# “Early warning systems for systemic banking risk: critical review and modeling implications”


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# Early warning systems for systemic banking risk: critical review and modeling implications

Abstract

Growing complexity and episodic turmoil in the financial system call for reassessment of existing early warning systems (EWSs) for systemic risk. This paper critically reviews the extensive EWS literature and typology and proposes a new class of supervisory models. The paper also discusses important design implications for an efficient EWS. The new class of supervisory models for systemic risk should be built from an integrated perspective and model EWS according to the users' objectives and competencies. It should incorporate both microprudential and macroprudential perspectives, as well as the structural considerations of the financial system itself. From the financial supervisor's point of view, an EWS involves an ex ante approach to regulation designed to highlight conditions that have in the past been associated with systemic risk. Forward-looking supervisory instruments become more important as they allow ex ante policy action and can reduce the need for ex post regulation.

**Keywords:** early warning system, systemic financial risk, financial supervision, systemic risk factor, systemic risk model.
**JEL Classification:** G01, G17, G21, G28, C53.

## Need for an early warning system for systemic risk. Introduction

From the financial supervisor's point of view, an early warning system (EWS) involves an ex ante approach to regulation, that is, one designed to highlight conditions that have in the past been associated with systemic risk. Forward-looking supervisory instruments become more important as the speed and amplitude of financial crises increase. For example, the IMF (2009, Responding) estimates the costs of the most recent financial crises at approximately USD 12 trillion, reaching up to 20% of GDP in the most hit countries. Following Honohan and Klingebiel (2003), economic studies suggest that systemic downturns last from two to three years and cost, on average, 5% to 10% of pre-crisis GDP, but can cost as much as 50%. However, the tab is much higher if it includes total economic costs, such as the implied waste of investible funds on inefficient projects, the subsequent loss of consumption and production, and higher spreads on new borrowing. An efficient EWS allows ex ante policy action and can reduce the need for ex post regulation. Conversely, a poor EWS may send false signals, leading to actions that may amplify systemic crises. Clearly, an EWS presents a supervisory model risk.

As crises have become more prominent, the literature and models of EWSs have also grown. We discuss some of the key overviews of EWSs in section 1 of this paper. However, the most recent turmoil has demonstrated that most existing EWSs do not fully capture the conditions that cause normal market relationships to fail. In this context, existing approaches should be extended and assessed critically: an updated EWS should reflect improved understanding of how financial markets are affected by changes in risk factors, risk connections, and risk transmission. Although academics, policymakers, and financial practitioners continue to debate the definition of systemic risk, its broad outlines are generally accepted: it is the possibility that an event will trigger a negative feedback loop that significantly affects financial markets' ability to allocate capital and serve intermediary functions, which, in turn, will create spillover effects on the real economy that have no clear self-healing mechanism[1]. It has become especially evident that financial institutions' exposure to systemic risk is not only a function of individual risk profiles, but is also affected by the amplification and propagation effects of links among these institutions, that is, by the structure of the financial system.

The need for an extended EWS approach is particularly urgent for supervisory authorities. Future regulation must widen the monitoring focus from the safety and soundness of individual banking institutions to the assessment of systemwide implications and the risk to supervisors' portfolios of financial institutions. Timely ex ante stabilizing measures can be established, provided that systemic risk is adequately monitored. Therefore, based on a critical review of earlier EWS literature, this paper's objectives for a supervisory policy are as follows:

1. provide an overview of the main directions and results of EWS research on systemic risk;
2. review the research results critically in light of recent crises, changing financial markets, and risk factors;
3. trace the theoretical underpinnings of a revised EWS of systemic risk and propose a direction for future research.


The views expressed in this paper are those of the authors and not necessarily those of the Federal Reserve Bank of Cleveland, the Board of Governors, or the Federal Reserve System.
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[1] Group of Ten (2001, p. 126); Hendricks, Kambhu, and Mosser (2007, p. 65).

Focusing on the conceptual aspects of EWSs, this paper reviews selected literature that discusses key elements in a consistent, useful way.

## 1. Concepts of early warning systems

Early warning systems are functional, data-driven approaches that draw attention to variables associated with past crises in order to alert policy makers of potential for future crises. They are grounded in economic theories of financial crisis and are designed to provide risk alerts on an objective, systematic basis. In a financial context, they may be used to extrapolate the risk of a single financial institution (micro risk) as well as that of the financial system as a whole (macro risk)[1]. They build on two fundamental assumptions: (1) that causality (stability of relations) exists between crises and crisis-driving factors, and (2) that crisis-driving factors can be identified ex ante. In microprudential terms, EWSs typically focus on the stability of single banks, usually expressed in terms of capitalization. Examples of such models in the U.S. include Canary (Office of the Comptroller of the Currency) and SR-SABR (Federal Reserve), which strive to identify banks in an early stage of capital distress[2]. Although these models provide substantial insight as to individual banks' exposure, they do not capture the overall risk effects of spillovers in the banking system. Nevertheless, their results may serve as a basis for assessing systemic risk.

Most early theories of macro risk focused on currency crises. Krugman's (1979) seminal paper, for example, argued that under a fixed-rate exchange system, credit expansion that exceeds money demand growth erodes foreign reserves and eventually leads to a speculative attack on the currency. The crisis literature – including the meaningful publications of Kaminsky, Lizondo, and Reinhart (1998), Demirgüç-Kunt and Detragiache (1998), Kaminsky and Reinhart (1999), and Reinhart and Rogoff (2009) – has grown and become more nuanced, but a core story has emerged. Banking crises occur when rapid credit expansion fuels sustained asset-price growth that substantially deviates from trend[3]. Sovereign debt default occurs when a country borrows foreign-denominated, short-maturity funds without maintaining sufficient foreign reserves or having adequate trade capacity to generate foreign currency[4]. For currency crises, the current account balance dominates.

