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Monitoring banking sector risks: An applied approach

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Monitoring banking sector risks: An applied approach

This paper develops an early-warning system for banking sector risks.

The proposed model is tailored to meet the professional needs of an internationally operating private sector financial institution and can be applied across a wide range of developing and industrial countries.

The model exploits historical evidence, suggesting that banking crises are often linked to financial cycles. Typically, a simultaneous boom in lending and asset prices, followed by a sharp decline, could be observed prior to a crisis. In some emerging market crises, an appreciating real effective exchange rate, accompanied by deteriorating trade competitiveness and subsequent capital flight, has played a major role too.

Without loss of generality, only a small number of input variables is considered. For the industrial countries the model combines measures of housing and equity prices, domestic credit to GDP and economic output. For the emerging markets the model is based on domestic credit to GDP, the real effective exchange rate and equity prices.

Complementing previous research, the paper focuses on how such a model can be implemented in practice. It describes the methodology in some detail and applies it to a broad sample of industrial countries and emerging markets. The requirements and obstacles are addressed which analysts face when implementing the model in day-to-day business.

Overall performance of the model is robust and in line with existing empirical evidence. It may thus serve as a useful screening tool across a large number of countries. However, it cannot substitute for an in-depth and thorough risk assessment of the banking sector at an aggregate as well as micro-prudential level.

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Monitoring banking sector risks

An applied approach¹

Christian Weistroffer², Veronica Vallés³

Abstract

Despite abundant empirical evidence on the merits and limits of early-warning systems for banking crises the day-to-day use of such systems seems to be limited. Reluctance to use such systems may partly be explained by the difficulties to operationalise the proposed models, which are often demanding in terms of data requirements and/ or methodologies.

We try to overcome these difficulties and show how an early-warning system can be implemented in practice. Drawing on existing empirical work, we develop a model that provides timely and readily digestible information on macroeconomic developments, e.g. booming credit volumes, excessively rising asset prices or exchange rates, which in the past typically preceded banking crises. Our model is tailored to meet the professional needs of an internationally operating private sector financial institution and can be applied across a wide range of industrial countries and emerging markets.

Keywords: banking crisis, early-warning system, credit risk management

JEL Classification: E44, F37, G21

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1 Introduction

Large-scale banking sector problems have been a persistent threat to both the advanced and developing financial systems in the past. Exploring financial history of the last eight centuries, Reinhart and Rogoff (2008a) conclude that crisis events that appear to be rare in a three-decade span “may not be all that rare when placed in a broader context.” Considering the last 120 years, Bordo et al. (2001) find that the “crisis problem” has not grown less severe over time – except for a 25-years relatively calm period under the system of Bretton Woods and the classical gold standard. Since then, national and international efforts to avoid systemic banking sector problems have had limited success and there is a chance that we will have to live with the risk of crises.

However, there is hope that one day it will be possible to identify crisis developments in advance and mitigate adverse consequences in due time. Among others, Borio and Lowe (2002a, 2002b, 2004) worked to that goal and found that banking crises during the past three decades were closely linked to boom and bust cycles in economic output, asset prices, lending or exchange rates. Typically, a simultaneous boom in lending and asset prices, followed by a sharp decline, could frequently be observed prior to a crisis. An appreciating exchange rate, accompanied by deteriorating trade competitiveness and subsequent capital flight, has played a major role in many emerging markets too. Most prominent examples include the 1997/98 Asian crisis, the Japanese experience since the early 1990s, and the experiences of the Nordic countries during the late 1980s and early 1990s. More recently, Russia (1998), Ecuador (1999) and Argentina (2001) experienced crises that followed similar patterns. The latest US sub-prime crisis is yet another case in point. Reinhart and Rogoff (2008b) point out that there are many parallels to previous crises, most notably a boom in lending and housing markets prior to crisis.

So why not exploit these findings to prevent or at least identify banking sector risks before they materialise? Supervisors, central banks and international institutions such as the BIS, IMF and the World Bank all have made first steps into that direction, developing early-warning systems that assist these institutions in monitoring banking sector risks. Internationally operating private sector financial institutions likewise have an innate interest to monitor banking sector risks, as they are exposed to credit and market risk across a broad range of countries. However, despite abundant empirical evidence on the merits and limits of early-warning systems for banking crises the implementation and day-to-day use of such systems by the private sector seems to be limited. Reluctance to use such systems may partly be explained by the difficulties to operationalise the proposed models. Often, they are demanding in terms of data requirements and/ or methodologies and do not allow for a differentiated but consistent treatment of industrial countries and emerging markets. We try to overcome these difficulties – at least to a reasonable extent – and show how an early-warning system can be implemented, which is tailored to meet the professional needs of an internationally operating financial institution.

Based on previous work by Kaminsky and Reinhart (1999), Kaminsky (1999) and Borio and Lowe (2002a, 2002b, 2004), we develop a new early-warning system that aims at detecting the economic patterns described above. Complementing previous studies, we focus on the requirements and obstacles that researchers face when designing, implementing and up-dating an early warning system in day-today business. In doing so, we differentiate between industrial countries and emerging markets. For the industrial countries we combine measures of housing and equity prices, domestic credit to GDP and economic output. For the emerging markets we develop a model based on domestic credit to GDP, the real effective exchange rate and equity prices. Indicators are calculated as percentage deviations from their longer-term trends.

Our aim is to capture adverse macroeconomic and financial developments that have led to banking sector problems in the past. Ideally, our model can be deployed to serve as a timely snapshot on macroeconomic banking sector risks across a wide range of industrial countries and emerging markets. To exemplify, the model would have captured the US lending and housing price boom prior to the current crisis. However, it could not have foreseen the drying-up of the interbank market, the spread of problems to other countries or the magnitude of the crisis. Such limits of the early-warning system emphasize the need to conduct a quantitative as well as qualitative micro-prudential analysis in order to thoroughly assess banking sector risks. This includes analysing the resilience of national banking systems to internal or external shocks.

The remainder of the paper is organised as follows. Section 2 asks why a private sector financial institution should care about monitoring banking sector risks. Section 3 elaborates on the specific (technical) requirements when designing a model for day-to-day use. Section 4 provides information on the methodological background and describes our approach. Section 5 presents further details on the implementation of the model, each with the industrial countries and the emerging markets. Section 6 concludes.

2 The private sector's case for an early-warning system

Systemic banking crises are associated with sizable costs for the tax payer and the overall economy. Fiscal and quasi-fiscal costs to rehabilitate banking systems after crisis periods are calculated at 12.1% of GDP on average in developed countries and 17.6% of GDP in emerging market countries (Hoggarth et al, 2002). Systemic banking crises have caused significant output losses, with estimates ranging from 10.2% (IMF, 1998) to 20.7% (Hoggarth et al, 2002) in developed countries and from 12.1% (IMF, 1998) to 13.9% (Hoggarth et al, 2002) in medium-and low-income countries¹.

¹ The IMF (1998) measures output losses as the difference between the trend and the actual growth rate during crisis periods, where the trend growth is calculated over a short three-year period before the crisis. Hoggarth et al (2002) calculate output losses as the cumulative difference between the actual output level and its trend over a ten-year period before the crisis.

The avoidance of major economic costs, stemming from problems in the banking sector, rank high on the agenda of regulators and policy makers and receive enhanced attention from the academic community.² But why does the private sector have an interest in monitoring systemic banking sector risk? Simply, because at the level of individual institutions systemic banking sector risk translates into business risk. In order to make sound strategic decisions regarding credit risk and portfolio management the outlook on future banking sector risk is of utmost relevance, both within the home market and in foreign markets.

To the extent that large international banks since the early 1990s have raised their foreign exposures³ they face new challenges in monitoring country-specific credit risk. Within the context of the implementation of Basel II, large international banks have developed sophisticated internal sovereign risk rating systems. Given the close link between systemic banking crises and sovereign risk these rating systems encompass the assessment of national banking sectors as an integral part. However, when it comes to the assessment of rare but extreme events, such as banking crises, the private sector is often suspected of being short-sighted in its judgement. There is a large body of literature that tries to rationalise fluctuations in credit policies by pointing towards disaster myopia, herd behaviour, agency problems and limited institutional memory.⁴ From a macro perspective these problems account for the so-called procyclicality of the financial system – that is the provisioning of excess credit during economic boom phases followed by a sharp contraction of credit during bust periods.⁵

The formulation and implementation of strategies to address these problems poses a great challenge. First steps in that direction are the introduction of through-the-cycle rating systems and the proposal of counter-cyclical capital requirements rules. The use of early-warning systems for extreme but rare events, which incorporate a longer-term perspective, can be another building block. Such systems can help institutionalise the memory of an organisation with respect to past crisis experience. They also offer a systematic approach for identifying possible turning points of the financial cycle at an early stage. While private sector institutions certainly cannot prevent the regular emergence of financial cycles, at least not by their isolated efforts, they can try to monitor cyclical macroeconomic movements and be prepared for the emergence of possible banking sector problems.

Towards this end, the model presented in this paper tries to anticipate adverse macroeconomic developments that eventually evolve into banking sector distress or outright crisis. As part of a more comprehensive risk assessment programme it needs to be complemented by the analysis of other

² For a survey of early-warning systems for banking crises see Bell and Pain (2000) as well as Demirgüç-Kunt and Detragiache (2005). Other reviews can be found in Illing and Liu (2003), Edison (2004), King, Nuxoll and Yeager (2004).

³ e.g. Schildbach (2008) highlights the increasing participation of European banks abroad.

⁴ See Guttentag and Herring (1984), Herring (1999), Jiménez and Saurina (2005).

⁵ See Borio, Furfine and Lowe (2001).

factors of systemic relevance as well as the assessment of individual institutions (e.g. the institutional environment, interbank exposures and international links).

3 User requirements

When implementing an early warning system for day-to-day use, the requirements of at least two target groups need to be taken into account. First, results must be easily accessible and presented in a format that is straight-forward to interpret by the end-user. Second, there should be easy-to-handle implementation and updating procedures, which suit the requirements of the model developer.

For *the end-user*, the model should serve as a timely snapshot on potential banking sector risks. The user should be able to analyse the most recent information on the macroeconomic variables and to compare them with evidence from past crises. This should include the possibility of monitoring indicators individually but also as a combined measure. Simple charts to contrast indicators with their respective thresholds would be helpful to identify the main drivers of banking sector vulnerabilities. In addition, the user should be allowed to monitor the original time series that are used to calculate the signals, as this would provide a useful cross-check of and more intuitive access to the underlying methodology. Ideally, dynamic website implementation should allow straight-forward interpretation of the model's results (see appendix figures A-1 and A-2).

As to the specific needs of the *developer*, the model should be supportive to the data management process, i.e. the frequent updating of input variables and the recalibration of thresholds on a regular basis. The model should be implemented in a dynamic framework that allows the developer to test alternative specifications. The developer should be able to compare results for different indicators, forecast windows and alternative methodologies to build up individual and composite indicators. Once the model is implemented, input time series to calculate the indicators and signals should be automatically updated.

Without loss of generality, only a small number of input variables should be considered to keep the model as lean as possible. Also, the scope of the system in terms of country coverage, data frequency and sample period should account for possible data limitations. Consistent treatment of data errors and outliers should be warranted. Finally, reproducible and robust calculation procedures need to be at the core of the system in order to meet internal and external documentation requirements. Documentation of the model should specify the main objectives, definitions, assumptions and calculations. A clear description of the implementation processes and the rationale behind it would help ensure the system's continuity.

4 Methodological background and model design

In this and the following section, we develop an early-warning system that is designed to meet the requirements postulated above and show how it can be implemented in practice. We analyse two distinct datasets: One for the *industrial countries* and one for the *emerging markets*. Separate analysis of industrial countries and emerging markets allows us to consider different regimes as regards the selection of indicators, data frequency, forecast horizon and sample periods. Despite both groups sharing common macroeconomic threats to banking sector stability, i.e. excessive lending, booming equity or property prices, there is good reason to analyse the two groups separately. First, data availability is a major issue, as reliable time series of property prices for the emerging markets are hardly available. Likewise, for some emerging markets equity price data has become available only after the 1990s since national stock markets were not developed before that time. Second, to the extent that the origins of banking crises vary between the two sub-samples the separate consideration of emerging markets and industrial countries allows us to tailor the set of indicators to the specific requirements of each group.

While the different model specifications and results for the two sub-samples will be presented in section 5, this section focuses on the common methodological framework used in both sub-samples.

4.1 The signalling approach

Our model is based on the so-called signalling approach, which builds on a simple idea: A single binary indicator is related to a binary crisis variable. In order to trigger a signal the underlying indicator, e.g. domestic credit to GDP, must exceed a predefined threshold. If a signal is preceding a crisis episode it is considered a good signal, otherwise it is considered a false alarm. An indicator is said to have good predictive power if it calls most of the crises while not producing too many false alarms. Within this framework, individual indicators can be monitored on a stand-alone basis but can also be combined to form a composite index.

