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Comparing early warning systems for banking crises

E. Philip Davis [a,b,*], Dilruba Karim [a]

[a] *Department of Economics and Finance, School of Social Sciences, Brunel University, Uxbridge, Middlesex UB8 3PH, UK*
[b] *NIESR, Dean Trench Street, Smith Square, London SW1P 3HE, UK*

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Abstract

Despite the extensive literature on prediction of banking crises by Early Warning Systems (EWSs), their practical use by policy makers is limited, even in the international financial institutions. This is a paradox since the changing nature of banking risks as more economies liberalise and develop their financial systems, as well as ongoing innovation, makes the use of EWS for informing policies aimed at preventing crises more necessary than ever. In this context, we assess the logit and signal extraction EWS for banking crises on a comprehensive common dataset. We suggest that logit is the most appropriate approach for global EWS and signal extraction for country-specific EWS. Furthermore, it is important to consider the policy maker's objectives when designing predictive models and setting related thresholds since there is a sharp trade-off between correctly calling crises and false alarms.

JEL classification: C52; E58; G21

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1. Introduction

Over 1980–1996, three-quarters of IMF countries experienced banking distress (Lindgren et al., 1996). Crises were not restricted to particular geographic regions, levels of development or banking system structures.[1] A working definition of a banking crisis is the "occurrence of severely

* Corresponding author. Tel.: +44 1895 266643; fax: +44 1895 267900.
E-mail addresses: Philip.Davis@Brunel.ac.uk, e_philip_davis@msn.com (E.P. Davis), dilly.karim@gmail.com (D. Karim).
[1] Caprio and Klingebiel (1996).

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impaired ability of banks to perform their intermediary role". Restriction to a few banks constitutes a localised crisis whereas collapse of the banking system constitutes a systemic crisis.

Systemic crises have significant direct and indirect costs. According to Caprio and Klingebiel (1996), bailout costs average 10% of GDP, with some crises much more costly, e.g. the Mexican Tequila Crisis (1994) cost 20% of GDP whilst the Jamaican crisis (1996) cost 37% of GDP. There are additional costs of foregone economic output (notably reduced investment and consumption) owing inter alia to credit rationing and uncertainty. Hoggarth and Saporta (2001) estimate that cumulative output losses from banking and twin crises[2] were much greater in OECD countries (23.8% of GDP) than in emerging market economies (13.9%). Banking crises alone cost an average of 5.6% of GDP and twin crises 29.9%.

Such historic episodes of financial crises and their high direct and indirect costs highlight the need for Early Warning Systems (EWSs) for overall banking crisis prediction;[3] an effective early warning system showing that there are heightened risks[4] of bank runs and bank failures could facilitate policy action that could head off the potential crisis or limit its effects. Indeed, there is a menu of policy measures that authorities can adopt if a banking crisis is predicted. At the first level, an EWS could enable the authorities to warn financial market participants of potential risks in speeches and Financial Stability Reviews; furthermore, it could warn bank regulators that heightened vigilance is needed in their bank examinations. At a second level, it could justify direct policy action to seek to avoid a crisis. This could be in respect of discretionary prudential policy (e.g. limits on loan portfolio shares of vulnerable sectors), and possibly monetary and fiscal changes also. Naturally, there is a danger of false alarms leading to inappropriate policy action, implying that accuracy of the EWS is essential. This is particularly the case for direct policy action that may have wider adverse macroeconomic effects. Furthermore, it is essential that the EWS gives advance warning, given the lags in effective policy action, this implies a need either for lagged variables or appropriate forecasts. Finally, the output and procedure of the EWS must be comprehensible for the policy maker.

Viewed in this light, we contend that it is a paradox that the IMF uses an early warning system to monitor currency crises but has no explicit EWS for banking crises. Likewise, private sector institutions focus on currency crisis prediction. This may partly reflect the historically high prevalence of currency crises; in a study of 20 countries, Kaminsky and Reinhart (1999) found that during the 1970s there were 26 currency crises and only 3 banking crises (due to financial repression). However, banking crises quadrupled in the post-liberalisation period of the 1980s and 1990s. Further increases are foreseeable as additional emerging market countries undergo financial liberalisation, whilst in more advanced economies, securitised financial markets develop new financially engineered products whose behaviour during recessions is not well understood. For example, Chan et al. (2006) note the close relationship between banks and hedge funds which undertake unregulated investments. Related risks are not well understood, but as the LTCM crisis

[2] Defined as cases where a currency crisis occurs within the period 2 years before and after the banking crisis. Whereas one might anticipate that a currency crisis would mitigate the impact of the banking crisis by increasing the profitability of export- and import-competing firms, it seems that this is more than offset by a greater level of financial disruption in a twin crisis, in many cases including a cut-off of international credit, that may aggravate the banking crisis (Kaminsky and Reinhart, 1999).

[3] Note that this is distinct from the literature which seeks to predict individual bank problems, see for example King and Nuxoll (2004) and Gaytán and Johnson (2002).

[4] Note that EWS methodologies cannot offer precise predictions of these, rather they are able to indicate heightened vulnerability of the banking system.

in 1998 demonstrated,[5] hedge funds with highly leveraged positions can rapidly magnify domestic and international systemic risks, thereby increasing chances of contagion. Hence the need to devise a reliable EWS for banking crisis prevention remains more pressing than ever.

Although models have been developed to allow banking crisis prediction, their comparative performance is difficult to evaluate. Ideally, a functional EWS would have a clear quantitative definition of crisis where the chosen definition would reflect the policy maker's concerns, such as "crisis occurs if there are runs on a bank holding more than *x* percent of banking system deposits", or "indirect costs of failure amount to *y* percent or more of GDP". The EWS output would then indicate the risk of crisis materialising based on the particular crisis definition and would enable direct comparisons of forecasts at different points in time and across different countries. However, current models have been derived from various historic datasets and more importantly, by using different dependent variables and overall methodologies. Consequently, leading indicators may appear inconsistent and in-sample and out-of-sample results differ. This paper attempts to resolve some of the current ambiguity on predictive efficiency and indicator robustness. Our contribution includes the following: We test two of the main EWS in the literature (multivariate logit and signal extraction) using a single panel dataset. The cross-country and time-series coverage is more extensive than most previous studies. We also consider refinements to current EWS by considering how banking crisis theory could help to improve specification and variable choice. In the specific case of signal extraction work we also distinguish country-specific from general effects and construct composite indicators.

In sum, our results show (1) that given the same underlying data, the choice of EWS does make a difference to predictive efficiency. (2) Given the EWS model, the choice of dependent variable determines predictive capacity. (3) Transforming indicators including standardisation, lags and interaction terms improve the performance of the EWS. (4) Some models are better for developing country-specific EWS whilst others are suited to global EWS. (5) Combining variables into composite indicators improves crisis predictive ability. The remainder of the article proceeds as follows: Section 1 provides a brief theoretical review of banking crises which motivates the choice of indicators. Section 2 explains the methodology we adopt, including the theory behind the logit and signal extraction methods, construction of the banking crisis dependent variable and our dataset. Section 3 presents our results, whilst Section 4 concludes.

1.1. Theoretical overview of banking crises

This section briefly indicates why the indicators used in EWS models such as Demirgüç-Kunt and Detragiache (1998) (who use the logit method) are associated with banking crises.[6] This enables us to assess the variables' validity and also to recommend extensions.

Generally, banking systemic risk reflects a correlation of performance between institutions. One possibility is that such crises can be purely self-fulfilling, i.e. they materialise through individual liquidity failures of solvent banks that become contagious. In these cases, crises can be driven by asymmetric information and associated bank runs. Diamond and Dybvig (1983) emphasised the role of confidence in precipitating runs and that arbitrary

[5] Davis (1999).

[6] We note that Kaminsky and Reinhart (1999) (who use the signal extraction method) use a different set of variables more closely associated with currency crisis prediction.

shifts in investors' risk expectations explain seemingly irrational behaviour of consumers running on banks; a bank's underlying financial position is almost irrelevant once panic ensues. Hence individual bank failure may spread through contagion associated with asymmetric information and in this context systemic banking crises are self-fulfilling. This view has been criticised on the view that there is usually a fundamental explanation for such events.

George (1998) suggests that systemic risks arise "through the direct financial exposures[7] which tie firms together". If systemic risk is sufficiently deep (i.e. if correlations between individual bank risks are particularly high), then crises could be triggered. Hence a further possibility is that there could be counterparty claims between banks (e.g. via interbank exposures) that lead to widespread failures.