Once a crisis emerges, the institutional and market microstructure can determine its path and severity. For example, information asymmetries may cause banks to stop lending to each other during a crisis because they are unsure which of them hold toxic assets. Likewise, asset valuations may fall significantly below fundamental value during a severe market dislocation. If not addressed by a liquidity lender of last resort, these types of market failures can spread solvency problems throughout the financial system (contagion).

Despite the emerging core-story consensus, EWSs have produced mixed results. In a comparison of leading-indicator models, Bell and Pain (2000) argue that EWS approaches principally provide reduced forms for modelling banking crises and that some variables seem to be coincident factors rather than leading indicators. The authors suggest that, if financial crises are predictable at all, then EWSs should capture the increasing complexity and transmission of changes in financial markets. Berg et al. (2004) report "pure" out-of-sample results for four currency crisis models[5]. They note that the model of Kaminsky, Lizondo, and Reinhart found "statistically and economically significant predictors of actual crises" and, further, that the model generated similar insights for both out-of-sample and in-sample data. But the IMF model provided little meaningful data, and the private models produced none.

Further survey articles, such as Gaytán and Johnson (2002), Demirgüç-Kunt and Detragiache (2005), and Davis and Karim (2008), describe different concepts of EWSs, including variations in the number, type, and weight of risk factors. To be considered reliable, models must be thoroughly calibrated (balancing first- and second-order mistakes) and able to show adequate results under various crisis scenarios. Hence, if fully reliable forecasts are not possible, an EWS should be interpreted cautiously. Following Edison (2003, p. 11), an EWS might be regarded as a diagnostic tool for monitoring the relative direction of the financial system, rather than a gauge of definitive crisis signals; in other words, a weathervane rather than a barometer. Neither type of EWS, well-calibrated or relative, may be considered static in light of rapidly changing markets, but must be reassessed continually, incorporating evidence from new data and events[6].

EWSs assess the risk of systemic crises on the basis of underlying factors. Hence, it is crucial to have:

[1] Borio (2003) classifies supervisory EWS models as micro- or macroprudential. Hanschel and Monnin (2005, p. 439) use the term "macro approach" in reference to systemic risk.

[2] An overview of EWSs for micro risk is presented by Gaytán and Johnson (2002, pp. 21-36), and King, Nuxoll, and Yeager (2006, pp. 58-65). Jagtiani et al. (2003) test the validity of three micro-risk EWSs (SCOR, SEER, Canary) empirically.

[3] Borio and Lowe (2002, Asset).

[4] Manasse, Roubini, and Shimmelpfennig (2003).

[5] These include a "signals" model developed by Kaminsky, Lizondo, and Reinhart (KLR), a probit model developed by IMF staff, and logit models developed by three investment banks, Goldman Sachs, Credit Suisse First Boston, and Deutsche Bank, tracked between 1999 and mid-2001.

[6] Similarly, the Federal Reserve's SR-SABR model as an EWS for individual banks is tested using each new quarter of data. See Federal Reserve Board (2005, p. 3).

- the operationalization of systemic risk (risk measures);
- the selection of relevant risk factors (risk indicators); and
- a theory on how to combine both (risk model)[1].

Because there are many possible combinations of these elements, there must be some a priori EWS design principle to facilitate specification of an efficient set of variables. The literature shows that one critical design element is a tight correspondence between the outcomes of the EWS and the objectives of its user. Gaytán and Johnson (2002, p. 3), and Davis and Karim (2008, pp. 89, 118) emphasize the need for clarifying the user's objectives in order to model the EWS in a consistent way. De Bandt and Hartmann (2000) point out connections between crisis definition and regulatory policy[2]. As a consequence, in modelling EWSs, special emphasis should be laid on putting together different elements in a comprehensive, integrated framework. An overview of EWSs' key elements and the related literature is shown in Figure 1.

**Early Warning Systems (EWSs) for systemic banking risk**

Overview: (Bell, Pain, 2000), (Gaytán, Johnson, 2002), (Jagtiani et al., 2003), (Berg et al., 2004), (Demirgüç-Kunt, Detragiache, 2005), (Davis, Karim, 2008)

**Objectives**

**Efficiency**
**Timeliness**
**Usefulness**
-Supervision
-Institution
-Research
**Transparency**
- Gaytán, Johnson, 2002
- Bussière, Fratzscher, 2002

**Risk measure**
(Stress assessment)

**Definition crisis**
- De Bandt et al., November 2000
- Bordo et al., 2001
- Hendricks et al., 2007
- Boyd et al., 2009
- IMF, 2009, Responding

**Binary index**
- Kaminsky, Reinhart, 1999
- Edison, 2003

**Three-state index**
- Bussière, Fratzscher, 2002

**Continuous index**
- Illing, Liu, June, 2003
- Hanschel, Monnin, 2005
- Illing, Liu, 2006
- IMF, 2008, Financial
- IMF, 2009, Crisis

**Other**
- Lehar, 2005
- Gray et al., 2007
- Huang et al., 2009
- Moshirian, Wu, 2009
- Segoviano, Goodhart, 2009

**Risk factors**
(Risk indicators)

**Micro risks**
- FRB 2005
- Arena, 2008
- Viale et al., 2009

**Macro risks**
- Caprio, Klingebiel, 1996
- Demirgüç-Kunt, Detragiache, 1998
- Kaminsky, Reinhart, 1999
- Bordo et al., 2001
- Borio, Lowe, 2002, Asset
- Borio, Lowe, 2002, Crises
- Borio, Drehmann, 2009
- Reinhart, Rogoff, 2009