While the signalling approach was originally developed to predict turning points of business cycles,⁶ Kaminsky and Reinhart (1999) and Kaminsky (1999) were the first to adopt it to analyse early-warning signs of currency and banking crises. More recently, Borio and Lowe (2002a, 2002b, 2004) applied a similar approach to analyse the build-up of “financial imbalances” prior to banking crises. In contrast to these studies, Demirgüç-Kunt and Detragiache (1998, 1999) prefer using a multivariate logit model in order to analyse early-warning signs of banking crises. Although this approach is commonly used in the literature, no consensus has been reached on whether one approach dominates the other.⁷ Both the signalling approach and the qualitative response models

⁶ See Stock and Watson (1989), Diebold and Rudebusch (1989).

⁷ For a general discussion of different early-warning systems of banking crises see Demirgüç-Kunt and Detragiache (2005). For a direct comparison of the multivariate logit and the signalling approach see Davis and Karim (2008).

such as logit or probit offer unique advantages. On the one hand, multivariate qualitative response models should generally outperform the more parsimonious signalling approach, as they account for more than one indicator at a time and do not restrict the indicators' variability to the discrete states of zero and one. On the other hand, the non-parametric signalling approach holds the advantage of not relying on strict assumptions on the variables' distributional characteristics. Thereby, it avoids one possible source of estimation error compared to the more sophisticated regression models. In addition, the relatively simple calculation routine of the signalling approach can be implemented without comprehensive training in complex regression techniques. As mentioned above, each indicator can be easily followed and interpreted on a stand-alone basis as well as within an index combining individual indicators. Finally, the concept of indicator thresholds allows the model developer to explicitly weigh type-I errors (missed crises) against type-II errors (false alarms). Thus, for our purpose of developing a straight-forward, easy-to-interpret early-warning system we consider the benefits of the signalling approach to outweigh those of the qualitative response models.

4.2 Defining past crisis dates

The careful identification and timing of in-sample crisis dates is one of the key challenges in designing an early-warning system. To this end, two approaches can be distinguished. One is based on the quantitative analyses of more or less high frequency data (e.g. Von Hagen and Ho, 2007) the other is based on characteristic crisis events.⁸ Following the event-based approach, Demirgüç-Kunt and Detragiache (1998) identify a banking crisis if at least one of the following conditions holds: The ratio of non-performing assets to total assets in the banking system exceeded 10 percent; the cost of the rescue operation was at least two percent of GDP; banking sector problems resulted in a large-scale nationalisation of banks. Extensive bank runs took place or emergency measures such as deposit freezes, prolonged bank holidays, or generalized deposit guarantees were obliged by the government in response to the crisis. According to Caprio and Klingebiel (1996, 2003) a banking crisis is defined as a situation where much or all of the banking systems' capital is exhausted. Lindgren, Garcia and Saal (1996) distinguish between (i) "significant extensive unsoundness short of crisis", which are localised crises or non-systemic episodes, and (ii) systemic banking crises, characterized by bank runs, collapsing financial firms or massive government intervention.

Admittedly, such dating schemes are more arbitrary in assigning crisis dates than measures that relying solely on higher frequency data. However, to the extent that high frequency indicators used to define crisis dates are tested for their ability to predict the crisis, it will be difficult to identify the direction of causal effects. Moreover, since high frequency quantitative indicators will merely cover the symptoms of a crisis, a crisis will not be identified if it does not display the specific symptoms. Conversely, a crisis will be assigned to those periods that displayed the relevant symptoms

⁸ See Jacobs et. al (2005) for a review of different approaches to identify banking crises.

regardless of whether there were systemic problems or not. Because of such difficulties associated with purely quantitative measures, the literature predominantly uses the event-based identification schemes described above. We do the same, combining and consolidating the different event-based approaches. Thus, we consider events that qualify either as banking sector distress or as systemic crisis according to the following criteria:

- (i) ***Banking sector distress** is indicated by the failure of a number of institutions within a short interval, or the failure of a single institution of systemic relevance. Even in the absence of failures, an episode qualifies as banking sector distress if policy and regulatory actions to overcome strains in the banking sector are taken. Such actions may be revealed by (de facto) forced takeovers or mergers, or by the extension of public assistance (financial or otherwise) to the banking sector.*
- (ii) *An episode evolves into a **systemic crisis** if most or all of the system's bank capital is depleted. Widespread bank runs, large-scale failure of banks, or massive public intervention to avoid systemic breakdown will be considered as indications of a systemic crisis.*

Note that our identification scheme also encompasses borderline events and smaller episodes of systemic relevance. This deviates from the more commonly followed approach in the literature to consider full-blown systemic crises only. However, such a broad crisis definition allows us to analyse the industrial countries separately, as those countries experienced only four instances of large-scale systemic crises during the past 25 years, i.e. the Nordic countries' crises and the Japanese crisis during the 1990s. Moreover, to the extent that banking sector problems in modern financial systems do not emerge as full-blown systemic crises – but rather display the symptoms that qualify for banking sector distress as described above – they too will be captured by our crisis definition.

For the dating of systemic crises, we rely mainly on the studies by Caprio and Klingebiel (2003) as well as Lindgren, Garcia and Saal (1996) who provide comprehensive and original research on historical crises dates. Further papers by Laeven and Valencia (2008), the Bank for International Settlement (2004) as well as our own estimates complement these sources.

4.3 Selecting indicators

In selecting early-warning indicators we closely follow Borio and Lowe (2002a, 2002b, 2004). The authors calculate indicator deviations (gaps) from their country-specific longer-term trend, i.e. credit gap, equity price gap, output gap and exchange rate gap. They use a relatively long forecast horizon of one up to five years prior to the crisis, trying to capture the “build-up of financial

imbalances” in the run-up to a crisis. Their results reflect recent international experience, which highlights the role of financial cycles as a frequent cause for banking sector problems. Typically, a simultaneous boom in asset prices and lending followed by a sharp decline could be observed prior to a crisis. Historical evidence seems to confirm the close link between property price cycles and banking sector problems, while the link with equity prices seems to be not as close.⁹ In many cases, financial liberalisation or (de facto) deregulation through financial innovation have promoted the development of excessive lending which in turn fuelled rising asset prices.¹⁰

Theory suggests that rising prices for equity or property during boom markets may have a twofold effect on lending: On the one hand, rising asset prices tend to stimulate economic activity, increasing the need for private sector financing. On the other hand, higher prices raise the value of collateral, thereby reducing the cost of borrowing. As a result, lending will be stimulated, which in turn fuels a further rise in asset prices. Moreover, banks tend to underestimate credit risks when prices are rising and economic conditions are rosy. In light of fierce competition, credit risk premia are squeezed and more risky projects receive financing. When economic conditions are deteriorating, self-enforcing interaction between lending and asset prices may be even more pronounced. As defaulting borrowers are forced to sell their assets, prices decline. Collateral value diminishes, credit costs increase, and credit supply is constrained. If credit is no longer available to finance the purchase of assets, prices will decline further. Eventually, falling asset prices, reduced collateral value, and defaulting borrowers will reinforce each other, forcing banks to realise losses.¹¹

An appreciating real effective exchange rate accompanied by deteriorating trade competitiveness and capital flight may further contribute to crisis developments, especially in the emerging markets. During the Asian financial crisis of 1997/98, for instance, banking sector vulnerabilities arose from short-term foreign borrowing and portfolio investment, which were used to finance long-term projects (maturity mismatch). Formal or informal regimes of pegged exchange rates further increased vulnerabilities by creating incentives to borrow in foreign currency, while lending or investing in local currency (currency mismatch). During the boom phase prior to crisis, lenders tended to underestimate credit risks, while borrowers took the risk associated with foreign currency exposures too lightly. In the run-up to the crisis, speculative inflows contributed to the overvaluation of national currencies in real terms. As a consequence, trade competitiveness declined, weighing on exports and eventually leading to an economic slowdown. As soon as capital flows started to reverse and asset prices fell, maturity and currency mismatches on bank and corporate balance sheets led to a vicious circle: Collateral value declined and borrowers were no longer able to repay their debt. At the same time, banks experienced liquidity problems because they found it difficult to refinance themselves short-term or in foreign currency. Financial sector

⁹ See BIS (2001), Borio and McGuire (2004).

¹⁰ Reinhart and Rogoff (2008b)

¹¹ See Kindleberger (1996), Kiyotaki and Moore (1997), BIS (2001), Borio and Lowe (2002a).

problems in turn undermined confidence in the stability of the currency, fuelling further capital flight and eventually leading to the abandoning of the currency peg (twin crises).¹²

Exploiting the economic patterns described above, Borio and Lowe (2004) find for the industrial countries that a composite indicator combining the credit and the equity price gap performs best in predicting in-sample banking crises. Thus, for the industrial countries, we use the domestic credit gap, equity price gap and output gap.¹³ Furthermore, we are able to extend the analysis by including also the property price gap, using a measure of nominal residential property price data.¹⁴ Since the property price indicator is available on a quarterly basis only, we base our model for the industrial countries on quarterly observations. The real effective exchange rate gap does not contain significant information on the likelihood of banking crises in the industrial countries, therefore it is not included.

For the emerging markets, we find that the best composite indicator combines the credit gap with the equity price and exchange rate gap. Thus, we use those indicators in our model. Due to data constraints for property prices in the emerging markets, using equity prices as a proxy for overall asset prices is the best we can do.

4.4 Computing indicator gaps

Following Borio and Lowe (2002a, 2002b, 2004) we identify financial imbalances by looking at indicator percentage deviations from a longer-term recursive Hodrick-Prescott (HP) trend (gaps)¹⁵. We use a recursively calculated HP filter, with the recursive calculation ensuring that only information that was available at the time of judgement is taken into account. More than just a technical refinement, a recursively calculated HP filter yields different results from the standard HP filter which uses information from the entire time series: Turning points are much earlier for the standard HP filter, since for each considered point in time (except the last observation) future information is taken into account. Using a standard HP filter would thus lead to a misjudgement of the actual early warning capabilities of the indicator in question.

The calibration of our model is based on revised data instead of real-time data. However, in the day-to-day use, only real-time data will be available for the most recent observations. This could lead to a noisier signal when trying to forecast banking sector risks out of sample. The updating procedure of our model, however, assures that estimations are automatically updated as soon as the

¹² See Kaminsky and Reinhart (1999), Glick and Hutchison (2001), Eichengreen and Hausmann (1999), Radelet and Sachs (1998), Hardy and Pazarbasoglu (1998).

¹³ For an overview of the indicator sources, see appendix tables A-3 and A-4.

¹⁴ The dataset is constructed according to Arthur (2006).

¹⁵ Variations in the growth rate of the trend component are penalised by a factor of 400,000. Although we use monthly observations for the emerging markets and quarterly observations for the industrial countries, we use the same factor for the two distinct samples, with one exception: For the emerging markets we apply a factor of 1,500,000 to the real effective exchange rate (REER).

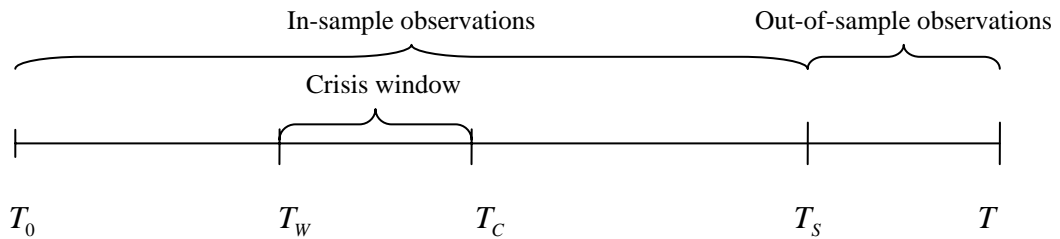
provider publishes the revised data.¹⁶ In addition, to overcome possible problems related with the use of real-time data the composite indicator is calculated as a moving average of signals from the last three quarters for industrial countries, and nine months for emerging markets. Also, we use a long forecast horizon (from three to five years), which further dissipates the possible noise stemming from the revision of individual real-time observations.

4.5 Deriving signals

The following section describes the methodological heart of our approach. We believe this section encompasses significant value-added by describing the methodology in technical terms. To our knowledge this has not been accomplished by the existing literature – at least not in detail. The description will be helpful to the reader interested in developing a similar model and all others who wish to follow the technical details. Although more technical than the rest of the paper, we tried to reduce the complexity of formulas and highlighted the intuition behind them.

The database used in the model has three dimensions: (i) indicator, (ii) country, and (iii) time. For each crisis episode we define a corresponding “crisis window”, which precedes the actual crisis starting date. A signal falling into the “crisis window” will be counted as a “good” signal and as “noise” otherwise. Outside the “crisis window” a signal will be counted as “noise”. In section 5 we will show that a suitable window for industrial countries is four years and three years for emerging markets.

Before going into the formulas we provide some notation: There are I total number of indicators ($i=1, \dots, I$), J total number of countries ($j=1, \dots, J$) and T number of observations ($t=T_0 \dots T$). In addition, there are C number of crisis or distress episodes ($c=1, \dots, C$). The following time line defines the different time periods used for calculation in our model, ranging from the beginning of the sample to the most recent available data.



