for policy dialogue with governments and development partners.

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