**Structural risks**
- Allen, Gale, 2000
- Furfine, 2003
- Müller, 2006

**Changing risks**
- Stiroh, 2006
- King et al., 2006
- CRMPG, 2008
- IIF, 2008

**Risk model**
(EWS Concept)

**Causality-focused: transmission, network**
- Elsinger et al., 2006
- Goodhart, 2006
- BoE 2007, October
- BoE 2008, April
- Aikman et al., 2009

**Data-focused: leading indicator (signaling)**
- Kaminsky et al., 1998
- Borio, Lowe, 2002, Asset
- Edison, 2003
- Misina, Tkacz, 2008
- Borio, Drehmann, 2009

**Data-focused: regression model**
- Demirgüç-Kunt, Detragiache, 1998

**Comparisons**
- Beckmann et al., 2005
- Demirgüç-Kunt, Detragiache, 2005
- Davis, Karim, 2008

**Neuro fuzzy approach**
- Lin et al., 2006

**Measures**
(Crisis management)

**Capital Controls**
- Bordo et al., 2001

**Safety nets**
- Hoggarth et al., 2005

**Information**
- IMF, 2009,

**Fig. 1. Key elements of early warning systems**

[1] Berg, Borensztein, and Portillo (2004, pp. 35-39). Kaminsky and Reinhart (1999, p. 487), point out the need to make four sets of judgments: (1) define the crisis, (2) agree on a list of variables as indicators for risk, (3) define signals, and (4) determine reasonable period of time between signal and crisis. Gaytán and Johnson (2002, pp. 2-3), say EWSs should have (1) a definition of the scope of the system, that is, individual bank failure or system distress, crisis assessment or only signal, and (2) a mechanism for generating predictions from a set of explanatory variables.

[2] As shown by De Bandt and Hartmann (2000, pp. 11, 16), the definition of a systemic crisis (narrow or broad) affects crisis management policies, tackling the source of the problem (e.g., micro- or macro- oriented measures). Demirgüç-Kunt and Detragiache (2005, p. 20), relate the type of bank crisis (long-simmering or sudden) to the relative importance of macroeconomic variables as underlying factors.

The objectives, and consequently the requirements, of an EWS depend on its intended use. Though one might imagine a variety of interested parties, such as risk managers, asset managers, and economic and financial forecasters, most EWSs are constructed with policy makers in mind. In the literature, the importance of well-defined objectives for EWS modelling is mentioned but not investigated in detail. Supervisors have an interest in constructing EWSs in a way that allows key regulatory variables such as capital adequacy, common risk factors for banks, or bank spillovers to be useful to understand past crises and informative for forecasting future critical conditions. They are also interested in signalling potential financial distress from a set of data monitored by supervisors. The forecasting interval should allow sufficient time for supervisory intervention. The longer the gap between signal and crisis occurrence, the more ambiguous the results. The search for an appropriate forecasting interval may involve running EWSs for different short- and long-term forecasting horizons.

Given the varying relevance of individual institutions for financial markets and systemic risk, EWSs may concentrate on "systemic institutions". From a supervisor's point of view, this may help allocate personal resources efficiently. Consequently, an EWS may be tailored to the specific needs of the user. Concentrating on the user's objectives may help increase an EWS's efficiency by keeping its design simple and avoiding over-specification. Conversely, a multiplicity of EWS users, each with unique objectives, means that no single "correct" approach exists. Therefore, an EWS should be conceived of as a trade-off between user objectives, model complexity, and data availability.

## 2. Measuring financial instability: dependent variable

The measurement of financial stress is based on a notion of what constitutes a financial crisis (extent of distress), a systemic financial crisis (transmission of distress), and the markets involved (type of distress). From a supervisor's perspective, the definition of financial instability or systemic risk is important because the supervisory remedy could require additional regulation; it is based on balancing the costs of regulatory actions against their benefits. To a certain extent, the normal business cycle brings contractions in asset values, credit volumes, and profits. Although this leads to a decline in economic value, the intensity of stress does not necessarily represent a crisis in the sense of existential exposure. There may be critical exposure with firms on a regional level, but such exposure appears insignificant on a countrywide or global level. Financial stress may be applied to the banking system, to a broader set of financial companies, or to securities and FX markets[1]. Thus, there is obviously some "subjectivity associated with banking crisis identification" (Figure 2)[2].

Berg, Borensztein, and Pattillo (2004, pp. 6-7) present five EWS models with different specifications for defining and quantifying currency crises. The models differ in considering exchange rates and reserves as proxies for crises and in treating the current account, the stock market, and the price of oil as explanatory variables. Investigating the definitions applied in 13 research studies, Ishihara (2005, p. 8) finds six different types of financial crises and defines and measures them individually[3]. Because excessively narrow definitions may lead to inconsistent policies, and crises are increasingly multidimensional, the author suggests a broader concept for conceptualizing and assessing financial crises.