Only time periods between T_0 and T_s will be considered for in-sample calculations. Observations from T_s up to T are used for the out-of-sample judgment.¹⁷ T_w is the starting period of the time window set before a crisis date and T_c is the crisis window’s end-period. There will be as many crisis windows (T_w to T_c) as systemic crises and distress episodes included in the sample.

¹⁶ An alternative way to address this problem would be to use real-time data for in-sample calculations.

¹⁷ In-sample observations are used to calculate indicators thresholds. These thresholds will also be employed to compute signals for the out-of-sample period. However, observations from the out-of-sample period will have no influence in the threshold optimisation process.

A warning signal will be issued if an indicator (e.g. domestic credit to GDP) lies above a critical threshold. More formally, the (continuous) indicator value X_{ijt} is transformed into a (binary) signal at the (time discrete) period t when it crosses the threshold x_{ij} , which is a country specific threshold to the indicator i :

$$S_{ijt} = \begin{cases} 1 & \text{if } X_{ijt} \geq x_{ij} \\ 0 & \text{if } X_{ijt} < x_{ij} \end{cases} \quad (1)$$

The following paragraphs lay out how thresholds are defined and how various indicator statistics, e.g. type-I error, type-II error and noise-to-signal-ratio, are derived. These statistics are used to select optimal thresholds. In contrast to Borio and Lowe, (2002a, 2002b, 2004) who employ thresholds that are invariant across countries, our approach takes country-specific differences into account. In this regard, we follow Kaminsky and Reinhart (1999) and use percentile rankings of time series values to derive critical thresholds. This ensures that the critical percentile cut-off is common across all countries, while accounting for country-specific absolute threshold levels.

Suppose now that X_{ijt} is a real-valued random variable and its cumulative distribution function (cdf) is given by $F(x_{ij}) = P(X_{ijt} \leq x_{ij})$, for $x_{ij} \in R$. If we assign probability of $1/T_s$ to each of the observations X_{ijt} , we are able to define the empirical distribution function as:

$$F_{ij}(x_{ij}) = \frac{\sum_{t=T_0}^{T_s} I(X_{ijt} \leq x_{ij})}{T_s}, \quad \text{for } x_{ij} \in R \quad (2)$$

With $I(\cdot)$ being the indicator function, which – for a given threshold x_{ij} – yields one if the indicator is equal to or below the threshold and zero otherwise. T_s is the number of time periods included in the sample and $F_{ij}(x_{ij})$ is the cumulative frequency of observations less than or equal to x_{ij} , increasing from zero to one. This is how we calculate the percentage share of signals for a given threshold x_{ij} . If we want to calculate the country specific thresholds, given a certain percentile level, we need to use the quantile function:¹⁸

$$F_{ij}^{-1}(p_{ij}) = \inf\{x_{ij} \in R : F_{ij}(x_{ij}) \geq p_{ij}\}, \quad \text{for } 0 < p_{ij} < 1 \quad (3)$$

First, we chose a certain percentile level $p_{ij} = \alpha_i$, then, we determine the country-specific thresholds so that $F_{ij}^{-1}(\alpha_i) = x_{ij}$. In order to derive indicator signals, we insert the country-specific

¹⁸ Where *inf* is the abbreviation of “infimum”, meaning the largest lower boundary.

thresholds x_{ij} that will trigger individual signals into equation (1). We can now calculate the (aggregate) empirical distribution of signals – spanning the time as well as the country dimension. This corresponds to one minus the (aggregate) frequency of signals. Using the signals S_{ijt} as defined in equation (1) we receive:

$$F_i(\alpha_i) = 1 - \frac{\sum_{j=1}^J \sum_{t=T_0}^{T_S} S_{ijt}}{m} \quad (4)$$

Where $m = J * T_S$, which is the total number of observations for all countries and all time periods within the sample (number of panel observations), and α_i is the common percentile threshold for indicator i . Note that each percentile threshold at the aggregate level corresponds to the same percentile threshold at the country level, while the absolute thresholds $x_{ij} = F_{ij}^{-1}(\alpha_i)$ are country-specific. To exemplify, the common percentile threshold level for the credit gap is 70%. Looking at the historic time series of Singapore reveals that 30% (100%-70%) of all credit gap observations are above 4%. By contrast, Estonia has seen more episodes of comparably high output gaps – here the 70% percentile threshold level corresponds to a threshold value of 5.8%. Consequently, a warning-signal for Singapore will be issued as soon as the credit gap exceeds 4%, while Estonia will not trigger a signal unless the credit gap exceeds 5.8%.

4.6 Measuring indicator performance

Once raw time series have been transformed into signals finding the “optimal” threshold becomes an iterative process. For each threshold level p_i four possible combinations need to be considered: A signal preceding a crisis episode is counted as a good signal (A), while a signal that is not followed by crisis is counted as noise (B). If no signal is issued, a crisis may nonetheless evolve (C), or it may not (D). The higher the amount of good signals and the lower the number of noisy signals, the better the indicator’s performance. In order to find the optimal threshold level, type-I and type-II errors¹⁹ as well as the ratio of noise to good signals is evaluated at different percentile levels. If the null hypothesis is defined as H_0 : “Given a signal a crisis is evolving”, we can derive the following relations:²⁰

¹⁹ Type-I error is the error committed when a “correct” null hypothesis is rejected. Type-II error is committed if a “false” null hypothesis is not rejected.

²⁰ Note that the conventional approach has been to define tranquil times as the null hypothesis. Yet, in order to make ‘bad’ signals (B) compatible with the concept of noise the null hypothesis is defined as crisis times.

	<i>Crisis</i>	<i>No crisis</i>
<i>Signal</i>	<i>A</i>	<i>B</i>
<i>No signal</i>	<i>C</i>	<i>D</i>

$$A_i = \sum_{c=1}^C \sum_{j=1}^J \sum_{t=T_w}^{T_c} S_{jt}, \quad B_i = \sum_{c=1}^C \sum_{j=1}^J \sum_{t=T_0}^{T_s} S_{jt} - A_i, \quad (5)$$

$$C_i = \sum_{c=1}^C \sum_{j=1}^J \sum_{t=T_w}^{T_c} 1 - S_{jt}, \quad D_i = \sum_{c=1}^C \sum_{j=1}^J \sum_{t=T_0}^{T_s} 1 - S_{jt} - A_i$$

$$\text{Type-I error}_i = \frac{C_i}{A_i + C_i} \quad (6)$$

Which is the probability of not signalling a realised crisis.

$$1\text{-type-I error}_i = \frac{A_i}{A_i + C_i} \quad (7)$$

Which is the probability of correctly signalling a crisis.

$$\text{Type-II error}_i = \frac{B_i}{B_i + D_i} \quad (8)$$

Which is the probability of incorrectly signalling a crisis.

$$Nsr_i = \frac{\text{type-II error}_i}{1 - (\text{type-I error})_i} = \frac{B_i / (B_i + D_i)}{A_i / (A_i + C_i)} \quad (9)$$

Which is the noise-to-signal ratio according to Kaminsky and Reinhart (1999).

Since the crisis window encompasses several periods, and thus potentially captures several signals, it is not clear from the 1-type-I error statistics (7) how many crises are actually predicted. In other words, a (1-type-I error) statistic of 0.5 could mean that 50% of all crises are signalled by the model, but only if the indicator signals in every time period of the crisis window for half of the crises. It could also mean that 100% of all crises are signalled if the indicator signals in only half of the periods within the crisis window, but for all crises. To overcome this problem, we developed an additional indicator, which captures the actual number of correctly signalled crises. We call this measure “indicated crises”, which is the share of crises correctly signalled in at least one time period within the crisis window over the total number of crises.

$$\text{Indicated crises}_{ij} = \sum_{c=1}^C \frac{S_{ijc}}{C}, \quad \text{where } S_{ijc} = \begin{cases} 1 & \text{if } \sum_{t=T_w}^{T_c} S_{ijt} > 0 \\ 0 & \text{if } \sum_{t=T_w}^{T_c} S_{ijt} = 0 \end{cases} \quad (10)$$

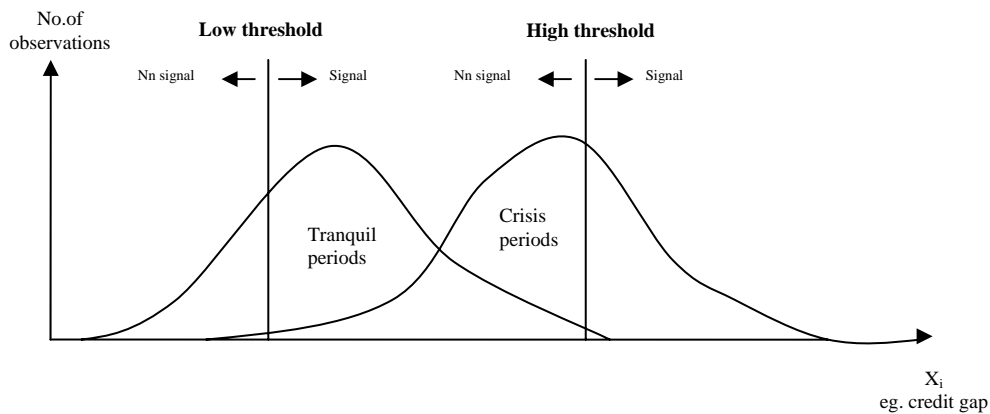
Although the statistic overstates the interpretation of a single signal, it is a useful measure to select percentile thresholds in combination with the other measures defined above. In addition to minimising the noise-to-signal ratio, we will therefore ensure that each individual indicator signals a reasonable percentage of past crises²¹.

4.7 Balancing type-I and type-II errors

Kaminsky and Reinhart (1999) suggest optimising critical threshold levels along the noise-to-signal ratio. However, optimising thresholds solely on the basis of the noise-to-signal ratio would in some cases achieve low numbers of false alarms, but possibly at the expense of too few crises being detected. If the analyst views the risk of missing a crisis more important than falsely calling one, then more weight should be given to minimising type-I errors.²² Thus, the optimisation rule should involve a careful weighing between the two objectives of predicting most crises and not producing too much noise.

The following figure visualises the trade-off between these two objectives. While a low percentile threshold will generally produce more false alarms (high type-II error), a high threshold level is likely to miss all but the severest crises (high type-I error). The better the indicator, the larger is its power to distinguish between crisis and tranquil periods.

Figure 1: Low versus high thresholds²³



Since we want to place a relatively large weight on minimising type-I error (avoid missing a crisis) we set a rule to choose thresholds that ensure at least 80% of in-sample crises are correctly signalled. We use our measure “indicated crises” as in equation (10) to capture the actual number

²¹ This is in line with Borio and Lowe (2004), p. 10. Rather than minimising the noise-to-signal ratio, they ensure that a satisfactory number of crises are predicted.

²² For instance, Demirgüç-Kunt and Detragiache (1999), pp. 12-13, propose a decision-maker loss function which allows to formally assign weights (costs) to type-I and type-II errors, respectively.

²³ Observations of crisis periods on the left-hand side of the vertical threshold line represent crisis periods that were missed (type-I error). Observations of tranquil periods on the right-hand side of the threshold represent noisy signals (type-II error).

of crises predicted correctly. If predicting 80% of all crises leads to a percentile threshold below 50%, the threshold is assigned to that percentile.²⁴

4.8 Constructing a composite index

The construction of a composite index rests on the idea that simultaneous signals coming from multiple indicators imply a higher possibility of impending banking sector distress. We thus combine individual indicators into a composite index.

Assessing different weighting schemes, Kaminsky (1999) finds that weighing individual indicators by their inverse noise-to-signal ratio is the most efficient way to combine individual indicators. This ensures that indicators with a relatively good track record and a low noise-to-signal ratio will be assigned relatively greater weights than indicators that in the past showed a less accurate prediction performance. We thus combine individual indicators in the manner described above. In addition to adding individual indicators, we filter out noisy signals, by averaging signals across three quarters for quarterly time series and nine months for monthly time series. Averaging over time also ensures that individual indicators which may signal in nearby periods, but not exactly at the same time will be captured simultaneously:

$$\textit{Quarterly series:} \quad \textit{Composite}_{jt} = \frac{1}{3} \sum_{i=1}^I \frac{(S_{ijt-1} + S_{ijt-2} + S_{ijt})}{Nsr_i} * \frac{1}{\sum_{i=1}^I \frac{1}{Nsr_i}} * 100 \quad (11)$$

$$\textit{Monthly time series:} \quad \textit{Composite}_{jt} = \frac{1}{9} \sum_{i=1}^I \frac{(S_{ijt-9} + S_{ijt-8} + \dots + S_{ijt})}{Nsr_i} * \frac{1}{\sum_{i=1}^I \frac{1}{Nsr_i}} * 100$$

5 Implementation of the model

This section implements the model described above for the emerging markets and the industrial countries, respectively. For both the emerging markets and the industrial countries we consider crisis as well as non-crisis countries in order to avoid selection bias.²⁵ Including non-crisis countries, however, comes at a cost: Since the concept of common percentile thresholds ensures that a certain fraction of signals will be generated for each country, each signal in non-crisis countries within the sample period, by definition, will be a false alarm. Thus, overall noise levels will be higher compared to a sample that includes crisis countries only.