EWS to date have typically ignored the possibility of pure self-fulfilling crises and crises caused simply by counterparty exposures. On the one hand, pure spikes in the need for liquidity can in principle be catered for by appropriate monetary action to offset the excess demand for liquidity (as for example on 9/11). More importantly, this neglect can be justified because historically the vast majority of banking crises have been caused by financial institutions underestimating their common exposure to economy wide systematic risk (Borio et al., 2001) so that some or all banks risk becoming directly insolvent rather than illiquid. This may link to asymmetric information as if one significant bank fails, a systemic crisis may develop because the presence of such asymmetric information means depositors are unable to evaluate prospects for "similar" banks in terms of balance-sheet exposure to economy wide systemic risks (Kaufman and Scott, 2003).

Accordingly, macroeconomic movements that crystallise risks particular to banking systems, namely interest rate, credit, liquidity and market risk have been the key determinants of banking crises in the last 20 years (Ergungor and Thompson, 2005). Correspondingly, in most EWS studies, the explanatory variables used mainly capture macroeconomic factors that could generate systemic risk via such common shocks.

Interest rate risk forms an inherent part of banking activities since assets have longer duration than liabilities. Term structure shifts towards short-term liabilities (inverted yield curves) adversely affect bank balance sheets by eroding bank spreads. Simultaneously, banks may suffer prepayment risk if long-term rates decline and borrowers refinance at lower rates. These outcomes adversely affect bank balance sheets and if there is significant exposure to interest rate risk, net worth of the banking system becomes vulnerable.

Oviedo (2004) highlights the counter-cyclicality of interest rates; lower interest rates are associated with economic booms when crises are less likely. Consequently, during booms, banks may use low-cost deposit financing to invest heavily in particular sectors which appear profitable and where collateral values are high. This increased appetite for long-term projects means duration mismatch and interest rate risk are likely to accumulate during the boom phase so that unexpected interest rate increases or moves towards inflation targeting in the downturn could lead systemic interest rate risk to materialise. Hence the inclusion of real interest rates in EWS and the observed, positive correlation between real interest rates and banking crisis probability in recent work (Demirgüç-Kunt and Detragiache, 1998; Hardy and Pazarbasioglu, 1998; Kaminsky and Reinhart, 1999; Gourinchas et al., 2001).

[7] Exposures include inter-bank transactions, counterparty risk, or third party (non-bank institutional) failure.

Another symptom of banking crises is increased credit risk or the probability that a borrower will default, converting an asset into a "bad" or non-performing loan (NPL). Although banks enjoy advantages in screening and monitoring borrowers, both of which reduce credit risk, the high levels of NPLs associated with crises indicate risk assessment by banks deteriorates during pre-crisis periods.

One reason for and consequence of inadequate credit risk evaluation is the procyclical movement of lending and asset prices which allows for interaction of financial cycles and business cycles. Periods of high output growth raise collateral values and as a result, during booms loan contracts become less informationally dependent. Asymmetric information does not restrict credit availability because bank managers succumb to "euphoric" and "herding" behaviour,[8] utilising biased information sets to make investment decisions, possibly succumbing to "disaster myopia". As a result, they ignore the potentially high default probabilities that could occur under recessionary states and under-price credit risk. Guttentag and Herring (1984) suggests that this results from managers overweighting current positive experience in booms due to various psychological biases. Borio et al. (2001) attribute these sub-optimal behavioural responses to difficulties in measuring time series of credit risk and to incentive-based managerial contracts which reward loan volume. As lending increases, this further inflates asset prices, which raises collateral values and perpetuates the endogenous cycle (Davis and Zhu, 2004). The boom phase ends when shocks, such as asset price collapses, turn the process backwards; during recessions managers may overestimate risk so that cyclical downturns reverse the financial accelerator. As assets markets collapse, collateral values decline and NPLs rise. Because asymmetric information becomes disproportionately important for loan officers, lending spreads are artificially high and intermediaries hold excess capital and provisions. Ultimately, credit rationing prevents borrowers with profitable projects from obtaining funds and the recession deepens.

Credit risk may be particularly high and correlated between institutions when herding focuses boom-phase investment to specific sectors of the economy. Over-investment in real estate (particularly commercial) has been a well-documented feature of banking crises[9] because the value of bank capital increases if real estate forms the asset base. Bank lending therefore magnifies the real estate cycle, leading to further financial acceleration and financial instability (Herring and Wachter, 1998; Borio et al., 2001; Davis and Zhu, 2004, 2005). Furthermore, credit risk may be magnified by regulation that limits diversification.[10]

In the context of banking crises, market risk is intertwined with credit risk. Market risk reflects the probability that price-volatility of specific assets affects the net worth of banks. Such adverse price movements may arise through shifts in market expectations in anticipation of cyclical downturns. Alternatively, specific asset groups may be hit by idiosyncratic factors, e.g. oil price volatility following political events. Although market risk is diversifiable, regulation limiting types of assets held may impede this. Alternatively, excessive market risk may be borne during boom phases, as over-optimism may concentrate portfolios in assets whose prices move procyclically, e.g. real estate (Gonzalez-Hermosillo, 1999; Craig et al., 2005). Since credit risk is also procyclical, the link between the two risks becomes apparent when asset price collapses realise market risk and low collateral values realise credit risk. Banks may also be exposed to market risk if

[8] Davis (1995).

[9] See FDIC (1997) for the relationship between commercial real estate and US banking crises during the 1980s and 1990s.

[10] The Texan Banking crisis was driven by regulation which forced regional banks and S&Ls to invest within their state. Texan institutions over-invested in the Texan oil industry which entered recession in 1987 (FDIC, 1997).

their portfolios are concentrated on equities and currencies; if they fail to adequately provision against price volatility, then adverse price shocks can jeopardise the net worth of the banking system.

Banking liquidity risk reflects the probability that banks will be unable to satisfy the claims of depositors because the ratio of illiquid assets relative to liquid liabilities is too high. In the Diamond and Dybvig (1983) model, liquidity risk drives idiosyncratic bank runs. Liquidity risk also links to adverse information models of banking crises (Santos, 2000). Chari and Jagannathan (1988) modify the Diamond and Dybvig model to show that when depositors assimilate adverse information (e.g. signals of recession or asset market collapses) they anticipate that bank profitability will suffer. Resulting bank runs generate systemic liquidity problems. These runs are distinct from the Diamond and Dybvig model where runs on solvent banks occur even when depositors have no legitimate evidence to suspect insolvency. Rather, in this case, depositors are more likely to run on genuinely insolvent banks. Hence Gorton (1988) observation that panics are associated with recessions and Jacklin and Bhattacharya (1988) suggestion that the release of information indicating low asset values or poor performance of a bank can generate liquidity risk.

Financial liberalisation provides another source of the systemic risks mentioned, hence the well-documented association between liberalisation and crises; in the Kaminsky and Reinhart (1999) sample, over 70% of banking crises were preceded by financial liberalisation within the last 5 years and the probability of banking crisis conditional on financial liberalisation having occurred is higher than the unconditional probability of banking crisis. Demirgüç-Kunt and Detragiache (1998) also find that financial liberalisation increases crisis risk within a few years of the liberalisation process.

High real interest rates and increased interest rate volatility are typical consequences of financial liberalisation, especially in developing countries (Honohan, 2000). During financial repression, imposed ceilings mean real interest rates cannot adjust to clear credit markets and credit rationing results in "non-market", usually state-directed, credit allocation. Although interest rate risk considerations are likely to be subordinate when states allocate credit, interest rate ceilings have some risk limiting effect. However in post-liberalised environments, wider spreads and increased competition could cause an accumulation of systemic interest rate risk which may be more likely to materialise because of higher interest rate volatility.

Another effect of financial liberalisation may be to increase credit risk. In liberalised markets, increased competition may erode bank charter values so that without adequate supervision and regulation, banks forgo prudent credit risk assessment in a bid to catch borrowers. Hence financial liberalisation can exaggerate procyclicality of asset prices by fuelling a consumption boom (Borio and Lowe, 2002). Craig et al. (2005) suggest that credit risk increases following liberalisation because the rapid increases in loan volumes constrain credit risk assessment. Guttentag and Herring (1984) note that financial liberalisation poses a particular problem to a "disaster myopic" bank focused excessively on current performance since not only is there usually a low level of defaults for some time after liberalisation, but also there is no history of adverse experience to draw upon.