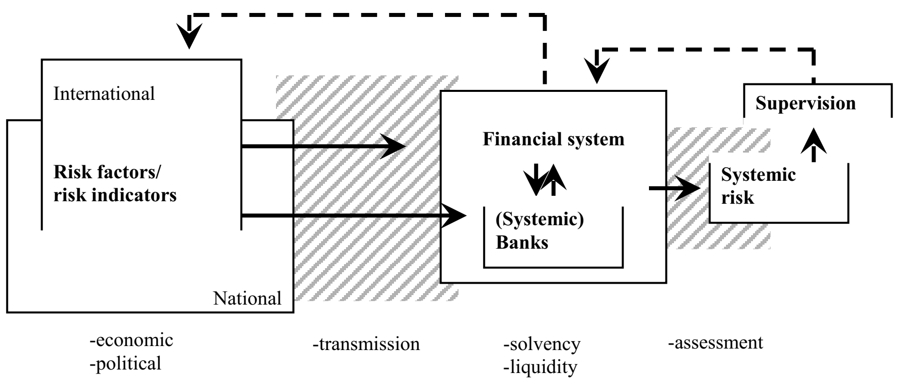


**Fig. 2. Risk transmission and assessment**

[1] EWSs in finance started in the 1990s with models for predicting currency and national debt crises; specific EWSs for banking system distress have been proposed more recently, for example, by Berg, Borensztein, and Pattillo (2004, pp. 4, 7).
[2] Davis and Karim (2008, p. 97).
[3] The types of crisis are: banking liquidity, banking solvency, balance of payments, currency, external debt, growth rate, and financial crisis.

With regard to the identification problem for the systemic dimension of crises, Caprio and Klingebiel (1996) and Demirgüç-Kunt and Detragiache (1998) make the point that most of the capital in financial firms is exhausted. In their broad survey of systemic risk, De Bandt and Hartmann (2000) define a systemic crisis as an "event that affects a considerable number of financial institutions or markets in a strong sense"[1]. Hendricks, Kambhu, and Mosser (2007, p. 65), emphasize transmission structures as characteristics of systemic crises; in these structures, "systemic risk is the movement from one stable (positive) equilibrium to another stable (negative) equilibrium". They suggest focusing future research on systemic risk and the propagation mechanisms of transition from one phase to another. The extent and speed of contagion depend mainly on the system's complexity and the shift from classical bank-based crises to more recent, market-based financial crises. Similarly, Kambhu, Weidman, and Krishnan (2007, p. 6), refer to systemic risk as a "tendency toward a rapid and large transition from one stable state to another, possibly less favorable, state." They point out that the physical and financial worlds are both characterized by nonlinear, complex adaptive systems.

From a technical point of view, a measurement of systemic risk is constructed with variables representing systemic stress, a means of making those variables operational, and a concept for aggregating them. Illing and Liu (2006) provide an overview of different variables used to assess crises originating in the banking, foreign exchange, debt, and equity sectors, as well as composite crises. They show how stress measures vary between and within the crisis categories, sometimes referring to more subjective or objective criteria. In their survey on banking crisis variables, Davis and Karim (2008, pp. 95-97), list the variables used in the literature, pointing out that there are no standard variables because crises arise from different events. Aggregation of the variables is associated with subjectivity and varies according to the purpose of the crisis analysis. This is also reflected in research by the IMF (2009, Responding) on the links between stress in advanced versus developing economies. Because of the characteristics specific to financial stress in each type of economy, the IMF uses two different indexes to measure it.

In early work on EWSs in the 1980s and 1990s, economists tended to define the crisis variable as binary – either crisis or no crisis – and relied on a historical list of crises as defined by professional consensus[2]. To avoid "post-crisis bias" resulting from a false assessment of recovery phases, Bussière and Fratzscher (2002) introduced a three-state classification of crises on the basis of a multinomial logit model. These concepts, however, have several serious drawbacks. The binary and the three-regime approaches ignore market stresses that approached (but never met) crisis standards; they also exclude situations that were successfully managed but might otherwise have become crises[3]. Reliance on professional judgment has the same drawbacks and also illustrates the operational ambiguity of some definitions of systemic crises. Boyd, De Nicolò, and Loukoianova (2009) argue that in most cases, "measured" crises are not "pure" crises but a mix of economy-driven shocks and governmental response. If the effects of governmental actions were not integrated, economic crises would occur much earlier, and conventional indicators would recognize them too late. It is, therefore, important to disentangle the economic shock from the governmental actions taken in response to it.

Consequently, more recent research suggests that financial stress is a continuous variable, with crisis as an extreme value. Illing and Liu (2003 and 2006) applied that approach to Canada, allowing more information to be contained in the stress measure and avoiding some arbitrary boundaries for the beginnings and ends of crises[4]. A continuous index is flexible as to the relative degree of financial stress and may be updated daily. The authors compare 11 differently constructed indicators, concluding that the most appropriate ones are based on standard variables and weighted by volume. Their index, which relies principally on spreads, betas, and interest rates, is employed in a further study by Misina and Tkacz (2008) to test crisis indicators for Canada. Hanschel and Monnin (2005) use the same type of stress index to investigate systemic risk in Switzerland[5]. Their index is based on market data (stock prices, spreads), balance sheet data (interbank deposits, return on assets), and supervisory information on risky banks. In all cases, the level of financial stress is an aggregation of various sub-indexes.

Similarly, a financial conditions index (FCI) derives potential financial stress by combining different price vectors on financial markets, principally vectors related to interest rates and equity prices[6]. Financial stress is most often referred to as the deviation of current financial conditions from their long-term trend and is measured in standard deviations from the

[1] De Bandt and Hartmann (2000, p. 11). Similarly, Elsinger, Lehar, and Summer (2006, p. 138), link systemic risk to assessing the probability of "joint default events".

[2] See, for example, Demirgüc-Kunt and Detragiache (1998) and Kaminsky and Reinhart (1999). Professional consensus is established by precedent and acceptance in the relevant literature.

[3] The IMF (2009, Responding, p. 145), emphasizes that binary variables do not measure the intensity of the stress.

[4] Illing and Liu show that in Canada, crises have been influenced by three broad sets of issues: country-specific issues, North American issues, and issues elsewhere.