²⁴ A percentile threshold below 50% will give a random character to signals instead of distinguishing between tranquil and crisis times.

²⁵ Compare Demirgüç-Kunt and Detragiache (1998), p. 90

A. Industrial countries

Our analysis of the industrial countries covers 21 OECD countries, namely Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Sweden, Spain, Switzerland, The United Kingdom and The United States.

The sample

Bordo et. al. (2001) observe that banking crises were almost absent during the period of the Bretton-Woods arrangement. They count only one larger banking crisis between 1944 and 1973 but a total of 19 crises thereafter until 2001. According to their analysis, the more recent period of frequent crises is only rivalled by the inter-war years from 1919 to 1939.²⁶ However, data limitations prevent us from considering crisis episodes that evolved before the Bretton Woods era. Due to the unique environment in which banks were operating during the Bretton Woods system and the reduced risk of banking crisis during that time there is little benefit in extending the sample to include the period between 1944 and 1973. Therefore, we limit our sample to quarterly observations from the beginning of 1975 until the end of 2001. Observations of the composite index from the beginning of 2002 until the end of 2007 (see appendix) will be out-of sample predictions.

During that period we identify a total of 18 episodes of banking sector problems. 16 out of 21 industrial countries experienced either banking sector distress or systemic banking crises. Only Spain (1978), Japan (1991) and the Nordic countries, Norway (1988), Finland (1991) and Sweden (1991) experienced full-blown systemic crises (see appendix). The US distress period of 2007 is not considered for in-sample testing. Likewise, the Spanish crisis of 1978 is excluded from our sample since a 5-year forecast horizon prior to the crisis is not available.

The crisis window

Crisis starting periods are arbitrarily assigned to the last quarter of the crisis year according to the identification scheme described above (see also the appendix for an overview of crises dates). Our crisis window – as introduced in section 4 – captures a leading horizon of 4 to 16 quarters before the actual crisis starting date. Comparing indicator performance for different horizons, we find that this horizon yields superior results in terms of the share of crises predicted and noise-to-signal ratio (see sensitivity analysis below). The individual indicator results as well as the results of the composite index in the appendix are based on this crisis window.

The indicators

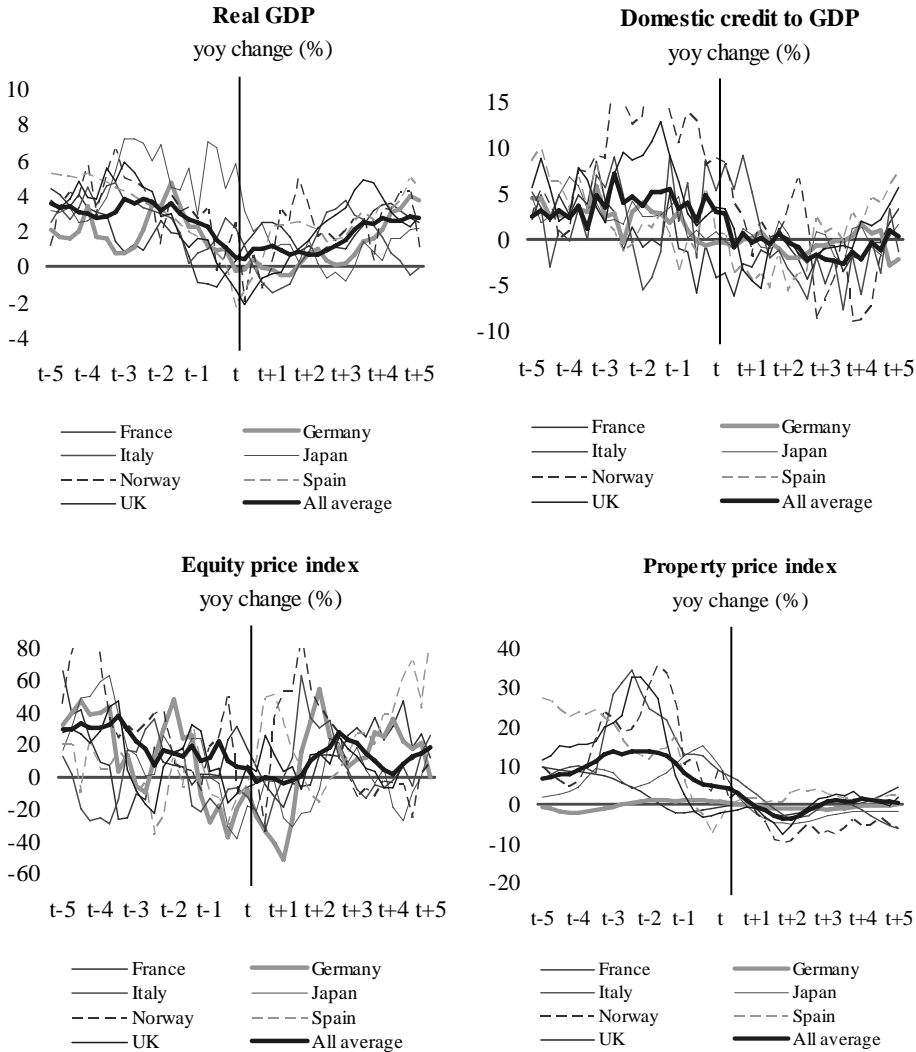
The following figures display how indicators behave around crisis starting dates. For instance, property prices display a typical boom and bust cycle around crises starting dates: On average, yoy

²⁶ Bordo et. al. (2001), p. 56

growth in property prices peaks three years prior to crisis. Property prices decline or remain depressed for at least five years following the onset of a crisis. Also for domestic credit and real GDP the boom and bust cycles around crisis starting dates are quite pronounced, whereas for equity prices the development is more ambiguous.

Indicator behaviour around crisis dates also allows us to narrow down possible options for setting the forecast horizon. Later in this section we compare different forecast horizons ranging from 2 years until 5 years before crisis starting dates. Note that for descriptive purposes the figures below show yoy percentage changes. For our analysis, however, indicators are computed as percentage deviation from their respective long-term trend and translated into signals based on common percentile threshold according to equations (1) to (4).

Figure 2: Indicator behaviour around crisis starting dates – industrial countries

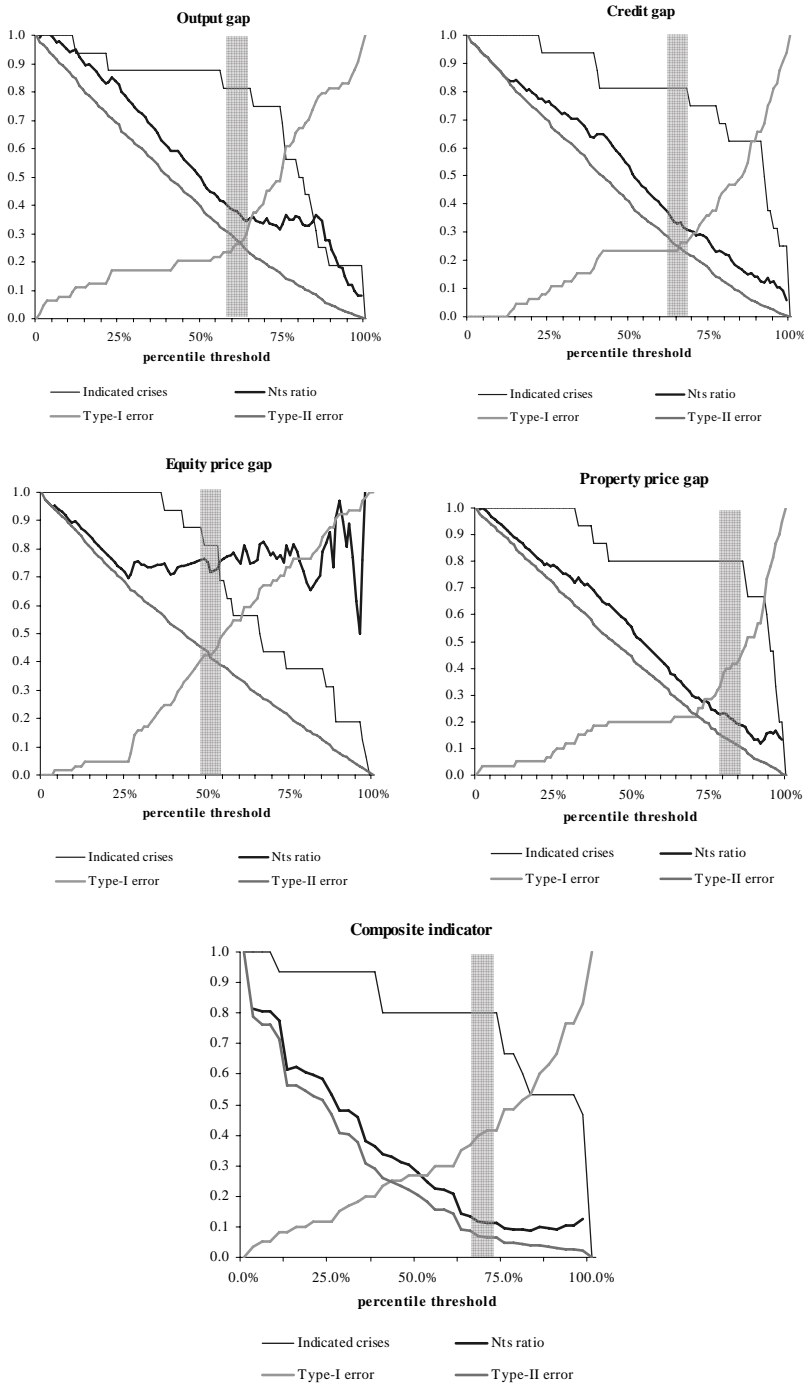


The indicator thresholds

At this point we want to determine the “optimal” threshold levels for the indicators in question. However, optimality in this case depends on our somewhat subjective decision on how to balance

type-I error (missing too many crises) against type-II error (producing too much noise) as discussed above. To be able to make an informed choice, a grid search is performed.²⁷ The results of this grid search are summarised by the charts depicted below: Each point on the x-axis represents a percentile threshold for which the type-I error, type-II error, share of indicated crises and noise-to-signal-ratio are calculated respectively.

Figure 3: Indicator performance – industrial countries²⁸



²⁷ By using the term “grid search” we refer to the calculation of the statistics used to assess indicator performance, i.e. type-I error, type-II error, nts ratio, indicated crises, for each indicator and each percentile threshold.

²⁸ The grey bars indicate the area of +/-5 percentage points around the selected threshold.

Table 1: Individual thresholds and weights within the composite indicator – industrial countries

Indicator	Percentile threshold	Type-I error	Type-II error	Nts ratio	Indicated crises	Weight within composite
Output gap	60%	0.25	0.29	0.38	81.3%	23%
Credit gap	65%	0.23	0.25	0.33	81.3%	27%
Equity price gap	50%	0.42	0.43	0.75	81.3%	12%
Property price gap	80%	0.38	0.14	0.23	80.0%	38%
Composite	73%	0.42	0.06	0.11	80.0%	100%

For the output gap, we find a common percentile threshold of 60% to satisfy our selection rule as postulated in section 4.7.²⁹ For the credit gap, equity price gap and property price gap the threshold is 65%, 50% and 80%, respectively. Comparing the performance of different indicators, the property price gap offers the lowest noise-to-signal ratio of 0.23 as most of the crises were preceded by booming property prices. The credit gap is the second best indicator with a noise-to-signal ratio of 0.33 and the output gap is the third best with a noise-to-signal ratio of 0.38. The equity price gap is the worst performing indicator, with a noise-to-signal ratio of 0.75. Compared to property prices, fewer crises were preceded by booming equity prices and more equity price boom and bust cycles did not lead to subsequent banking crises. The composite index displays a lower noise-to-signal ratio (0.11) than any of the individual indicators. Apparently, combining information from individual indicators reduces overall noise levels. The weights within the composite indicator reflect individual indicator performance, with the property prices gap constituting the most important individual indicator.