These effects may be exacerbated in the presence of government safety nets; Demirgüç-Kunt and Detragiache (1998) show deposit insurance is a significant leading indicator of banking crisis and the same authors (2002) show explicit deposit insurance increases the risk of moral hazard when institutions are weak. Where financial liberalisation does increase asset price volatility, there may also be increased liquidity risk borne by the system since banks are unable to sell assets at par when asset prices collapse.

Looking at the indicators typically used in EWS models, in the light of the discussion above, we would thus expect rapid *real credit growth* and increases in *private sector credit/GDP*[11] during pre-crisis periods, indicating credit risk accumulation. Similarly, procyclicality of financial instability implies *GDP growth* should capture boom and bust cycles. Liquidity risk is shown by *bank cash plus reserves as a proportion of total bank assets*; the lower this ratio the higher the systemic liquidity risk. Macroeconomic shocks which could trigger cyclical downturns thereby increasing NPLs include adverse movements in *terms of trade* and correspondingly *currency depreciations*, especially for small open economies. The latter also indicates vulnerability to currency crisis, as does *M2/foreign exchange reserves* since lower ratios imply impaired ability to defend the currency. *Real interest rates* are used as a direct indicator of interest rate risk. High *inflation* signals policy mismanagement which causes higher nominal interest rates at the expense of lenders. Corresponding increases in interest rate volatility should also capture interest rate risk. Higher *inflation* may also, to a certain extent, reflect market risk of asset price booms. Direct use of asset prices such as real estate for proxying market risk in EWS models has been limited due to lack of data outside the OECD countries. On the other hand exchange rate based market risk is proxied by the *terms of trade and currency depreciations*.

Policy mismanagement is also reflected in *low fiscal surpluses/GDP*. Demirgüç-Kunt and Detragiache (1998) include this variable because it indicates governments' reluctance to restructure fragile banking systems and because high deficits prevent successful financial liberalisation. *Real interest rates* also act as a proxy for financial liberalisation. Furthermore, Demirguc-Kunt and Detragiache rely on the level of *GDP per capita* as a structural economic development measure which should be positively related to the quality of banking regulation.[12] Given these leading indicators, we now turn to describe the construction of the banking crisis dependent variable and the actual models used to predict banking crises.

2. Data, variables and specifications

2.1. The banking crisis variable

The most commonly cited problem with EWS developed to date is the inconsistency in the banking crisis dependent variable, which is necessarily defined with a degree of subjectivity (Kaminsky and Reinhart, 1999; Demirgüç-Kunt and Detragiache, 1998; Eichengreen and Arteta, 2000). There is no unique quantitative variable for banking crisis. The problem lies in the fact that banking crisis is an event, so proxies for banking crises would not necessarily be perfectly correlated with banking crises themselves. For instance, if we were to use a measure for banking insolvency such as aggregate banking capital, we would need to define a lower bound threshold for a crisis event. However, government intervention or deposit insurance could prevent crisis and the threshold could still be violated. Another issue is that not all crises stem from the liabilities side (Kaminsky and Reinhart, 1999); problems in asset quality can also erode banking capital so that a single proxy variable would not pick up all crisis events. Furthermore, there may be underreporting of data indicating risks in financial accounts of banks in advance of crises.[13] As a

[11] However, the *level* of the credit/GDP ratio is rather an indicator of economic and financial development.

[12] Demirgüç-Kunt and Detragiache (1998) also incorporate two other institutional variables: a deposit insurance dummy (where explicit deposit insurance means the dummy value is 1) and a law and order dummy.

[13] Note that this gives rise to problems in using EWS in a practical policy environment, and argues in favour of the approach of the literature, to focus on bank balance sheets as well as macroeconomic and financial market data rather

result the dummy is constructed on the basis of several criteria which vary according to the study, and often using accurate, post-crisis data. The main classifications are to be found in Caprio and Klingebiel (1996, 2003), Demirgüç-Kunt and Detragiache (1998, 2005), Kaminsky and Reinhart (1999) and Lindgren et al. (1996).

Caprio and Klingebiel (1996) focus on the solvency side of crisis and define systemic crisis as an event when "all or most of banking capital is exhausted".[14] Insolvency was judged on the basis of official data and published reports by financial market experts; if official data recorded positive banking system capital but experts judged it to be negative, they recorded systemic crisis.[15] Caprio and Klingebiel (2003) subsequently updated their database to the period 1980–2002 and identified 93 countries as having experienced systemic crises.

Demirgüç-Kunt and Detragiache (1998) used a more specific set of four criteria[16] where achievement of at least one of the conditions was a requirement for systemic crisis, otherwise bank failure was non-systemic. The authors admitted they relied on judgement if there was insufficient evidence to support their crisis criteria; on this basis they established 31 systemic crises in 65 countries over the 1980–1994 period. Demirgüç-Kunt and Detragiache (2005) conducted a follow up study and extended the sample to 1980–2002. Using the same criteria as before, they find 77 systemic crises over 94 countries.

Kaminsky and Reinhart (1999) and Lindgren et al. (1996) use criteria similar[17] to Demirgüç-Kunt and Detragiache (1998). Kaminsky and Reinhart (1999) identified 26 systemic banking crises over 20 countries during the period 1970–1995. Of the 26 crises, 19 are twinned with currency crises and the remaining 7 are pure banking crises.

Even if systemic crises unambiguously occur, identifying their starting and ending dates is hazardous and the same episode may have a different duration in different studies. Where runs do not occur and banking system data are either unavailable or unreliable, locating the exact time when the system became insolvent is impossible. Even if runs do occur, this may be a culmination of a prolonged period of systemic insolvency, which was either unknown to depositors or supported by government assistance at and earlier stage. Based on the run, the start date would "time" the crisis too late.

Kaminsky and Reinhart (1999) note that crises can also be dated too early, since the worst of the crisis could unfold after the subjective start date. Dating is also problematic when there are successions of crises episodes; in many such instances it is arguable that later crises are extensions or re-emergences of previous financial distress as opposed to distinct crises events (Caprio and Klingebiel, 1996). Judgment is also required to distinguish between periods of systemic and non-systemic crisis; a degree of banking system insolvency must be decided upon whereby failure

than banks' profit and loss accounts.

[14] They stipulate that non-performing loans as a proportion of entire loans of the banking system must be in the range of 5–10% or less.

[15] On this criterion, they judged 58 countries to have experienced systemic crisis over the post-1970s period with many experiencing repeated episodes.

[16] The proportion of non-performing loans to total banking system assets exceeded 10%, or the public bailout cost exceeded 2% of GDP, or systemic crisis caused large scale bank nationalisation, or extensive bank runs were visible and if not, emergency government intervention was visible.

[17] For Kaminsky and Reinhart (1999), a crisis is systemic if banks runs result in closure or nationalisation of at least one bank, or if there are no runs, large-scale government intervention, merging or nationalisation of one bank marks the beginning of the same for other banks. Lindgren et al. (1996) classify systemic crises on the basis of whether bank runs, portfolio shifts, bank collapses or large-scale government intervention occur. Any other episodes of financial instability are classed as non-systemic crises.

of a few banks is recorded as a localised crisis and beyond this crisis becomes systemic. Not all studies make this distinction in the same way so that a crisis may be a systemic event in one paper but remain excluded from the banking crisis dummy in another.

Whichever crisis definition is used, the crisis duration must be handled carefully in order to avoid endogeneity; once a crisis occurs it is likely to deepen any recession and affect the explanatory variables. Studies have addressed this feedback in various ways: Demirgüç-Kunt and Detragiache (1998) conduct two sets of regressions, one by discarding all observations after a crisis begins and another by discarding observations after a crisis has ended.[18] Others have arbitrarily assumed a common duration for all crises, e.g. 18 months (Kaminsky and Reinhart, 1999) or 1 year (Eichengreen and Arteta, 2000; Glick and Hutchison, 1999).

The subjectivity associated with banking crisis identification may explain why almost all authors have relied on the studies mentioned above, either wholly or in combination, to construct their banking crisis variable. The disadvantage of this is that all research has focused on a few assessments of crisis occurrence. The advantage is that it reduces multiplicity in the dependent variable amongst studies. In this vein, we will also rely on the Demirgüç-Kunt and Detragiache (2005) and Caprio and Klingebiel (2003) crises lists. Henceforth, we refer to the Demirgüç-Kunt and Detragiache (2005) dates/dummy as DD05 and the Caprio and Klingebiel (2003) dates/dummy as CK03.