[5] Construction of a continuous index is well described in Illing and Liu (2006, pp. 250-256) and Hanschel and Monnin (2005, pp. 432-438).

[6] An overview is given by Swiston (2008, pp. 3-5).

mean[1]. Deviating prices are thought to lead to further consequences in a broader economic framework. English, Tsatsaronis, and Zoli (2005), Rosenberg (2008), and Swiston (2008) connect FCIs to subsequent bank lending standards and from there to macroeconomic activity and inflation. Financial stress is, thus, connected to overall fluctuations in the economy, and the FCI is used for predicting economic up- and downturns. In addition, systemic risk has to be measured more directly in the context of further price or risk factors, such as housing prices and FX rates, as well as considerations of risk capital and risk management.

As a consequence, the impact of systemic risk can also be assessed using more-direct, risk-related approaches. These build mainly on computing banks' potential losses and aggregating them for the overall market or comparing risk capital with the level of losses from risks. Lehar (2005) models the risk of a regulator's portfolio of banks using a contingent approach, in which the expected shortfall depends on the volatility and correlation of bank assets on one hand and bank capitalization on the other. The systemic risk index is derived from the market value of correlated equity prices, which serve as a proxy for bank assets. Gray, Merton, and Bodie (2007) use contingent claim analysis to assess macroeconomic financial risk. They model an economy composed of four different sectors and as a set of interrelated balance sheets in which the value of assets is taken from market-traded securities. Carlson, King, and Lewis (2008) apply a distance-to-default measure for large financial institutions in order to explore relationships between economic activity and the health of the financial sector. Segoviano and Goodhart (2009) measure distress linkages in a regulator's bank portfolio on the basis of non-linear and dynamic dependencies. Using a specific type of copula function[2], they derive the common distress of banks within a system, the risk between two specific banks, and the systemic risk associated with a single bank. The stability index, which is calculated for major European and American banks, reflects the number of banks that are becoming distressed.

The contingent and copula approaches are impressive for their sophistication and elegance; however, they are based on multiple assumptions and are not easy to handle. Nevertheless, they might serve as tools for gauging systemic risk and for comparison with the indicator-based concepts. Further improvements of systemic risk measures may need to be reconsidered constantly in light of the continual innovations of modern financial markets, the availability of data (for example, credit spread instruments), and new evidence on the nature of modern financial crises. It may be argued that progress in risk measurement comes less from the refinement of index construction than from the variables included.

## 3. Assessing systemic risk factors: independent variables

The search for drivers of systemic risk (risk factors) and their operationalization (risk indicators) is based on a theory of what causes risk. There are competing theories about the origins of systemic risk that change over time. The financial system's exposure may derive from deteriorating macroeconomic conditions, more precisely, from diverging developments in the real economic and financial sectors, shocks inside the financial system, banks' idiosyncratic risks, and contagion among institutions. Hence, systemic risk is

- initiated by primary risk factors, and
- propagated by means of markets' structural characteristics[3].

The structure of financial markets makes them vulnerable to initial risk factors and may itself constitute a risk. Within the different theories, a multiplicity of factors may contribute to systemic risk and be made operational in various ways, according to different time horizons and weightings.

Early research focused mainly on deteriorating economic conditions. Caprio and Klingebiel (1996, pp. 21-32), state that banking crises worldwide since the late 1970s were mostly induced by recessions, insolvent enterprises, and insufficient supervision. Kaminsky and Reinhart (1999), who investigated the relations between banking and currency crises worldwide, conclude that financial crises arise after a prolonged economic boom and that bank crises precede currency crises[4]. They use a set of 16 macroeconomic and financial variables to predict future financial distress. In a comprehensive analysis of crises in 29 countries from 1981 to 1994, Demirgüc-Kunt and Detragiache (1998) investigate the effects of the economic environment that contribute to banking systems' fragility. The principal explanatory components are real gross domestic product (GDP), terms of trade, interest rates, and the ratio of credit to GDP. From their investigation of crises spanning 120 years, Bordo et al. (2001) conclude that the frequency of crises has increased: from 1973 to 2000, it was almost double the frequency under the Bretton Woods system, which prevailed from the end of World War II until the

[1] For example, Bloomberg uses a set of three vectors – money market rates, bond market spreads, and equity prices – equally weighted and calculated for the period of 1994-2008. See Rosenberg (2008, p. 8).

[2] Banks' individual and joint asset-value movements are characterized by the banking system's multivariate density (BSMD). The BSMD is based on an information-optimization technique and can be applied using alternative estimates of an individual bank's probability of distress (for example, credit spreads and option prices).

[3] Illing and Liu (2006, p. 244), postulate that financial stress "is the product of a vulnerable structure and some exogenous shock".

[4] A first version of their research was presented in Kaminsky and Reinhart (1996), "The Twin Crises: The Causes of Banking and Balance-of-Payments Problems", unpublished manuscript, Federal Reserve Board and International Monetary Fund.

early 1970s. However, they find no evidence that the severity of crises has increased.

Using the concept of deviating macroeconomic and financial variables, Borio and Lowe (2002, Asset and 2002, Crisis), and Borio and Drehman (2009) developed a series of gap indicators. Gaps are calculated as deviations of variables from their mean, so they represent pressures in the system. In terms of computation, gaps avoid the problems associated with calculating risk factors on an absolute basis. The authors' earlier work viewed the credit/GDP gap as a fundamental mismatch between economic variables. In their later work, the relevance of commodity prices and international factors is admitted but not incorporated due to data limitations.