Sensitivity analysis: time horizon

Both the time horizon as well the threshold levels are important parameters to calibrate the model, which determine its overall performance. Thus, in order to assess the robustness of the chosen parameters we run different specifications of the model varying either the forecast horizon or the threshold level of individual indicators.³⁰

We start by looking at different forecast horizons. The forecast horizon is defined as the time before the crisis date, where a signal is considered a “good” signal or a “false alarm“ as described in section 4. Recall that a horizon of three years would mean an alert of banking crisis after the signal is triggered for the following three years. In order to find the optimal forecast horizon we test for a

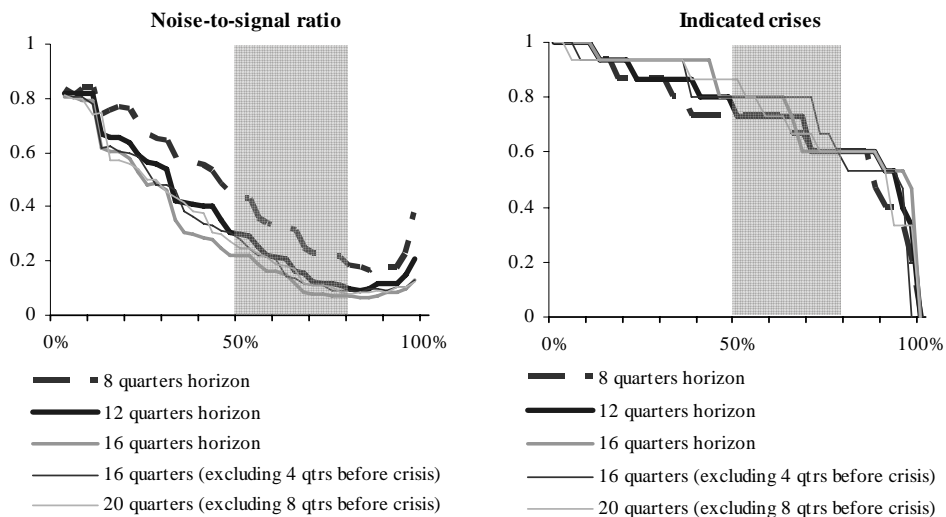
²⁹ This rule ensures that at least 80% of in-sample crises are signalled correctly. If that constraint yields a percentile threshold below 50%, the threshold is assigned to that percentile.

³⁰ Out-of-sample tests further confirmed the robustness of the model. However, given a limited number of crises and country observations, absolute threshold levels vary depending on the chosen in-sample definition.

wide range of different horizons.³¹ We consider 8, 12 and 16 quarters prior to crisis, as well as 16 quarters excluding the first 4 quarters before crisis, and 20 quarters excluding the first 8 quarters. In order to compare model performance across different specifications, we determine individual thresholds but also thresholds for the composite indicator as stated above: Percentile threshold must not exceed 50%, while the percentage of indicated crisis should exceed 80%.

A horizon of 16 quarters (excluding the first 4 quarters before a crisis) yields the lowest noise-to-signal ratio, holding the level of indicated crises constant. The results confirm the importance of property prices as an important indicator for assessing the risk of banking sector problems. Except for the 8 quarters horizon, the property price gap has the largest weight in all the specifications, reflecting its superior performance relative to the other indicators. The domestic credit gap together with the property price gap constitutes 58%-60% of the composite index. The results confirm that the equity price gap displays the least favourable performance as measured by noise-to-signal ratios and percentages of indicated crises.

Figure 4: Composite indicator performance with varying time horizons – industrial countries³²



³¹ Borio and Lowe (2004) find that for the industrial countries a crisis window encompassing five years prior to crisis (excluding the 2 years before the crisis) yields superior results. By contrast, Kaminsky and Reinhart (1999) and Kaminsky (1999) use a crisis window encompassing 12 months before and 12 months after the defined starting date of a crisis.

³² The grey bars indicate the range of selected thresholds for the composite indicator.

Table 2: Indicator performance with varying time horizons – industrial countries

Time horizon	Percentile threshold	Type-I error	Type-II error	Nts ratio	Indicated crises	Weight within composite
8 quarters						
Output gap	50%	0.28	0.44	0.61	75%	21%
Domestic credit gap	65%	0.22	0.28	0.36	81%	36%
Equity price gap	50%	0.63	0.48	1.27	38%	10%
Property price gap	65%	0.23	0.29	0.38	80%	34%
Composite	50%	0.27	0.32	0.44	73%	100%
12 quarters						
Output gap	60%	0.34	0.31	0.48	81%	21%
Domestic credit gap	70%	0.30	0.22	0.31	81%	32%
Equity price gap	50%	0.50	0.46	0.91	75%	11%
Property price gap	75%	0.32	0.19	0.28	80%	36%
Composite	50%	0.32	0.21	0.30	73%	100%
16 quarters						
Output gap	60%	0.31	0.29	0.42	81%	21%
Domestic credit gap	75%	0.36	0.17	0.26	81%	33%
Equity price gap	50%	0.46	0.43	0.81	81%	11%
Property price gap	80%	0.41	0.14	0.24	80%	36%
Composite	63%	0.36	0.10	0.15	80%	100%
16 quarters (excluding 4 qtrs before crisis)						
Output gap	60%	0.25	0.29	0.38	81%	23%
Domestic credit gap	65%	0.23	0.25	0.33	81%	27%
Equity price gap	50%	0.42	0.43	0.75	81%	12%
Property price gap	80%	0.38	0.14	0.23	80%	38%
Composite	73%	0.42	0.06	0.11	80%	100%
20 quarters (excluding 8 qtrs before crisis)						
Output gap	65%	0.23	0.21	0.28	88%	28%
Domestic credit gap	65%	0.23	0.25	0.32	81%	24%
Equity price gap	50%	0.33	0.41	0.61	88%	13%
Property price gap	80%	0.35	0.15	0.23	80%	34%
Composite	55%	0.30	0.16	0.23	80%	100%

Sensitivity analysis: threshold level

Next, we assess two additional specifications: One with a 10% higher threshold of individual indicators; the other with a 10% lower threshold compared to the base case. This allows us to check the robustness of the composite indicator with regard to our threshold selection rule. Ideally, the composite index should display superior performance qualities compared to the two alternative cases. For the individual indicators, we expect the higher threshold (+10%) to produce fewer false alarms, while missing more crises. The lower threshold (-10%) is likely to predict most of the crisis but only at the expense of producing more noise than the base case.

In this exercise, we stick to the crisis window of 16 quarters (excluding 4 qtrs before crisis). Again, we keep to our rule that thresholds for the composite index are set at either 80% of indicated crises or the 50% percentile. Results are summarised in figure 5 and table 3.

Figure 5: Composite indicator performance with varying threshold levels – industrial countries

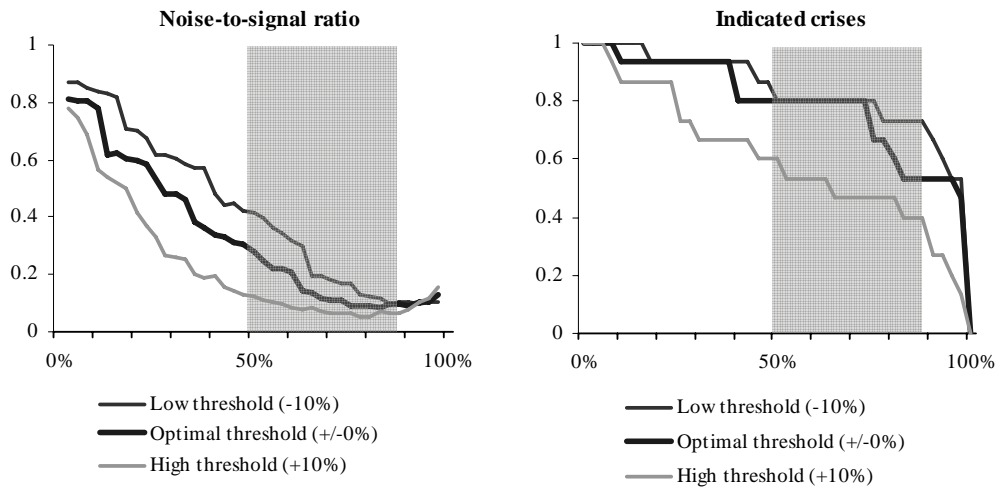


Table 3: Indicator performance with varying threshold levels – industrial countries

	Percentile threshold	Type-I error	Type-II error	Nts ratio	Indicated crises	Weight within composite
Low threshold (-10%)						
Output gap	50%	0.20	0.40	0.50	88%	22%
Domestic credit gap	55%	0.23	0.35	0.45	81%	25%
Equity price gap	40%	0.27	0.52	0.71	94%	16%
Property price gap	70%	0.22	0.23	0.30	80%	37%
Composite	75%	0.27	0.12	0.17	80%	100%
Base threshold (+/-0%)						
Output gap	60%	0.25	0.29	0.38	81%	23%
Domestic credit gap	65%	0.23	0.25	0.33	81%	27%
Equity price gap	50%	0.42	0.43	0.75	81%	12%
Property price gap	80%	0.38	0.14	0.23	80%	38%
Composite	73%	0.42	0.06	0.11	80%	100%
High threshold (+10%)						
Output gap	70%	0.45	0.19	0.35	75%	18%
Domestic credit gap	75%	0.36	0.17	0.27	75%	24%
Equity price gap	60%	0.55	0.34	0.75	56%	9%
Property price gap	90%	0.52	0.06	0.13	67%	49%
Composite	50%	0.45	0.07	0.13	60%	100%

This test confirms the robustness of our threshold selection rule, as the overall performance of the composite indicator (measured by the noise-to-signal ratio) is best for our base case. Comparing individual indicator performance, the low threshold yields a higher type-II error and a lower type-I error. The reverse is true for the high threshold. While these results do not come as a surprise, it is noteworthy that they are not necessarily mirrored by the composite index. Holding the percentage of crises predicted constant, the -10% threshold yields a noise-to-signal ratio of the composite equal to that of the “optimal” specification. This can be explained by the trade-off between type-I and type-II errors within the composite. Apparently, the more noisy signals will be compensated by a higher

number of crises predicted, resulting in a relatively low noise-to-signal ratio at the chosen high threshold of the composite. Also, the differences in weighing and the accumulation across signals of different kinds play an important role for the performance of the composite indicator.

B. Emerging markets

Our analysis of emerging markets covers 36 countries from different regions. In Latin America we include: Argentina, Brazil, Chile, Colombia, Mexico, Peru and Venezuela; in Eastern Europe: Bulgaria, Croatia, Czech Republic, Estonia, Hungary, Kazakhstan, Latvia, Lithuania, Poland, Romania, Russia and Ukraine; in Asia: China, Hong Kong, India, Indonesia, Malaysia, Pakistan, Philippines, Singapore, South Korea, Taiwan, Thailand, Vietnam and in Africa & Middle East: Egypt, Israel, Nigeria, South Africa and Turkey.

The sample

Kaminsky and Reinhart (1999) mentioned that the event of banking crisis was rather seldom with regulated financial markets during the 1970s. The number of crises increased significantly in the post-liberalisation period during the 1980s and 1990s. We observed that several Latin American countries experienced banking crises during the 1980s, mainly driven by the withdrawal of international capital, inadequate regulation, real effective exchange rate appreciation combined with pegged exchange rates and highly dollarised banking systems. In the early 1990s, with the monetary and fiscal convergence in the preparation for possible future EMU accession, many Eastern European countries experienced banking crises. Between 1997 and 1998, Asian banking sectors collapsed when capital inflows turned into outflows with currency pegs, highly leveraged corporate sectors and unhedged short-term debts. Afterwards, similar macroeconomic vulnerabilities triggered banking crises in Mexico (1994), Russia (1998), Turkey (2000) and Argentina (2001). The appendix lists the periods of distress and banking crises experienced by emerging markets since 1990.

Data restrictions prevent us from starting our in sample calculation before January 1990, leaving out Latin American and Eastern European banking crises but including Asian crises and other significant banking crises experienced in the 1990s³³. Within the sample of 36 countries a total of 28 systemic crises and 8 periods of banking sector distress were identified but only 19 of these periods (15 systemic crises and 4 periods of distress) are captured by the composite indicator on account of data restrictions. The remaining crises and distress periods are still in the model, captured by individual indicators. The in-sample calculation of the model runs from 1990 to 2004. Observations of the composite index from the beginning of 2005 until the end of 2007 (see appendix) will be out-of-sample predictions.

³³ Many Eastern European countries suffered banking crises between 1990 and 1992 which are excluded from our sample since a 3-year forecast horizon prior to crisis is not warranted.