Hence for our DD05 dummy, the dependent variable takes a value of one if at least one of the four conditions are satisfied: (1) the proportion of non-performing loans to total banking system assets exceeded 10%, (2) public bailout cost exceeded 2% of GDP, (3) systemic crisis caused large scale bank nationalisation, (4) extensive bank runs were visible or if not, emergency government intervention was visible. For the CK03 dummy, the dependent variable takes a value of one if non-performing loans as a proportion of entire loans of the banking system were in the range of 5–10% or less or if banking experts on the country in question felt a crisis was systemic. The DD05 crisis criteria therefore result in a much clearer definition of crisis compared to CK03 which relies on more subjectivity and makes different EWS responses more difficult to compare. From the policy maker's perspective the DD05 dummy is better because policy responses can be geared to targeting the vulnerability attached to a specific crisis definition, e.g. if the proportion of non-performing loans in the banking system exceeds 10%, the policy maker can start by tightening lending criteria. The CK03 crisis definitions are vaguer, making it more difficult for the policy maker to target his response.

2.2. *The data sample*

The dataset of independent variables mimics the Demirgüç-Kunt and Detragiache (1998) approach, utilising most of their variables but for a wider selection of countries and for a longer time span. We have used the same data source they cite: IFS and World Bank Development Indicators to obtain annual data; full data sources are obtainable in Demirgüç-Kunt and Detragiache (1998). A maximum of 105 countries are included whilst the data spans the period 1979–2003. Under the DD05 dating this yields 72 systemic crisis episodes; under the less stringent CK03 definitions this yields 102 systemic crisis episodes. Almost half the countries included in our full sample experienced no systemic crisis based on DD05 dates, whereas under a fifth were non-crisis countries based on the CK03 dates.

[18] They find the results do not change significantly either way.

Table 1
The Demirgüç-Kunt and Detragiache (1998) variables

Macroeconomic variables	1. Real GDP growth (%) 2. Change in terms of trade (%) 3. Nominal depreciation (%) 4. Real interest rate (%) 5. Inflation (%) 6. Fiscal surplus/GDP (%)
Financial variables	7. M2/foreign exchange reserves (%) 8. Credit to private sector/GDP (%) 9. Bank liquid reserves/total bank assets (%) 10. Real domestic credit growth (%)
Institutional variables	11. Real GDP per capita 12. Deposit insurance (binary dummy)

As explained in Section 1.1, the explanatory variables chosen are macroeconomic, financial and financial liberalisation indicators of crisis. Table 1 below gives the indicator list.

2.3. The Demirgüç-Kunt and Detragiache (1998) Mulivariate Logit Model

The multivariate logit approach allowed Demirgüç-Kunt and Detragiache (1998) to relate the likelihood of occurrence or non-occurrence of a banking crisis to a vector of n explanatory variables. The probability that the banking dummy takes a value of one (crisis occurs) at a point in time is given by the value of the logistic cumulative distribution evaluated for the data and parameters at that point in time. Thus,

$$\text{Prob}(Y_{it} = 1) = F(\beta X_{it}) = \frac{\mathrm{e}^{\beta' X_{it}}}{1 + \mathrm{e}^{\beta' X_{it}}} \tag{1}$$

where Y_{it} is the banking crisis dummy for country i at time t, β is the vector of coefficients, X_{it} is the vector of explanatory variables and $F(\beta X_{it})$ is the cumulative logistic distribution. The parameters are obtained by maximum likelihood estimation where each possible value of Y_{it} contributes to the joint likelihood function so that the log likelihood becomes

$$\log_{\mathrm{e}} L = \sum_{i=1}^{n}\sum_{t=1}^{T}[(Y_{it} \log_{\mathrm{e}} F(\beta' X_{it})) + (1 - Y_{it})\log_{\mathrm{e}} (1 - F(\beta' X_{it}))] \tag{2}$$

The parameters obtained by maximising this function are not constant marginal effects of X_i on the crisis probability since the underlying relationship is non-linear. Rather, the marginal effect of X_{it} on Y_{it} is given by the probability of crisis times the probability of no crisis times the coefficient β_i.[19] Since the probabilities depend on the values of X_{it}, for a given coefficient, a single explanatory variable can have changing marginal contributions to crisis probability depending on its starting level. The sigmoidal logistic cumulative distribution shows that an explanatory variable

[19] The probit model is also equally valid for the banking crisis context; in this case the normal distribution underlies the likelihood function and the marginal effects are given by the variable's contribution to crisis, probability times the coefficient. Multivariate probit has been used by Eichengreen and Rose (1998) and Glick and Hutchison (1999) amongst others.

will make marginally little difference to crisis if the crisis probability is already at the extreme (low or high) but if crisis probability is around the 0.5 range then a change in the same variable is more likely to tip the balance and trigger crisis.[20] The sign on the coefficient still indicates the direction of change on crisis probability. To directly compare the individual contributions of each variable to crisis, their marginal effects can be computed for their mean values (Greene, 2000) or at a specific year before a crisis unfolds.

Demirgüç-Kunt and Detragiache (1998) do not use a fixed effects logit model; a fixed effects model would mean the country-specific dummy and the banking crisis dummy would be perfectly correlated for countries which never experienced a banking crisis. Excluding these countries would generate a biased sample and biased coefficients. Rather, they use a sample composed of crisis and non-crisis countries where the latter represent controls. In this way, variation in the explanatory variables is fully used to explain why crisis will or will not occur.

The advantage of this parametric approach is that it takes into account the interdependencies of explanatory variables which in combination could trigger crisis. In this sense, the model corresponds to much of the theory outlined in Section 1.1 where concurrent increases in real interest rates, GDP and credit growth in the presence of financial liberalisation seem to predispose economies to crisis.

2.4. The Kaminsky and Reinhart (1999) Signal Extraction Model

This is a non-parametric approach which assesses the behaviour of single variables prior to and during crisis episodes. The logic is that if aberrant behaviour of a variable can be quantitatively defined then whenever that variable moves from tranquil to abnormal activity, crisis is forewarned. Let

i: a univariate indicator
j: a particular country
S: signal variable
X: indicator

An indicator variable relating to indicator i and country j is denoted by X_i^j and the threshold for this indicator is denoted as X_i^{*j} A signal variable relating to indicator i and country j is denoted by: S_i^j. This is constructed to be a binary variable where $S_i^j = \{0, 1\}$. If the variable crosses the threshold, a signal is emitted and $S_i^j = 1$. This happens when

$$\{S_i^j = 1\} = \{|X_i^j| > |X_i^{*j}|\} \tag{3}$$

If the indicator remains within its threshold boundary, it behaves normally and does not issue a signal so $S_i^j = 0$,

$$\{S_i^j = 0\} = \{|X_i^j| < |X_i^{*j}|\} \tag{4}$$

Hence in a global EWS, panel data is used to derive a threshold for each variable, which distinguishes between normal and aberrant behaviour. Notice that the directional sign may vary depending on whether the indicator in question has an upper or lower bound; hence the variables

[20] Conversely, an improvement in the variable could cause a significant marginal reduction in crisis probability.

and thresholds in Eqs. (3) and (4) are expressed in absolute terms. Thus for a time series of t observations for country j and indicator i we can obtain a binary time series of signal or no-signal observations. This series is then checked against actual events to construct a measure of predictive accuracy. There are four possible scenarios:

	Crisis	No crisis
Signal	A	B
No signal	C	D

If the indicator signals crisis and this correlates with an actual crisis, the outcome is denoted ‘A’. If the signal is not matched by a crisis in reality, the outcome is denoted ‘B’. If no signal is emitted by the indicator but there was an actual crisis, the outcome is called ‘C’. If no signal is emitted and there really is no crisis, the outcome is ‘D’.