As financial markets evolved, new concepts emerged concerning the nature of crises and their underlying factors (Table 1)[1]. In a further study, Demirgüç-Kunt and Detragiache (2005, pp. 1-17, 21) posit that crises also arise from the problems of individual banks and the effects of financial liberalization. Ergungor and Thomson (2005, p. 4) conclude that contagion does not seem to be the cause of systemic crises; rather, increasing competition tends to shift bank portfolios toward riskier assets. Similarly, Kambhu, Weidman, and Krishnan (2007, p. 3) see new directions for understanding systemic risk during the transition from a bank-based system to a market-based one, with its increased vulnerability to asset prices. King, Nuxoll, and Yeager (2006) assess micro risk models in the light of technological and legislative changes and financial innovations. Their analysis concludes that more liberalized, more competitive markets call for two new directions in distress models: Models should be more precisely adjusted to a changing banking environment and should be able to integrate additional risks. Hendricks, Kambhu, and Mosser (2007) link the new character of systemic risk to changes in financial markets. Noting the increasing complexity of products, the evolution of large institutions, and many direct and indirect linkages that increase the system's vulnerability, they ask, "can new mechanisms on markets be fully captured?". From their investigation of eight centuries of financial crises, Reinhart and Rogoff (2009) conclude that banking crises can best be predicted from real exchange rates, real housing prices, capital inflows and real stock prices. Structural aspects of the financial system are not included as best indicators.

Table 1. Risk factors and indicators of systemic financial crises

| | Demirgüç-Kunt and Detragiache, 1998 | Kaminsky and Reinhart, 1999 | Borio and Lowe, 2002, Asset | Borio and Lowe, 2002, Crises | Edison, 2003 | Hanschel and Monnin, 2005 | King, Nuxoll, and Yeager, 2006 | Hendricks, Kambhu, and Mosser, 2007 | Borio and Drehmann, 2009 | Moshirian and Wu, 2009 | IMF, April 2009, Responding | Reinhart and Rogoff, 2009 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| National economic | | | | | | | | | | | | |
| a) GDP national | x | x | | | x | x | | | | x | | |
| b) Credit / GDP national | x | x | x | x | x | x | | | x | (x) | | |
| c) Equity | | x | x | x | x | x | (x) | x | x | x | (x) | x |
| d) Property | | | | | | x | x | (x) | x | | | x |
| e) Investments | | | x | | | x | | | | | | |
| International economic | | | | | | | | | | | | |
| a) GDP international | | | | | | x | | | | | | |
| b) Credit / GDP international | | | | | | | | | | | | |
| c) Equity | | | | | | | (x) | x | (x) | | (x) | x |
| d) Foreign Exchange Rate | (x) | x | | x | x | | | (x) | | | | x |
| e) Exports / Imports | (x) | x | | | x | | | | | | | x |
| Financial system | | | | | | | | | | | | |
| a) Interbank lending | | x | | | (x) | (x) | | | | | (x) | |
| b) Leverage | | (x) | | | | | | x | | | | |
| c) Interest rate | x | x | | | x | | x | | | x | x | |
| d) Competition, concentration | | | | | | | x | x | | | | |
| e) Risk appetite, discipline | | | | | | | | x | | (x) | x | |
| f) Complexity | | | | | | | x | x | | | | |
| g) Dynamics, volatility | | | | | | | | x | | x | x | |

[1] An overview of the recent evolution of financial markets is given by Hendricks, Kambhu, and Mosser (2007, pp. 73-79), and King, Nuxoll, and Yeager (2006).

The current crisis highlights the financial system's vulnerability and the need for further development of EWSs[1]. Whereas the basic pattern of crises (deviations of credit volume and asset prices from their mean) seems to have been proved, crises' impact and speed must be explained differently. Financial markets' new fragility is signaled by amplification in financial markets, which results mostly from risk opacity in relevant systemic institutions, subsequent funding problems, herding behavior, the price sensitivity of marketable financial assets, numerous international spillovers, and feedback effects. Davis and Karim (2008, p. 92) point out that until now, EWSs have typically ignored the possibility of crises caused by counterparties' exposure and the need for liquidity. Moshirian and Wu (2009) find that bank stocks' volatility can predict systemic crises in developed countries. An IMF investigation (2009, Responding) into the causes of the recent financial turmoil states that traditional measures of crisis, such as capital asset ratios and non-performing loans, lack predictive power. What is needed instead is a measure of risk-taking behavior, that is, risk appetite. Hence, we need to integrate aspects of structural fragility in an updated EWS. Connectivity between financial firms, the risk of contagion, and the relevance of structural factors has been analyzed by Allen and Gale (2000), Furfine (2003), Müller (2006), Allen and Gale (2007) and Bank of England (2008, October).

In choosing risk factors, the authors use a mixture of intuition and rationality. Kaminsky and Reinhart (1999, p. 480) select variables "in light of theoretical considerations and subject to data availability". Illing and Liu (2006, p. 244) conducted an internal Bank of Canada survey to determine which events were most stressful for Canadian banks. Misina and Tkacz (2008) choose explanatory variables from four categories and test these variables' relevance by adding them to a basic regression formula, both in isolation and pairwise[2]. Further suggestions for choosing optimal indicators are given in Borio and Drehmann (2009, pp. 33, 35). Clearly, risk factors and risk indicators can be chosen in many ways, which suggest the need for another degree of flexibility when constructing EWSs. Specific regressions ex ante make sense to underpin the chosen indicators and make assumptions more stable.