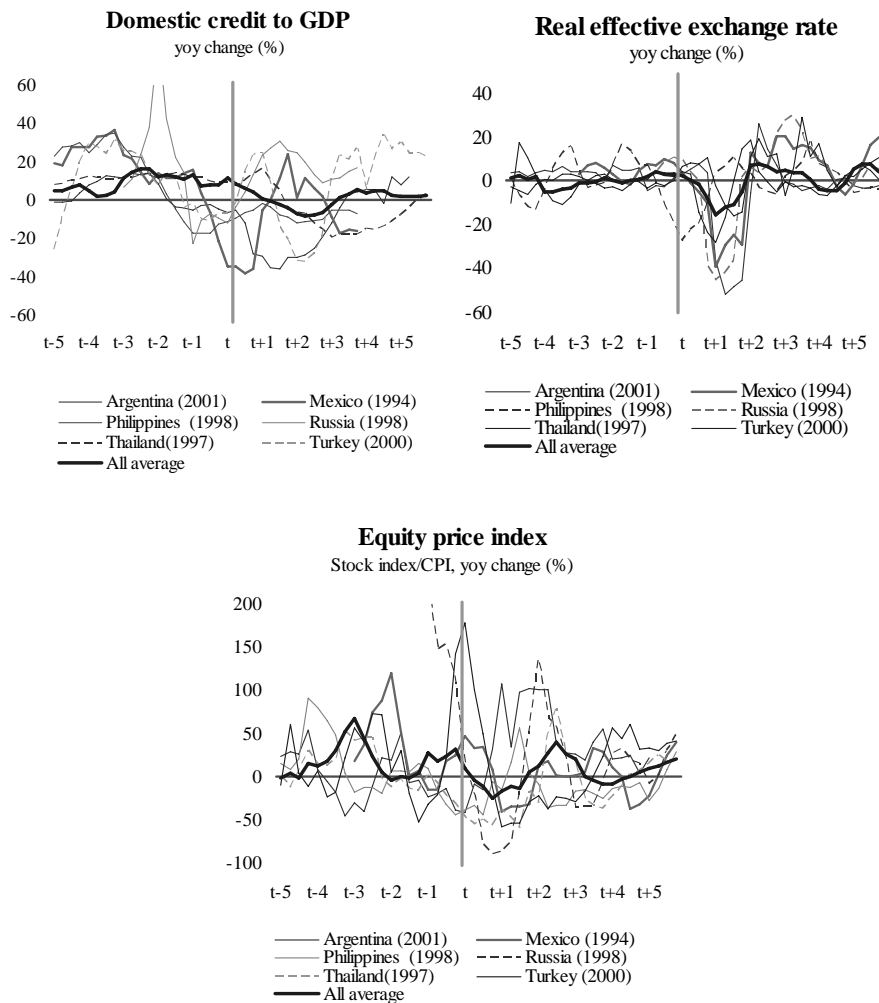
The crisis window

Since the precise months of banking crises are difficult to identify, systemic crises and distress periods are arbitrarily assigned to the month of December in the respective year. For emerging markets, the 36-months window before crisis dates was found to be the most efficient in terms of low noise-to-signal ratios and adequately predicted banking crises (see sensitivity analysis) which will be our benchmark model to assess individual indicator performance.

The indicators

Around crisis dates the boom and bust cycle of the explanatory variables can be also observed in emerging markets. On average, credit started to accelerate three years before crisis dates to slow down some months before crisis dates. The REER experienced a slow and modest increase about four years before crisis dates to plummet sharply after crises. Kaminsky and Reinhart (1999) observed that problems in the banking sector typically precede currency crises but sharp devaluations afterwards aggravate banking sector problems. Peaks of stock prices are distributed in different time periods five years before crisis dates.

Figure 6: Indicator behaviour around crisis starting dates – emerging markets

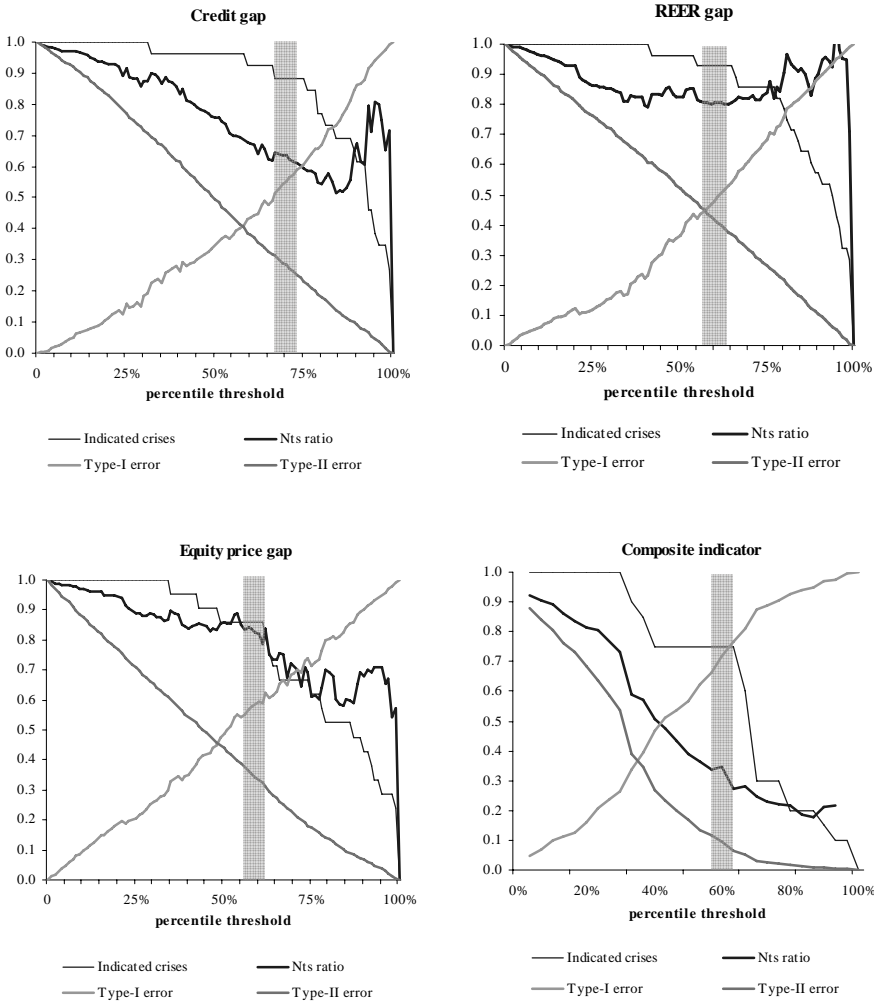


We test different time horizons to assess the performance of the model, but given the simultaneous approach of signals from individual indicators, we can anticipate an enhanced performance of the model on a 36-months time horizon.

The indicator thresholds

The selection of percentage thresholds for emerging market indicators follows the same rule of industrial countries, i.e. setting individual percentile thresholds to capture at least 80% of indicated crises and assigning a 50% percentile threshold when the first condition does not apply (in some models it is not possible to obtain the pre-fixed percentage of indicated crises).

Figure 7: Indicator performance – emerging markets ³⁴



³⁴ The grey bars indicate the area of +/-5 percentage points around the selected threshold.

Table 4: Individual thresholds and weights within the composite indicator – emerging markets

Indicator	Percentile threshold	Type-I error	Type-II error	Nts ratio	Indicated crises	Weight within composite
Credit gap	70%	0.55	0.28	0.63	88.%	39%
REER gap	60%	0.48	0.42	0.80	93%	31%
Equity price gap	60%	0.59	0.33	0.82	86%	30%
Composite	63%	0.77	0.06	0.27	75%	100%

The credit gap is the individual indicator with superior performance. The REER indicator displays a high percentage of predicted past crises but a relative sizable noise-to-signal ratio. The equity index is the indicator with inferior performance. Considering the superior performance the credit gap is the most important individual indicator for emerging markets.

Similarly to the industrial countries, the composite indicator displays a lower noise-to-signal ratio than all individual indicators, highlighting the advantage of combining individual signals. At 85% and 75% of indicated crises, the composite indicator has a noise-to-signal ratio of 0.58 and 0.29, respectively. Signals from the composite indicator present a satisfactory performance given that crisis probability reaches 36% at the 67 percentile threshold and increases to a maximum value of 50%.

Sensitivity analysis: time horizon

We ran the model for the same time horizons tested in industrial countries. To compare different models, we fixed the percentage of indicated crises at the values mentioned in the previous table with the condition that percentile threshold must be at least 50%.

With the percentage of indicated crises for the composite indicator fixed at 75%, the 36-months time horizon model minimises the noise-to-signal ratio. In the context of the selected time horizon, a composite indicator signal can be interpreted as possible banking sector distress within the next 36 months after the signal is triggered. The persistence of the signal should be also considered in assessing the probability of a distress period.

The superior performance of the credit gap indicator is verified given that this indicator gained the highest weight in all models but the 60-months (excluding 24 m before crisis) model. A longer time horizon benefits the equity price gap as peaks of this variable were distributed along a five-year horizon before crisis dates, but the two other indicators display a higher noise-to-signal ratio and smaller percentage of indicated crises in the 60-months time horizon model. The performance of the composite indicator worsens in longer time horizons on account of less simultaneous signals.

While the noise-to-signal ratio of the REER gap tends to increase in longer time horizons (from 24 to 48 months), the best performances of the credit gap indicator and the composite indicator are reached at a 36-months time horizon.

Figure 8: Composite indicator performance with varying time horizons – emerging markets

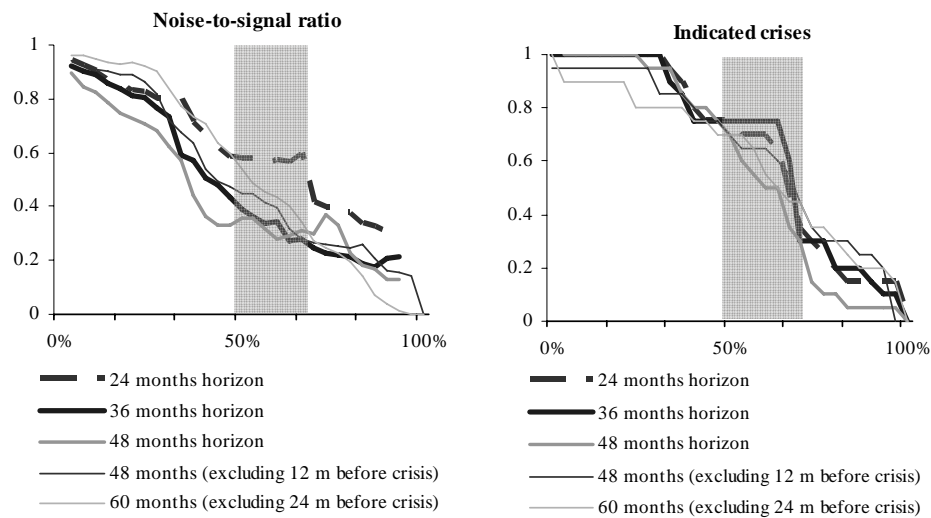


Table 5: Indicator performance with varying time horizons – emerging markets

Time horizon	Percentile threshold	Type-I error	Type-II error	Nts ratio	Indicated crises	Weight within composite
24 months						
Credit gap	59%	0.46	0.40	0.73	88%	33%
REER gap	54%	0.39	0.47	0.77	93%	31%
Equity price gap	60%	0.53	0.32	0.67	86%	36%
Composite	50%	0.51	0.29	0.58	75%	100%
36 months						
Credit gap	70%	0.55	0.28	0.63	88%	39%
REER gap	60%	0.48	0.42	0.80	93%	31%
Equity price gap	60%	0.59	0.33	0.82	86%	30%
Composite	63%	0.77	0.06	0.27	75%	100%
48 months						
Credit gap	75%	0.62	0.25	0.65	88%	37%
REER gap	70%	0.61	0.34	0.88	93%	28%
Equity price gap	63%	0.58	0.29	0.69	86%	35%
Composite	50%	0.78	0.08	0.35	70%	100%
48 months (excluding 12 m before crisis)						
Credit gap	65%	0.48	0.35	0.67	88%	38%
REER gap	51%	0.39	0.54	0.88	93%	29%
Equity price gap	62%	0.60	0.32	0.79	86%	32%
Composite	50%	0.49	0.23	0.45	75%	100%
60 months (excluding 24 m before crisis)						
Credit gap	50%	0.34	0.55	0.84	77%	31%
REER gap	50%	0.36	0.59	0.92	86%	28%
Equity price gap	75%	0.73	0.17	0.63	86%	41%
Composite	50%	0.55	0.24	0.54	70%	100%

Sensitivity analysis: threshold level

With the selected model of 36-months time horizon we analysed the indicators' performance with different individual thresholds, i.e. we analyzed a +/- 10% change in individual thresholds. To compare results we have fixed the percentage of indicated crises at previous levels.

In general, higher individual thresholds mean higher individual noise-to-signal ratios at a fixed percentage of indicated crises. However, base thresholds are the optimal thresholds for the composite indicator, given that the noise-to-signal ratio reached a minimum value at 75% of indicated crises.