Hence a perfect indicator would produce outcomes A and D only; it would correctly call all crises and would not issue signals unnecessarily. Outcome C represents a failure to call crisis (Type I error) and outcome B generates a false alarm (Type II error). Hence a measure of signalling accuracy can be constructed for each indicator, based on the proportion of false alarms and missed crises; there are various criteria (e.g. minimise Type I error only) so the chosen measure will reflect the desires of the policy maker or private institution using the EWS. This is based on the inherent trade-off between Type I and Type II errors which are functions of the threshold; changing the threshold to allow more crises to be picked up necessarily raises the likelihood of false alarms. A policy maker concerned with avoiding crises at all costs may choose to minimise Type I errors even if this entails unnecessary intervention (or at least, investigation) due to more Type II errors. Likewise, in currency crisis models, private sector investors with positions entailing a large amount of exchange rate risk may prefer wider thresholds giving them time to take alternative investment positions. On the other hand, policy makers with relatively stable financial systems may prefer avoiding Type II errors and undue intervention.

Kaminsky and Reinhart (1999) choose to minimise the probability of failing to call crisis and the probability of false alarms simultaneously. Specifically, the noise-to-signal ratio (henceforth NTSR) is given by (Type II error/1 − Type I error). As with normal hypothesis testing, changing the threshold to reduce Type I errors necessarily increases the number of Type II errors. The NTSR measure takes this trade-off into account; the optimal threshold will minimise the numerator and maximise the denominator of the NTSR. Different percentiles of the entire panel (i.e. cross-country) series are taken as thresholds and the corresponding NTSR is evaluated. The percentile that minimises the NTSR is selected and applied to each country to produce a country-specific threshold which forms the benchmark for the EWS. The advantage of this non-parametric approach is that it focuses on a particular variable’s association with crisis and that it can be based on high frequency data. Furthermore, it may be more comprehensible to the non-economically trained policy maker than the logit model.

3. Results

3.1. Replication of Demirgüç-Kunt and Detragiache (2005) (denoted DD05)

Following the DD05 procedure, regressions were conducted with three sets of explanatory variables: (i) macroeconomic only (minus fiscal), (ii) macroeconomic (minus fiscal) with financial, (iii) macroeconomic, fiscal and financial and (iv) macroeconomic, fiscal, financial and institu-

Table 2
Regression 1: Macroeconomic (minus fiscal) variables only

	Original	Replication	
	D&D (2005) paper (1980–2002) 94 countries, 77 crisis occurrences (1st crisis year only)	D&D (2005) crisis dummy (1979–2003) 105 countries, 72 crisis occurrences (1st crisis year only)	C&K (2003) crisis dummy (1979–2003) 105 countries, 121 crisis occurrences (1st crisis year only)
Real GDP growth	−0.0967*** (0.0259)	−0.1693*** (0.0332)	−0.1177*** (0.0240)
Change in terms of trade	0.0005 (0.0061)	−0.0285*** (0.0023)	−0.0191*** (0.0016)
Depreciation	−0.0675 (0.3892)	0.0000 (0.0011)	0.0000 (0.0003)
Real interest rate	0.0006*** (0.0002)	0.0243** (0.0108)	0.0416* (0.0242)
Inflation	0.0007** (0.0003)	−0.0012 (0.0000)	0.0010 (0.0006)
Real GDP per capita[a]	−0.0367* (0.0156)	−0.0347* (0.0196)	−0.0391*** (0.0139)
Fiscal balance/GDP	X	X	X
M2/international reserves	X	X	X
Private credit/GDP	X	X	X
Deposit insurance	X	X	X
Credit growth (−2)	X	X	X
Wald test statistic		412.67***	264.01***
AIC	593	0.3102	0.5084
Observations	1670	1314	1491

Note: *significant at 10%, **significant at 5%, ***significant at 1%, standard errors in parenthesis.
[a] Indicates a coefficient has been multiplied by 1000 to overcome scaling issues.

tional. Tables 2–5 show our results against the benchmark DD05 results. We also report the models' Akaike's Information Criterion and the Wald test statistic which tests the null that all coefficients equal zero. Note that most variables in DD05 are measured as current levels (i.e. current data is associated with a crisis in the current year) which limits the usefulness of the model as an early warning system for policy action, although it does not rule it out entirely, given the possible use of economic forecasts as inputs as well as current data. The possibility of reverse causation, where the crisis itself could cause the explanatory variables to change is avoided by discarding observations after the onset of crisis.

These regressions (Tables 2–5) show that real GDP growth, real interest rates and real GDP per capita are consistently and significantly associated with crisis. These results are consistent with the DD05 findings. However in our case, adding many of the financial variables makes little difference to the model (the coefficients are not significant) and actually reduce the AIC. This is in contrast to DD05 who found that increased budget deficits and private credit/GDP raised banking crisis probability.

In regression 3, we find inflation may have a weak negative effect on banking crisis which may reflect procyclical behaviour of asset prices, since during booms, crises are less likely. The fact that higher real GDP growth is consistently found to reduce banking crisis probability confirms it is a robust leading indicator of banking crisis. Apart from directly reducing non-performing loans (and concurrently credit risk), GDP growth may also delay banking crises, again due to procylicality. The coefficients on real interest rates are positive and apart from one regression, significant. This suggests interest rate risk materialisation and financial liberalisation could trigger crises. However, the effect of interest rates is not robust to the banking crisis dummy used; alongside the Caprio and Klingebiel (2003) (CK03) dummy, interest rates become insignificant.

Table 3
Regression 2: Macroeconomic (minus fiscal) and financial variables

	Original	Replication	
	D&D (2005) Paper (1980–2002) 94 countries, 75 crisis occurrences (1st crisis year only)	D&D (2005) crisis dummy (1979–2003) 105 countries, 42 crisis occurrences (1st crisis year only)	C&K (2003) crisis dummy (1979–2003) 105 countries, 77 crisis occurrences (1st crisis year only)
Real GDP growth (t)	−0.0991*** (0.0265)	−0.1964*** (0.0362)	−0.1368*** (0.0273)
Change in terms of trade (t)	0.0006 (0.0064)	−0.0273*** (0.0024)	−0.0193*** (0.0018)
Depreciation (t)	0.0713 (0.3830)	0.0000 (0.0001)	0.0000 (0.0003)
Real interest rate (t)	0.0005*** (0.0002)	0.0268** (0.0122)	0.0293 (0.0275)
Inflation (t)	0.0006** (0.0003)	0.0002 (0.0012)	0.0009 (0.0007)
Real GDP per capita (t)	−0.0359** (0.0168)	0.0000 (0.1718)	0.0000 (0.0000)
Fiscal balance/GDP (t)	X	X	X
M2/international reserves (t)	0.0012* (0.0007)	0.0000 (0.0003)	−0.0008 (0.0018)
Private credit/GDP (t)	0.0010*** (0.0003)	−0.0006 (0.0010)	0.0000 (0.0001)
Credit growth ($t-2$)	0.0038** (0.0019)	−0.0005 (0.0009)	0.0005 (0.0010)
Deposit insurance (t)	X	X	X
Wald test statistic		355.24***	365.05***
AIC	579	0.3200	0.5323
Observations	1612	1153	1327

One explanation may the less stringent crisis criteria CK03 use to classify systemic episodes in comparison to DD05. The DD05 crises are more likely to be fully systemic implying that real interest rates may become a more important trigger if financial instability is endemic as opposed to more localised insolvency. Lagged real credit growth is negatively significant in one specification

Table 4
Regression 3: Macroeconomic, financial and fiscal variables

	Original	Replication	
	D&D (2005) Paper (1980–2002) 94 countries, 65 crisis occurrences (1st crisis year only)	D&D (2005) crisis dummy (1979–2003) 105 countries, 42 crisis occurrences (1st crisis year only)	C&K (2003) crisis dummy (1979–2003) 105 countries, 70 crisis occurrences (1st crisis year only)
Real GDP growth (t)	−0.1115*** (0.0319)	−0.1891*** (0.0402)	−0.1677*** (0.0338)
Change in terms of trade (t)	−0.0024 (0.0066)	−0.0288*** (0.0030)	−0.0150*** (0.0028)
Depreciation (t)	−0.1037 (0.3918)	0.0000 (0.0002)	−0.0002 (0.0002)
Real interest rate (t)	0.0005*** (0.0002)	0.0313** (0.0128)	0.0034 (0.0138)
Inflation (t)	0.0007** (0.0003)	0.0002 (0.0014)	−0.0161 (0.0102)
Real GDP per capita (t)	−0.0414** (0.0175)	−0.0275 (0.0215)	−0.0303** (0.0147)
Fiscal balance/GDP (t)	0.0033** (0.0016)	−0.0498 (0.0348)	0.0402 (0.0314)
M2/international reserves (t)	0.0062*** (0.0021)	0.0000 (0.0002)	−0.0001 (0.0004)
Private credit/GDP (t)	0.0016*** (0.0004)	−0.0007 (0.0010)	0.0000 (0.0001)
Credit growth ($t-2$)	0.0044* (0.0023)	−0.0004 (0.0010)	−0.0117** (0.0048)
Deposit insurance (t)	X	X	X
Wald test statistic		293.58***	311.31***
AIC	494	0.3306	0.5276
Observations	1612	1153	1327