For modeling EWSs, the multiplicity, global reach, and dynamics of the risk factors imply further restrictions. As King, Nuxoll, and Yeager (2006, pp. 65) point out, the main criticism of existing EWSs "is the implicit assumption that future episodes of bank distress will look similar to past episodes". With rapidly changing markets, an EWS must also be constantly adjusted to a changing environment. This adjustment consists mainly of testing the relevance of existing factors, adding new ones, and modifying their weights[3]. The behavioral aspects and conventions of the market are difficult to capture, so the EWS will necessarily be incomplete. A further trade-off must be accepted, considering the time horizon of the model. Although supervisors would like to get information early and have sufficient time to react, the dynamic of the financial system makes it difficult to predict mid- or long-term developments[4].

From a policy perspective, the emphasis on economic fundamentals suggests that policy makers should track the gaps between economic and financial realities and should intervene when those gaps become too wide. Of course, there is extensive discussion about whether policy makers can "time" the market any better than professional investors. Even if they could, many wonder whether the political will for early intervention could be mustered when asset prices move towards seemingly unsustainable levels. This perspective suggests that market microstructure – its shared strategies, operations, and conventions – can sometimes drive market pricing through negative feedback loops. The policy implications would require that there be a lender of last resort, robust resolution procedures, and the elimination of negative feedback mechanisms.

## 4. Modelling early warning systems

We have discussed several different concepts for bringing the elements of EWSs together in an overall framework. There is also a need for a rule that links the information content of risk factors to the prediction of financial stress. As we have noted, suitable risk factors and stress indexes may be modeled backward, looking at the expected output of an EWS and its objectives. The functional design of the EWS implies linking time series, and the type of function depends on the availability of data. Hence, with new data from the markets or information collected by supervisors, the algorithm of EWSs may change as well.

Concerning computational methodology, Gaytán and Johnson (2002, p. 5) distinguish (1) qualitative approaches, (2) signal extraction methods, (3) dependent regression analysis, and (4) other approaches. Qualita-

[1] The most recent financial crisis is analyzed in more detail by the Counterparty Risk Management Policy Group (2008) and the Institute of International Finance (2008).

[2] In total, they test 11,250 different combinations.

[3] Demirgüç-Kunt and Detragiache (2005, p. 11) suggest improving monitoring capacities by developing alternative scenarios. The IMF (2009, Responding) suggests using stress tests.

[4] It seems difficult, therefore, to meet the requirement of Hanschel and Monnin (2005, pp. 439-440) that "variables should have a significant influence on the condition of the banking sector and should have proved to be robust across a number of other studies."

tive models are here referred to as causal models that predict financial crises by exploring logical dependencies between risk factors and crises. In many cases, these links are simulated for different scenarios. The Bank of England uses risk transmission maps and feedback techniques to analyze financial crises[1]. In its Risk Assessment Model for Systemic Institutions, the transmission of shocks to systemic crises is modeled in a bank solvency and liquidity framework. Another promising approach applies network theory to links in financial markets. Elsinger, Lehar, and Summer (2006) model domino effects between large U.K. banks, and run simulations on the basis of a network of linkages between banks.

Statistical approaches are primarily data-focused; they concentrate on regression models or on leading indicator- or signal-extraction models. Building on a forecasting technique proposed by Diebold and Rudebusch (1989) for economic indexes, Kaminsky, Lizondo, and Reinhart (1998), and Kaminsky and Reinhart (1999) were the first to apply this technique to financial crises: A potential crisis is signaled when risk factors or their indicators exceed a previously defined threshold. Borio and Lowe (2002, Asset), Edison (2003), and Borio and Drehmann (2009) also build on that approach; they assume that having fixed thresholds is crucial to forecast quality. Demirgüç-Kunt and Detragiache (1998) use regression analysis to assess the predictive power of selected risk factors for financial crises. Although the results of a regression analysis are more difficult to interpret, this method allows a high degree of flexibility and avoids the problem of fixing thresholds.

Demirgüç-Kunt and Detragiache (2005, pp. 5-9) compare leading-indicator and regression models, concluding that the logit regression model is more suitable. Misina and Tkacz (2008) show that forecast results are different for the two types of statistical models, but improve slightly when using the threshold approach. In a broad analysis, Davis and Karim (2008) find that both models should be respected, the signal model being better at predicting country-specific crises and the regression model more suitable for detecting global stress. The authors emphasize the importance of defining the crisis carefully; they show that the fit of variables (risk factors) may enhance the results considerably. Given the complexity and dynamics of today´s financial systems, selecting and weighting risk indicators is a major challenge, in which tools based on artificial intelligence may provide valuable assistance. Lin et al. (2006) use a neuro-fuzzy approach to identify the drivers of currency crises and find that it improves the prediction of crises. A neural network is especially useful in detecting the main drivers of risk and their relative importance. On the other hand, input data must be chosen by the user, and the way risk patterns are detected remains somewhat opaque. These drawbacks might impede the use of neuro-fuzzy models for those wishing to get a more comprehensive picture of the crisis mechanisms.

A good policy model must meet a variety of tactical standards. It should employ timely, accessible data; the use of less-frequent data not only impairs initial data construction but also reduces the frequency of model updates. Less-frequent updates, in turn, reduce a model's power to forecast a crisis significantly before it occurs. Most models have aimed to provide a 12- to 18-month look-ahead warning. It is important to explore whether such time periods are sufficient to indicate a policy change or are merely the best results of current models. Whatever the advance window, the potential for false alarms should be balanced against the possibility of missing important events by setting warning standards too high. But even the time warnings can be wasted if policy makers do not fully understand the model or communicate its results. Thus, it is essential that the model's logic, data inputs, computational methodology, and outputs be transparent and elegant.