Figure 9: Composite indicator performance with varying threshold levels – emerging markets³⁵

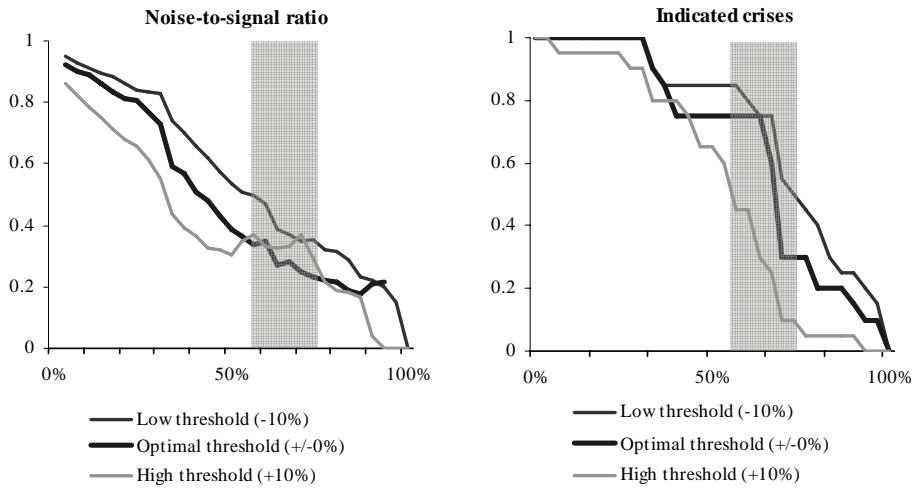


Table 6: Indicator performance with varying threshold levels – emerging markets

	Percentile threshold	Type-I error	Type-II error	Nts ratio	Indicated crises	Weight within composite
Low threshold (-10%)						
Credit gap	60%	0.43	0.38	0.67	92%	38%
REER gap	50%	0.37	0.52	0.82	96%	31%
Equity price gap	50%	0.49	0.44	0.86	86%	30%
Composite	67%	0.64	0.13	0.37	75%	100%
Base threshold (+/-0%)						
Credit gap	70%	0.55	0.28	0.63	88%	39%
REER gap	60%	0.48	0.42	0.80	93%	31%
Equity price gap	60%	0.59	0.33	0.82	86%	30%
Composite	63%	0.77	0.06	0.27	75%	100%
High threshold (+10%)						
Credit gap	80%	0.67	0.18	0.54	77%	41%
REER gap	70%	0.61	0.32	0.82	86%	27%
Equity price gap	70%	0.69	0.22	0.71	67%	31%
Composite	50%	0.77	0.07	0.31	65%	100%

³⁵ The grey bars indicate the range of selected thresholds for the composite indicator.

6 Conclusions

This paper develops an early-warning system to capture adverse macroeconomic developments, which in the past have led to large-scale problems in the banking sector. We show how such a model can be implemented in practice, addressing the specific requirements of an internationally operating private sector institution. We argue that the incorporation of an early-warning system into credit risk management can be an effective means to address disaster myopia and the lack of institutional memory, which have been blamed for short-sighted credit policy by the private sector before.

We implement the proposed model for both the industrial countries and emerging markets. Separate consideration of the two samples allows us to consider different indicators, sample periods and crisis forecast windows. Our results affirm those of previous studies, which show that excessively rising credit to GDP in combination with booming asset prices were often at the heart of banking sector problems. We contribute to that literature by also assessing property prices and show – for the industrial countries – that the property price gap is a superior indicator compared to the equity price gap.

Overall performance of the model is in line with the literature. At the reported threshold levels, the industrial countries composite indicator predicts 80% of the in-sample crisis periods, while achieving a relatively low noise-to-signal ratio of 0.11. For emerging markets, the composite indicator predicts 75% of in-sample crisis periods, with a noise-to-signal ratio of 0.29. For both models the equity price indicator seems to perform worse, while the domestic credit gap always ranks among the best indicators. Combining individual indicators into a composite index reduces overall noise levels.

While the model performs relatively well in terms of predicting in-sample crisis episodes, a number of limitations need to be taken into account when interpreting out-of-sample predictions: First, it will be difficult to determine future starting dates of banking sector problems once a signal is issued, because – by construction – the forecast horizon encompasses several years. Thus, a crisis may evolve shortly after the issuance of a signal or up to four years later in the industrial countries and up to three years later in the emerging markets. Second, just like any other forecasting tool, the predictive power of the proposed systems depends on future crises following patterns observed in previous ones. Third, given our preference for capturing a high fraction of crises and including countries that did not experience crises, the model will likely produce a considerable number of false alarms. Finally, the model looks only at common macroeconomic threats to the banking sector. It neglects the resilience of the banking system to deal with such threats, as well as further threats stemming from idiosyncratic shocks and subsequent contagion effects.

These caveats stress the necessity to regard the early-warning system as merely a further building block of a more comprehensive risk assessment programme, which also incorporates measuring the resilience of the banking sector at an aggregate as well as a micro-prudential level. In fact, a crisis signal should only be taken as a first call to monitor more closely banking sector vulnerabilities in the country concerned; while the absence of a signal should not lead to the negligence of possible banking sector risks.

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Appendix

Table A-1: Crisis dates industrial countries

Country	Date	Comment
Australia	1989 – 1992	Distress: Two large banks received government aid, fiscal costs amounted to 2% of GDP, NPL were 6% of total assets (1991-92)
Canada	1990 – 1992	Distress: Large loan losses at Canadian banks and trusts due to real estate price collapse
	1983 – 1985	Distress: Fifteen members of the Canadian Deposit Insurance Corporation failed, including two banks
Denmark	1987 – 1992	Distress: 40 out of 60 problem banks were merged, accumulative loan losses amounted to 9% of total loans (1990-92)
Finland	1991 – 1994	Crisis: Savings banks were badly affected by macro shocks, government took control of three banks representing 31% of total deposits
France	1994 – 1995	Distress: Credit Lyonnais experienced serious problems, estimated losses totalled USD 10 bn.
Germany	2002 – 2003	Distress: The banking sector experienced structural problems after equity market bust; failure of some smaller institutions (e.g. Schmidt Bank, Gontard & MetallBank, BkmU Bank, and others)
Greece	1991 – 1995	Distress: Significant injections of public funds into troubled specialised lending institutions
Italy	1992 – 1995	Distress: Between 1990-94, 58 problem banks were merged, accounting for 11% of total lending
Japan	1991 – 2003	Crisis: Up to March 2002, 180 deposit taking institutions were dissolved, fiscal costs for dealing with NPL amounted to 20% of GDP
New Zealand	1987 – 1990	Distress: Solvency problems of one large state-owned bank due to high levels of NPL, capital injection of 1% of GDP
Norway	1988 – 1993	Crisis: Smaller regional banks, and later large banks, experienced difficulties caused by deep recession, recapitalisation costs amounted to 8% of GDP
Spain	1978 – 1983	Crisis: 52 of 110 banks experienced solvency problems, broad government intervention, estimated losses amounted to 17% of GNP
	1993	Distress: First half of 1990s: failures of small banks; 1993: failure of Banesto
Sweden	1991 – 1992	Crisis: 2 large banks were insolvent, 5 out of the 6 largest banks experienced difficulties, recapitalisation costs amounted to 4% of GDP
Switzerland	1991 – 1996	Distress: Banks incurred estimated losses of more than 10% of GDP; regional problem-banks were merged to mitigate problems
UK	1991 – 1992	Distress: 'Small Banks Crisis': a number of small banks failed due to credit losses during recession
USA	1983 – 1991	Distress: 1320 savings and loans institutions failed, estimated resolution costs amounted to 3% of GDP, 1650 federally insured banks had to be resolved
	2007 – ongoing	Crisis. Major commercial banks and most large investment banks (incl. Bear Stearns, Lehman Brothers, Freddie Mac and Fannie Mae) either defaulted, were closed by the authorities or forced to merge. Large scale public assistance was granted to the banking sector in order to avoid systemic breakdown.

Sources: Caprio and Klingebiel (2003); Lindgren, Garcia and Saal (1996), BIS (2004); except for Germany (own estimate) and Canada (Illing and Liu 2003).

Although some sources identify an episode of distress also for Portugal (1986-1989), this episode is not included as major indicators for Portugal are only available from 1988 onwards.

Table A-2: Crisis dates emerging markets

Country	Date	Comment
Argentina	1995	Systemic crisis: By the end-1997, 63 of 205 banking institutions were closed or merged.
	2001-no end date	Systemic crisis: A bank run started in 2001, withdrawal restrictions on deposits were imposed and fixed-term deposits reprogrammed. In 2002, bank assets were asymmetrically pesified affecting banks solvency. One bank closed and three were nationalised by 2003.
Brazil	1994-1999	Systemic crisis: The central bank intervened or took the temporary administration of 43 institutions. NPLs reached 15% by end-1997.
Bulgaria	1995-1997	Systemic crisis: The banking system experienced a bank run in 1996 and 19 banks closed (one third of total banking assets).
China	1990s	Systemic crisis: Larger state-owned banks (68% of total banking assets) were deemed insolvent at the end of 1998. NPLs were estimated at 50%.
Croatia	1996	Systemic crisis: Five banks (about 50% of total banking system loans) were deemed insolvent and taken over by the bank rehabilitation agency.
Czech Republic	1991-no end date	Systemic crisis: Several banks closed and NLPs reached 38% in 1994-95.
Egypt	1991-95	Distress: Four banks received capital assistance.
Estonia	1992-1995	Systemic crisis: Several banks were deemed insolvent (41% of assets), five licences were revoked and four major banks were merged, nationalised or helped by the recovery agency.
	1994	Systemic crisis: One bank who controlled 10% of total assets failed.
	1998	Distress: Five small banks failed.
Hong Kong	1998	Distress: One large investment bank failed.
Hungary	1991-1995	Systemic crisis: 8 banks were deemed insolvent (25% of financial system assets).
India	1993-no end date	Distress: Non-performing assets reached 11% in 1993-94 and 16% in 1998.
Indonesia	1994	Distress: Non-performing assets reached 14% and more than 70% were held by state banks.
	1997-no end date	Systemic crisis: By 2007, 70 banks were closed and 13 nationalised of a total of 237 banks. NPLs were estimated at 65-75% at the peak of the crisis.
Korea, Rep. of	1997-no end date	Systemic crisis: By 2002, 5 banks were forced to exit the market, 303 institutions closed (215 credit unions) and 4 banks were nationalised. NPLs peaked to 30-40%.
Latvia	1995-no end date	Systemic crisis: Between 1994 and 1999, 35 banks saw their licences revoked, were closed or ceased operations.
Lithuania	1995-1996	Systemic crisis: 12 small banks (out of 25 banks) were liquidated, 3 banks failed (29% of banking system deposits) and 3 state-owned banks were deemed insolvent.
Malaysia	1997-no end date	Systemic crisis: Total number of finance companies was reduced to 10 from 39 and two insolvent banks merged. NPLs peaked at 25-35%.
Mexico	1994-1997	Systemic crisis: Government intervened at 9 banks and 11 of 34 commercial banks participated in a capitalisation programme.
Nigeria	1990s	Systemic crisis: Insolvent banks accounted for 20% of banking system assets were insolvent in 1993 and in 1993 almost 50% of banks reported financial distress.
	1997	Distress: Distressed banks accounted for 4% of total assets.
Philippines	1998-no end date	Systemic crisis: One commercial bank, 7 of 88 thrifts and 40 of 750 rural banks were placed under receivership. NPLs reached 12% in 1998.
Poland	1990s	Systemic crisis: 7 of 9 treasury-owned commercial banks (90% of the credit) and two other banks experienced solvency problems.
Romania	1990-no end date	Systemic crisis: NPLs reached 25-30% in six major state-owned banks in 1998.
Russia	1995	Systemic crisis: The interbank loan market stopped working in 1995 due to concerns about connected lending by new banks.

	1998-1999	Systemic crisis: About 720 banks (4% of total assets and 32% of retail deposits) were deemed insolvent and 18 banks (10% of total assets and 41% of deposits) experienced serious difficulties.
Taiwan	1995	Distress: Failure of an important credit cooperative sparked round on other credit unions.
	1997-1998	Systemic crisis: NPLs reached 15%.
Thailand	1997-no end date	Systemic crisis: 59 of 91 financial companies and one bank (of 15 banks) have to close. In addition, 4 banks were nationalised (of 15 banks). NPLs reached 33%.
Turkey	1994	Distress: three banks failed.
	2000-no end date	Systemic crisis: two banks closed and 19 banks were taken over by the Savings Deposits Insurance Fund.
Ukraine	1997-1998	Systemic crisis: 32 of 195 banks were liquidated and 25 underwent financial rehabilitation. Bad loans reached 50-60% of assets in some banks. In 1998, government's decision to restructure debt hit banks.
Venezuela	1994-1995	Systemic crisis: Insolvent banks accounted for 35% of financial system deposits, government intervened at 22 of 47 banks and 4 were nationalized.
Vietnam	1997-no end date	Systemic crisis: two of four state-owned banks were deemed insolvent and the other two experienced solvency problems (51% of total banking loans). NPLs reached 18%.

Sources: Caprio and Klingebiel (2003)

Table A-3: Indicators industrial countries

Indicator¹	Underlying series	Rationale	Data source
Credit gap	Domestic credit to the private sector / GDP	Banks will be adversely affected by an abrupt down-turn of the credit cycle. If credit and asset prices collapse simultaneously, adverse effects on bank stability will be even more pronounced.	Credit: IFS Line 22d; GDP: national sources
Equity price gap	Major national equity price index	An equity price collapse may adversely affect the banking system, either directly via bank balance sheets or indirectly via decreasing collateral value and fee & commission income.	OECD Main Economic Indicators and IFS Line 62
Property price gap	National residential housing price index (in nominal terms)	A property price collapse may adversely affect the banking system, either directly via bank balance sheets or indirectly via decreasing collateral value and fee & commission income.	BIS (Stephan Arthur)
Output gap	Real GDP (seasonally adjusted)	A fall in real economic activity will adversely influence the quality of banks' credit portfolios and reduce banks' income possibilities.	National sources

¹All indicators are constructed as gaps between the actual series and an underlying ex ante recursively calculated HP trend (expressed as percentage of the trend level). The larger the (positive) deviation from the long-term trend, the higher the risk of banking sector problems.