Table 5
Regression 4: All variables

	Original	Replication	
	D&D (2005) Paper (1980–2002) 94 countries, 77 crisis occurrences (1st crisis year only)	D&D (2005) crisis dummy (1979–2003) 105 countries, 38 crisis occurrences (1st crisis year only)	C&K (2003) crisis dummy (1979–2003) 105 countries, 61 crisis occurrences (1st crisis year only)
Real GDP growth (t)	−0.1175*** (0.0332)	−0.1925*** (0.0405)	−0.1706*** (0.0340)
Change in terms of trade (t)	−0.0028 (0.0067)	−0.0302*** (0.0034)	−0.0159*** (0.0030)
Depreciation (t)	−0.1233 (0.3946)	0.0000 (0.0002)	−0.0002 (0.0002)
Real interest rate (t)	0.0006*** (0.0002)	0.0314** (0.0131)	0.0009 (0.0145)
Inflation (t)	0.0007 (0.0003)	0.0003 (0.0013)	−0.0172* (0.0105)
Real GDP per capita (t)	−0.0544*** (0.0184)	−0.0318 (0.0220)	−0.0349** (0.0154)
Fiscal balance/GDP (t)	0.0014** (0.0020)	−0.0496 (0.0352)	0.0440 (0.0318)
M2/international reserves (t)	0.0066*** (0.0022)	0.0000 (0.0002)	−0.0001 (0.0005)
Private credit/GDP (t)	0.0012*** (0.0005)	−0.0008 (0.0011)	−0.0001 (0.0001)
Credit growth ($t-2$)	0.0041* (0.0022)	−0.0005 (0.0011)	−0.0120*** (0.0049)
Deposit insurance (t)	0.5859** (0.2786)	0.3477 (0.3607)	0.3549 (0.2942)
Wald test statistic		291.06***	416.11***
AIC	493	0.3318	0.5283
Observations	1356	952	1094

and insignificant in others whereas DD05 found this variable to be significant albeit in one model specification only. Similarly, they found domestic credit/GDP to be positively associated with crisis, but this variable was not significant in any of our initial regressions.

In contrast to DD05, we find that positive terms of trade shocks consistently reduce banking crisis probability. This may be due to the higher number of small open economies in our sample compared to DD05. Apart from the direct effects on increased loan repayments, favourable terms of trade are also likely to reduce chances of currency crisis. As Kaminsky and Reinhart (1999) show, once a banking crisis is underway, the onset of a currency crisis is likely to deepen banking difficulties.

The Wald test statistics show that all the coefficients are significantly different from zero. On the basis of the AIC it appears the most parsimonious model (regression 1) is the best specification of the four regressions. However, the changing signs on the coefficients and the insignificance of many variables which DD05 found to be significant indicate the specification may be improved.

3.2. *Improving the model: transforming variables*

Following the first set of regressions, we experimented with data transformations and lags to accommodate the dynamics of banking crises. Furthermore, the occurrence of a banking crisis leaves the economy vulnerable to further crises and may explain the successive crisis episodes observed in many economies. Omitting observations following crisis onset as in DD05 removes this vulnerability from the data. Hence we repeat the regressions retaining all observations.

DD05 do not mention heterogeneity of series but inspection of the data shows significant differences in the magnitude of variables within countries (i.e. between growth and level variables) and between countries. Accordingly, we standardise each series and log several variables (other series have been checked for stationarity). Standardisation takes into account the differing average levels

Table 6
Regression 5: All variables; standardisation, more lags and logs introduced

	D&D (2005) crisis dummy (1979–2003) 105 countries, 46 crisis observations (all years)	C&K (2003) crisis dummy (1979–2003) 105 countries, 81 crisis observations (all crisis years)
log (Real GDP growth ($t-2$))	-0.4026^{***} (0.1443)	-0.2978^{***} (0.1214)
Change in terms of trade (t)	0.0001 (0.0036)	0.0007 (0.0026)
Real interest rate ($t-2$)	0.5729^{*} (0.3499)	−0.0354 (0.2851)
Inflation (t)	17.1924^{***} (4.5638)	3.4592 (3.8379)
Change in real GDP per capita (t)	-16.6447^{**} (6.9907)	-16.5295^{***} (5.2466)
Fiscal balance/GDP (t)	-0.1711^{***} (0.0525)	-0.1238^{***} (0.0417)
M2/international reserves (t)	2.7189^{**} (1.3164)	1.9731 (1.3653)
log (Private credit/GDP) (t)	-0.4394^{***} (0.1208)	-0.3802^{***} (0.1007)
Credit growth ($t-5$)	4.2305^{**} (2.0514)	−0.1574 (0.2362)
Deposit insurance ($t-10$)	0.5755^{*} (0.3555)	0.1412 (0.2700)
Wald test statistic	113.27^{***}	97.03^{***}
AIC	0.6417	0.9564
Observations	368	368

of the variables across countries, and thus scales the impact of a shock to the mean and volatility of the variables to which the banking sector is habituated. From a theoretical and observational point of view, standardisation may be expected to improve results. If macroeconomic variables consistently align with a low, stable growth environment, banks can perform well; sustained periods of low growth mean loan managers are less likely to suffer from "disaster myopia" since they will have not experienced boom and bust cycles. Any herding that does occur, should merely imply common prudential lending practices. Consequently, credit risk should be lower so that a slight drop in growth rates would not cause bank collapses. Banks have been observed to remain healthy in slow growth environments. On the other hand, during a boom phase when credit risk is accelerating and "disaster myopia" may be present, a sudden, aberrant drop in growth can be extremely detrimental to bank balance sheets as suggested by the observed correlation between boom and bust cycles and banking crises.

The standardising process involves dividing the deviation of each observation from the pooled mean by the pooled standard deviation, $X^*_{it} = (X_{it} - \bar{X})/\sqrt{var(X)}$, where X_{it} is the observation for country i at time t, $\bar{X}$ is the pooled mean and $\sqrt{var(X)}$ is the pooled standard deviation. We remove depreciation since it is correlated with terms of trade and it was insignificant in the DD05 regressions. Also we assess for lags in a number of variables, the chosen lags were found from a grid search. Note in particular that credit growth and deposit insurance take quite long lags prior to the crisis, as is plausible (i.e. a crisis may be several years after the credit boom's peak, whilst deposit insurance takes time to affect risk-taking behaviour). Lags will make the results more helpful in practical policy applications, as it allows time for counteractive policy to have an effect.

Table 6 shows that more indicators now appear as significant predictors of crisis and more leading indicators appear robust to the banking dummy specification. Note however that the lags chosen have also reduced the number of observations compared with Table 5.

Standardising the variables and taking logs where necessary improves significance on many variables. This suggests that without a fixed effects model, unless data is restricted to a homogenous country set, some form of adjustment may be necessary to accommodate variation in the data. This allows a wider cross-country sample to underpin the EWS. We first discuss the overall significance of the explanatory variables following their transformation before explaining why we have selected the lags we have and discussing their significance in the context of banking crisis dynamics in Section 3.3.

Real GDP growth remains robustly significantly inversely related to crisis, whichever banking crisis definition used. High real interest rates now appear to significantly increase the probability of banking crisis in accordance with DD05. Moreover, the size of the coefficient implies the interest rate risk effect is much stronger in our model. A rise in inflation substantially increases the chances of crises. Unlike DD05, who did not find this variable to be significant, we find the inflation coefficient to be the largest of all. A healthy fiscal surplus seems to signal authorities' general ability to manage policy in a positive sense and their ability to intervene in the banking system if necessary, which reduces crisis likelihood. The significance of this variable increases under our specification compared to DD05. Conversely, the positive coefficient on M2/Reserves shows an increase in un-backed money adds to the chances of capital flight and thus to the probability of a pure banking or twin crisis. This coefficient was insignificant in our previous specifications.