This paper describes a wide range of crisis forecasting methods. Their application depends principally on the definition of crisis, the risk factors selected, and the data available. From a supervisor's perspective, approaches that provide transparency and are easy to communicate are best. Empirical research uses a variety of modelling techniques. Because no single model meets all requirements, it may be necessary not only to run models for different assumptions or scenarios, but also to apply multiple models in parallel. The desired outcome is that, in addition to the amplitude of results, the logic and design of the different models should improve our understanding of the overall situation.

## Conclusions and implications

To address changes in financial markets and risks, we need to develop fresh concepts for assessing systemic risk. The purpose of this paper is to assess existing concepts of EWSs, discuss their suitability in light of recent changes in financial markets, and suggest possible improvements, from a supervisor's viewpoint, for a new class of EWSs. This paper's findings can be seen in terms of the strategic and technical aspects of a new EWS design; furthermore, the paper finds that recent developments in the financial system, particularly the increased fragility of the system itself, make it necessary to modify the basic concept and perception of EWSs (Figure 3).

[1] Bank of England (April 2008, p. 51). See Aikman et al. (2009).

**Proposed EWS design principles**
Design principles refer to the appropriate way to construct EWSs. These principles provide guidance for selecting risk measures, risk factors, and risk models as key elements of EWSs as well as for combining these elements in an overall EWS structure.

1. Objectives/Outcome of an EWS

- Definition of intended purpose
- A tool for monitoring rather than forecasting

2. Risk measures

- Emphasis on representing variables based on market data
- Building a continuous index

3. Risk factors

- Economic variables; the gap concept
- Financial fragility
- Risk appetite

4. Risk model

- Regression approach with more flexibility
- Signal approach with more transparency
- Artificial intelligence to detect complex structures and weights

5. Handling an EWS

- Treating an EWS as a comprehensive set of elements
- Use of different models in parallel
- Running models for different scenarios
- Running models for different time intervals that are updated frequently

**Fig. 3. Proposed EWS design principles**

Because of the increased complexity of financial risk, a new EWS model should be used primarily as an orientation tool rather than a signaling technique. Its main value lies in providing a systemic overview and serving as a monitor. From a supervisor's perspective, it applies to the market as a whole as well as to the regulation of single institutions. Hence, it can overcome the fundamental limitations of traditional models, both micro and macro: microprudential EWS models cannot, because of their design, provide a systemic perspective on distress; for the same reason, macroprudential EWS models cannot provide a distress warning from individual institutions that are systemically important or from the system's organizational pattern. A new EWS methodology should combine both these classes of existing supervisory models.

The system's rapid transformation requires continual adjustments, which include verifying the changing relevance of risk factors as well as running analyses for different market scenarios[1]. Hence, an EWS's architecture must be accompanied by rules for managing it, that is, a policy for adapting to an environment in transition; moreover, the emphasis must shift from the EWS itself to the process of handling EWS models.

As a supervisory tool, an EWS should be used in combination with other regulatory instruments. Traditional rules for capital adequacy generally require ex post regulation, in the sense that in the worst case, banks can cover their losses. In the context of rapid market changes, these rules may be too weak and delayed. In particular, they fail to account for contagion effects in the market as a whole. More ex ante instruments would complement the available set of regulatory tools. Moreover, by observing the markets with the help of an EWS, regulators can gain knowledge that helps assess capital adequacy; there are also synergies of information. Of course, the results of an EWS should be treated carefully and not overestimated[2]. On the other hand, once critical signals are emitted, supervisory authorities need support for undertaking measures on the basis of an expected, but not yet realized, deterioration.

Whereas the literature focuses primarily on individual EWSs settings, without discussing possible combinations of risk measures, factors, and models, more comprehensive sets of these elements are needed. A consistent set of EWS elements may be obtained by adjusting the model to the users' objectives, particularly to the desired outcome (such as obtaining information for supervisory policy), possible actions (such as responses to solvency and liquidity of markets, the system's vulnerability, and the timeliness of information), and the user's specific competencies (such as data availability). Because one size of EWS clearly does not fit all needs[3], the case for efficient sets is underlined further.

Changing financial markets are characterized by new transmission patterns, higher transmission speed, greater opacity, and sometimes by irrational behavior. These effects are mainly related to the growth of derivatives, securitization, and structured products, which increase the system's vulnerability. In terms of systemic risk assessment, factors linked to the system itself have become more important than exogenous risk drivers and should be accounted for in an EWS. New elements relate mainly to market-traded instruments, concentration in the sector, international spillovers, and feedbacks. It is

[1] Borio (2003, p. 13), suggests stress tests to assess the damage likely to be caused by an adverse event.
[2] Berg, Borensztein, and Portillo (2004, p. 30), note that "EWS should not be the sole method to anticipate crises".
[3] According to Jagtiani et al. (2003, p. 50), EWS models "involve a set of trade-offs".

important to remember that what counts is not the number of elements added to an EWS but their usefulness under changing conditions. A measure of systemic fragility could also include the behavioral aspects of financial markets. That is, a new EWS may focus on the institutions that have the greatest impact on the system. Such a focus could limit the complexity of the EWS, which would otherwise increase along with the number of risk factors.

From a more technical perspective, the literature provides evidence for the usefulness of indexes on a continuous basis. Supported by the increased availability of data, such as spreads, and of data technology that is applicable to markets, this type of stress measure is more flexible and less subjective than a binary index. New concepts of an EWS for supervisory authorities should, therefore, also include setting up relevant databases, such as those for credit derivatives. Further research to identify evolving risk patterns in a more complex environment may be facilitated by using methods of neural networks and fuzzy logic. To summarize, changes in financial markets increase the need for EWSs and the complexity of EWS architecture. Further work is urgently needed to enhance the operational basis of EWSs, to identify additional risk factors, and to implement comprehensive sets of EWSs.

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