Table A-4: Indicators emerging markets

Indicator¹	Underlying series	Rationale	Data source
Credit gap	Domestic credit to the private sector / GDP	Banks will be adversely affected by an abrupt down-turn in the credit cycle. If credit and asset prices collapse simultaneously, adverse effects on bank stability will be even more pronounced.	Credit: IFS Line 22d/32d; GDP: national sources
Equity price gap	Major national equity price index	An equity price collapse may adversely affect the banking system, either directly via bank balance sheets or indirectly via decreasing collateral value and fee & commission income.	IFS Line 62, Bloomberg, Global Insight
Real effective exchange rate	Real effective exchange rate	For emerging markets, and specially for small and open economies, the REER appreciation captures capital inflows pressures as well as potential build-up of foreign currency mismatches	Global Insight, IFS, EUROSTAT, National Sources, DB Research calculations

¹All indicators are constructed as gaps between the actual series and an underlying ex ante recursively calculated HP trend (expressed as percentage of the trend level). The larger the (positive) deviation from the long-term trend, the higher the risk of banking sector problems.

Figure A-1: Example of web-based output – industrial countries

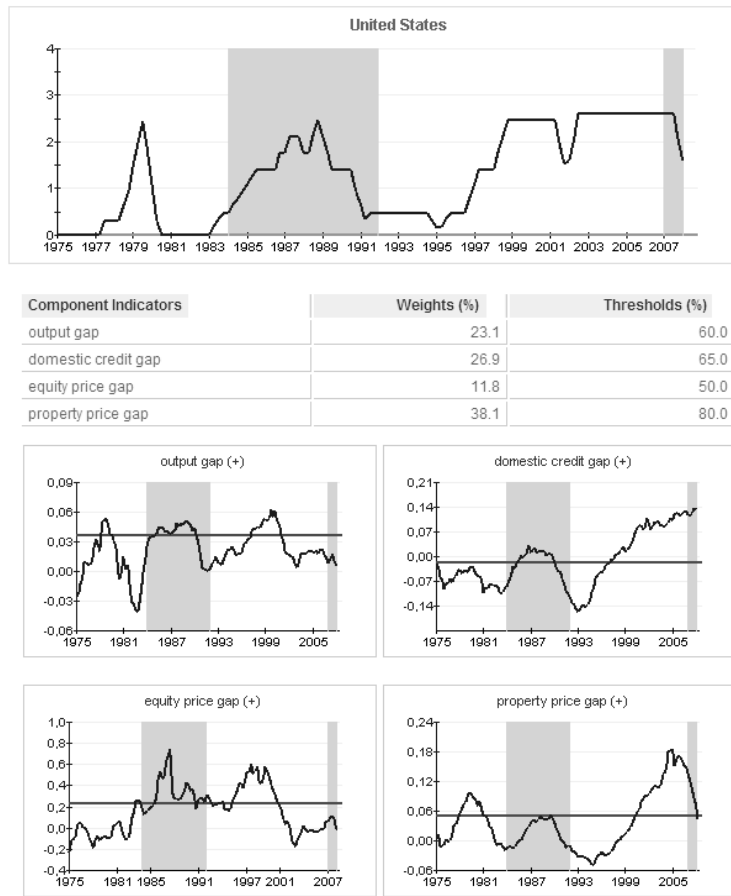


Figure A-2: Example of web-based output – emerging markets

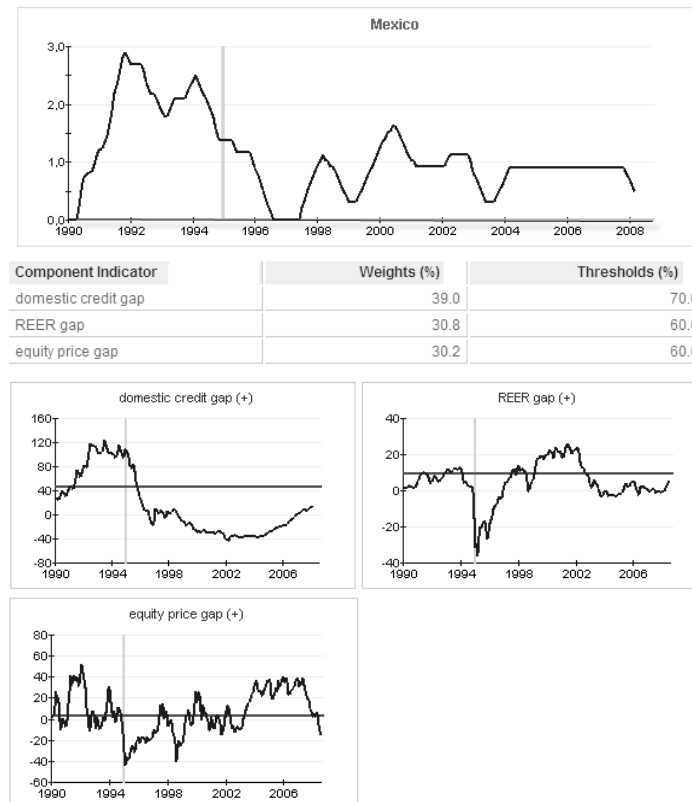
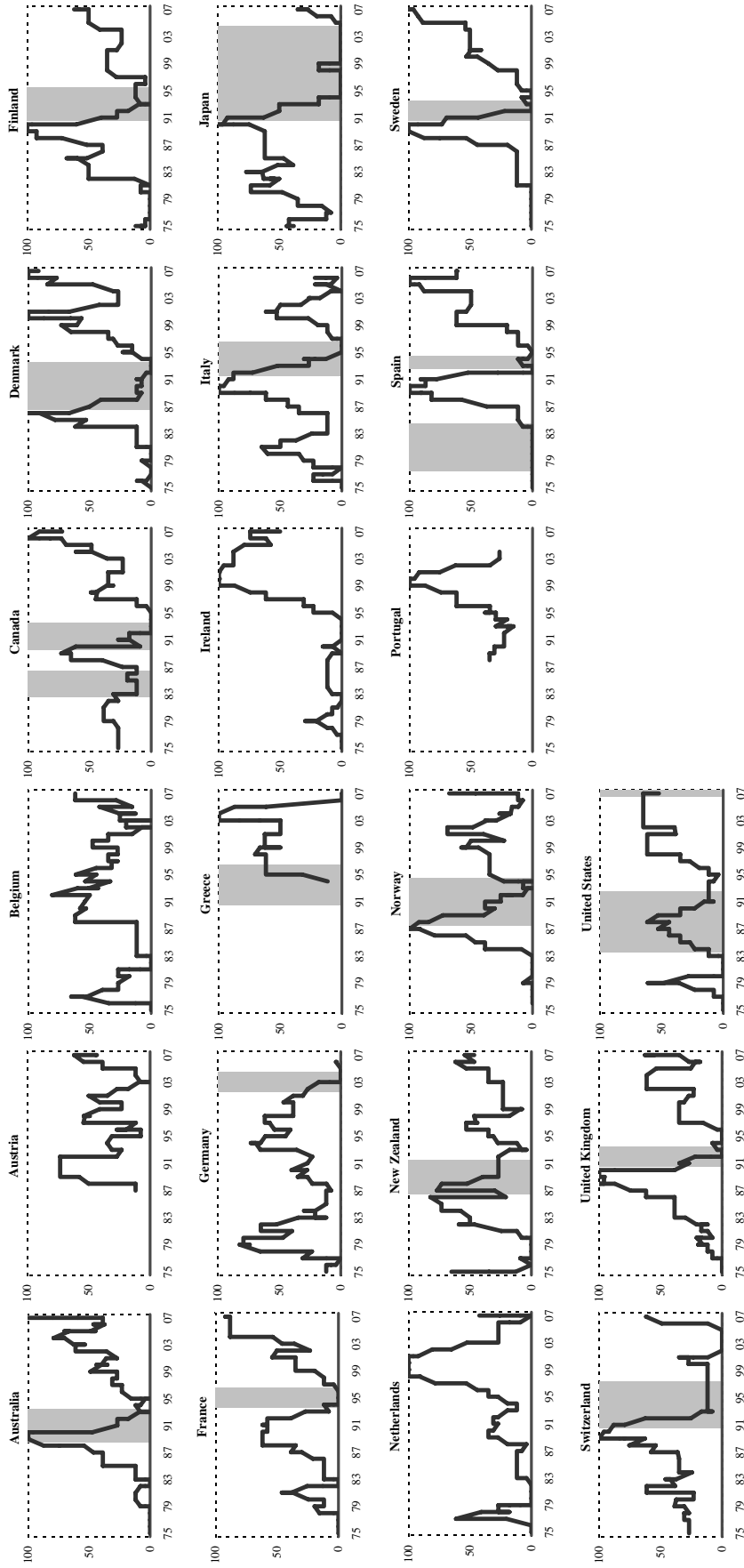
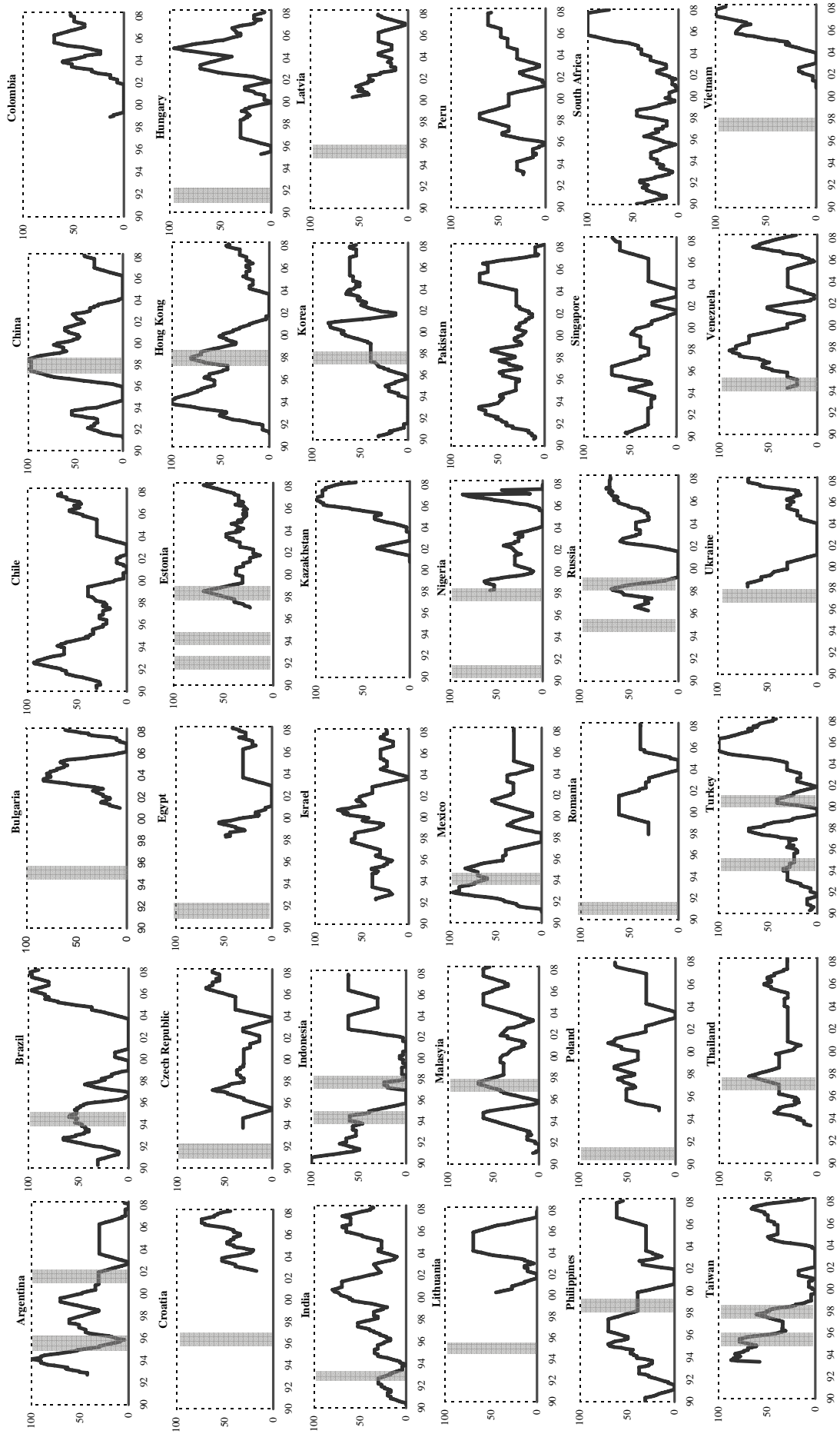


Figure A-3: Composite indicator - industrial countries*



*Shaded areas represent crisis times. Observations from 2002 onwards are out-of-sample predictions.

Figure A-4: Composite indicator - emerging markets*



* Shades areas represent crisis start dates. Observations from 2004 onwards are out-of-sample predictions.

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