The negative sign on the private credit/GDP coefficient indicates that crises are more likely in lesser developed economies where bank intermediation is the main mechanism of raising capital and regulation may be of lower quality. The coefficient on credit growth supports the theory that accumulations in credit risk are a cause of banking crises. The safety net of deposit insurance significantly raises the likelihood of morally hazardous lending by banks, which adds to the crisis probability. Again, this effect appears to be much stronger under our specification compared to DD05. The coefficient on the change in GDP per capita is strongly negative and significant, indicating that improvements in institutional quality associated with higher GDP reduce banking crisis risk.

Whilst the above results seem entirely consistent with banking crisis theory, they are not entirely robust to the choice of banking crisis dummy. Nevertheless, some variables which were insignificant alongside the CK03 definitions when untransformed data were used (regressions 1–4) now appear significant under both dummy definitions: fiscal balance/GDP and private credit/GDP. The significance of real GDP per capita now increases for the CK03 dummy in comparison to when data is not standardised. On the other hand, when the CK03 definitions of crisis are used, inflation and credit growth are less significant.

Under the new specification with lags introduced, terms of trade loses significance for both crisis definitions. This may imply that terms of trade shocks play little part in the accumulation of systemic risk, but that (as regression 1–4 show), once risk is amassed systemically, a sudden deterioration in an economy's terms of trade could precipitate a banking crisis.

3.3. Improving the model further: investigating dynamics

To model the dynamics of banking crises, we now introduce further lags and several interaction variables so that we use the data to mimic the procyclical build up of risk. Our banking crisis story unfolds as follows: credit booms are more likely to occur in an environment which allows imprudent lending, such as following the adoption of deposit insurance. Hence, after deposit insurance is introduced we expect to see rises in domestic credit growth being associated with imprudent lending. This may be tempered if agents are not so reliant on bank intermediation for funds when deposit insurance is installed. To test the impact of credit growth in the presence of deposit insurance, we interact credit growth and deposit insurance at different lags. The results in Table 7 clearly show the procyclical behaviour of credit growth. During the boom

Table 7
Regression 6: Procyclicality and moral hazard

	D&D (2005) crisis dummy (1979–2003) 105 countries, 70 crisis observations (all years)	C&K (2003) crisis dummy (1979–2003) 105 countries, 100 crisis observations (all years)
log (Real GDP growth) (t)	−0.1152 (0.1204)	−0.1329 (0.1083)
Change in terms of trade (t)	0.0013 (0.0031)	0.0009 (0.0027)
Real interest rate (t)	0.0030 (0.3013)	0.0506 (0.2821)
Inflation (t)	5.6593** (2.7485)	−1.6839 (2.9102)
Change in real GDP per capita (t)	−18.6873*** (6.9503)	−18.7623*** (5.9710)
Fiscal balance/GDP (t)	−0.0466 (0.0361)	−0.0843*** (0.0334)
M2/international reserves (t)	12.5815*** (4.7478)	5.4025** (2.7862)
log (Private credit/GDP) (t)	−0.2319** (0.1037)	−0.3905*** (0.0941)
Credit growth × Insurance (t)	−6.2798* (3.5159)	−8.3398** (3.6856)
Credit growth × Insurance ($t-1$)	−10.9812*** (4.2393)	−9.2458*** (3.7538)
Credit growth × Insurance ($t-2$)	−8.1842** (4.1300)	−8.5824** (3.7562)
Credit growth × Insurance ($t-3$)	−2.7540 (2.8714)	0.7778 (3.0085)
Credit growth × Insurance ($t-4$)	6.4430** (3.1518)	4.6280 (3.0500)
Credit growth × Insurance ($t-5$)	7.9458*** (3.1063)	4.7191* (2.8103)
Credit growth ($t-1$)	−1.3292 (2.5000)	2.4400 (2.3468)
Credit growth ($t-2$)	2.3022 (2.7396)	4.9375* (2.6044)
Credit growth ($t-3$)	0.1518 (1.4265)	−1.9288 (1.6528)
Credit growth ($t-4$)	−0.0899 (0.2471)	−0.3865 (0.3933)
Credit growth ($t-5$)	−0.0729 (0.1235)	−0.0251* (0.0846)
AIC	0.7089	0.8722
Wald statistic	156.07***	1.35***
Observations	484	484

phase up to 4 years prior to crisis, credit growth appears to generate credit risk. From 3 years prior to crisis, a cyclical downturn seems to occur with the coefficient sign switching so that credit rationing increases the likelihood of crisis. The fact that the interaction terms are significant (with credit growth alone insignificant) also demonstrates how moral hazard is more prevalent when deposit insurance exists so that credit booms generate considerable banking crisis risk.

3.4. In-sample predictive ability

We now turn to see the relative performances of the different specifications in terms of their ability to accurately call crises and non-crises episodes. It should be noted that the higher the probability threshold set for calling a crisis, the higher the probability of Type I errors (failure to call crisis) and the lower the probability of Type II errors (false alarm). In this regard, we initially set our threshold much higher than Demirgüç-Kunt and Detragiache (1998) who set their cut-off probability at 0.05.[21] In contrast we set our threshold at 0.5, arguing that from the policy maker's perspective, costly intervention on the basis of a crude EWS should be avoided unless the model seriously calls a crisis (Table 8a). However the threshold can be changed according to a policy maker's loss function; those that observe a higher historic crisis frequency or who

[21] They decide this threshold on the basis of the frequency of crisis episodes in their sample.

Table 8a
In-sample predictive ability: cut-off probability = 0.5

Probability cut-off = 0.5	Regression								
	1			2			3		
	DD05[a]	Our version		DD05[a]	Our version		DD05[a]	Our version	
		DD05	CK03		DD05	CK03		DD05	CK03
% crises correct	60	7	13	60	8	15	58	10	9
% no crises correct	67	96	92	70	96	92	70	96	94
% total correct	67	93	87	70	93	87	70	92	89

Probability cut-off = 0.5	Regression								
	4			5			6		
	DD05[a]	Our version		DD05[a]	Our version		DD05[a]	Our version	
		DD05	CK03		DD05	CK03		DD05	CK05
% crises correct	62	10	5	NA	31	34	NA	34	28
% no crises correct	68	96	95	NA	90	80	NA	98	96
% total correct	68	92	89	NA	82	70	NA	89	82

[a] For DD05 cut-off probability is 0.05.

Table 8b
In-sample predictive ability: cut-off probability = 0.05

Probability cut-off = 0.5	Regression								
	1			2			3		
	DD05	Our version		DD05	Our version		DD05	Our version	
		DD05	CK03		DD05	CK03		DD05	CK03
% crises correct	60	53	66	60	54	66	58	66	66
% no crises correct	67	78	50	70	78	34	70	76	48
% total correct	67	77	51	70	78	50	70	75	49

Probability cut-off = 0.5	Regression								
	4			5			6		
	DD05	Our version		DD05	Our version		DD05	Our version	
		DD05	CK03		DD05	CK03		DD05	CK05
% crises correct	62	66	66	NA	91	99	NA	91	99
% no crises correct	68	77	45	NA	44	12	NA	32	23
% total correct	68	76	50	NA	50	31	NA	40	39

wish to avoid "potential" crises at all costs can lower the cut-off probability. Accordingly, we re-estimate in-sample predictions using a cut-off probability of 0.05 identical to Demirgüç-Kunt and Detragiache (1998). When we reduce our threshold to the Demirgüç-Kunt and Detragiache (1998) level, our models, notably regressions 5 and 6 have dramatically higher crisis predictive ability (Table 8b).

Table 8a shows that with a cut-off probability of 0.5, our models are better at calling non-crisis periods correctly although the ability to call crisis episodes is substantially lower than DD05. This is as we would expect given the trade-off between Type I and Type II errors and the higher cut-off. However once we lower the threshold to the same level as DD05 at 0.05, our models out-perform the DD05 models in terms of crisis prediction (apart from regressions 1 and 2). This is independent of the crisis dummy used. Moreover, a dynamic model such as Model 5 is notably better at predicting crisis events with above 90% of crisis episodes being called correctly.

Both tables also show that given the same threshold, the CK03 crisis dummy generally is better predicted by these variables that the DD05 dummy. This may be due to the wider definitions of crisis that CK03 use so that the CK03 dummy is associated with a reduced ability to call non-crisis periods correctly and therefore a higher chance of Type II errors. Table 8b shows our models do not appear to lose much in terms of Type II errors when the cut-off probability is lowered to 0.05 since based on the DD05 dummy, our % of non-crisis events correctly predicted is marginally higher than the DD05 models. As a result, our models consistently outperform the DD05 models in term of total correct predictions but only if the DD05 dummy is used. If the CK03 dummy is used, our models underperform in total; again this is probably due to the wider crisis definitions of the CK03 dummy which results in reduced ability to identify non-crisis periods.

Overall these results show that incorporating dynamics substantially improves crisis predictive ability with no significant cost in terms of false alarms. It also illustrates the trade-off of Type I and Type II errors in logit models.

3.5. Out-of-sample predictive ability

Obviously, the value of any EWS lies in its ability to forewarn policy makers of impending crises and hence on their out-of-sample predictive ability. An assessment of the EWS in this context would take into account model mis-specification and potential reverse causality that might arise when using contemporaneous data to obtain parameters, although the latter can be reduced by using lagged explanatory variables as we have in regressions 5 and 6. However, given data limitations and the fact that crises are rare events, out-of-sample assessment of EWS based on recent data is difficult. In our case, the data end in 2003, after which there have been no unanimously agreed systemic episodes. Nevertheless, we evaluate crisis probabilities for 5 randomly chosen countries based on 2004 and 2005 data. This exercise demonstrates the informational problems associated with forecasting crises, since at present all 2006 data is not available for some countries. Because we do not assume any particular preferences of policy makers for Type I or Type II errors, we use regression 4 (based on the DD05 dummy) which has almost the highest overall (crisis and non-crisis) predictive accuracy whilst being able to call 66% of crises.[22]

The out-of-sample forecasts for Canada, Denmark, India, Iceland and Mozambique are presented in Box 2 below. Given that none of these countries experienced systemic crises in 2004 and 2005, the low probabilities indicate out-of-sample prediction of non-crisis episodes is good. Notably, the highest risk of crisis was faced by Iceland which did actually experience a substantial credit boom, house price and general inflation during 2004/2005 as well as rapid growth in the banking sector; bank balance sheets held assets worth 1.8 times GDP in 2003 but by 2006 this proportion had risen to 8 times GDP.[23] In other words, out-of-sample, our model is also able to

[22] The only other regression with higher overall accuracy is regression 2 (with the DD05 dummy) at 78% accuracy but this only calls 54% of crises.

[23] See Gudmundsson and Eliasson (2007).

Box 1. Out-of-sample forecasts for regression 4 (DD05)

	Crisis probability (%)	
	2004	2005
Canada	1.03	0.97
Denmark	1.25	0.94
Iceland	7.16	10.07
India	2.16	1.82
Mozambique	2.07	2.00

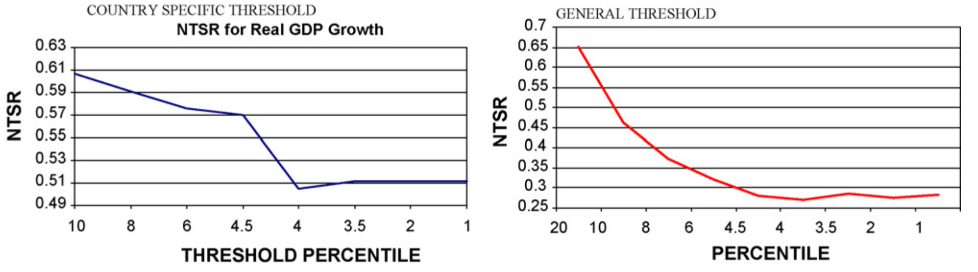
Box 2. Bootstrap results for out-of-sample performance of regression 4 (DD05)

Actual dummy series mean (μ_1)	0.039916
Actual dummy series variance (σ_1^2)	0.038363
Bootstrap sample mean (μ_2)	0.045091
Bootstrap sample variance (σ_2^2)	0.00439
• *t*-test for means T = 0814456*** (significant at 1%)	H_0: $\mu_1 = \mu_2$
• *F*-test for variances F = 575.6175	H_0: $\sigma_1^2 = \sigma_2^2$

detect vulnerability to banking crisis. Used on a regular basis, the model should indicate increasing vulnerability allowing the policy maker sufficient time to take remedial action.

To assess our EWS performance in the light of data constraints, we also use a bootstrap approach (Efron, 1979). We take the fitted values of our dependant variables and generate random samples from a logistic distribution with identical mean and variance. The random sample average mean and variance is then compared against the mean and variance of the actual dummy series to see if they are statistically significant. We use a *t*-test to test the null of identical means and an *F* test to test the null of identical variances. If the means of the random samples and the actual crisis observations are not significantly different then the model is a good out-of-sample predictor, since bootstrapping amplifies the number OF observations available to us from the model's forecasts. If the variances are not significantly different, there will be little discrepancy between the model's predictions and what actually materialises, i.e. there is no volatility in forecasting ability. For the same reasons given for the forecasting exercise in Box 1 , we use regression 4 to perform the bootstrap. The results are presented in Box 2 below.

Whilst the *t*-test passes, the *F*-test fails. Interestingly, this means that on average the model is excellent at forecasting the out-of-sample mean probability of crisis but that these forecasts are volatile. In other words on average, the model will call crises correctly but for individual forecasts there is a chance of false alarms or missed crises. Given that the cross-section is heterogeneous and that causes of crises are often unique to each episode, this seems unsurprising.



Graph 1. Real GDP growth.

In sum, our out-of-sample results suggest our model would provide valuable information for a policy maker who is monitoring crisis risk and who may need to take preventative action. Used in conjunction with macroprudential indicators and other subjective assessments, our EWS should give the policy maker sufficient forewarning to avoid the detrimental effects of crises.

3.6. Banking crisis prediction using the method of Kaminsky and Reinhart (1999)

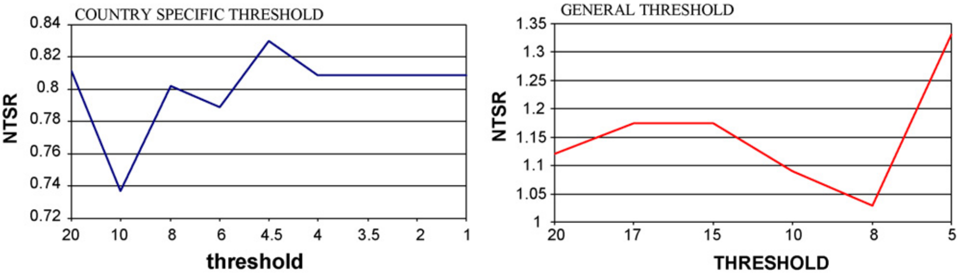
Using exactly the same dataset as the previous logit regressions, we now conduct a signal extraction approach in the manner of Kaminsky and Reinhart (1999), henceforth KR99.[24] The KR99 methodology locates the optimal threshold using a common percentile for the cross-country distribution of each variable. Whilst we will adopt this approach, we also argue that minimisation of a common percentile may be problematic. If the 20th percentile is chosen as the optimal threshold across all cross-sections, this is equivalent to the notion that whenever real GDP growth falls into the lowest 20% of observations in *any* country, a crisis is imminent. Whilst for some countries during some time periods this may be reasonably correct, for other countries it may not; certain countries may undergo structural changes (e.g. financial liberalisation, move from recession to boom) which generate different distributions for the indicator and their optimal threshold may differ accordingly. Hence generalisation to a common percentile threshold may limit the predictive ability of panel based EWS. Accordingly, we test whether country-specific and general grid searches give rise to different optimal thresholds. We then compare the in-sample predictive ability of the two approaches.

To optimise thresholds on the basis of country-specific data we compute the NTSR for each country having had a banking crisis using a selection of percentiles. We use a forecasting horizon of 2 years—1 year prior to the crisis and the crisis year itself. Our horizon is considerably more stringent than the KR99 signalling window which consists of 54 months (18 months before the crisis, an 18 month crisis episode and 18 months after the crisis). We choose a shorter signalling window because where there are multiple crisis episodes, signalling windows may overlap. Also, because we use annual data, our signalling window is restricted to yearly increments. The lowest NTSR given by the threshold corresponding to each country is then aggregated into a common threshold. Table 9 and Graphs 1–8 show our optimal thresholds (in terms of percentiles) and the corresponding correct predictions, where “General” refers to the common percentile approach used by KR99.Note that the term “country-specific” does not imply that the data used in the EWS are only from the country concerned. Rather it relates to the optimisation method used to

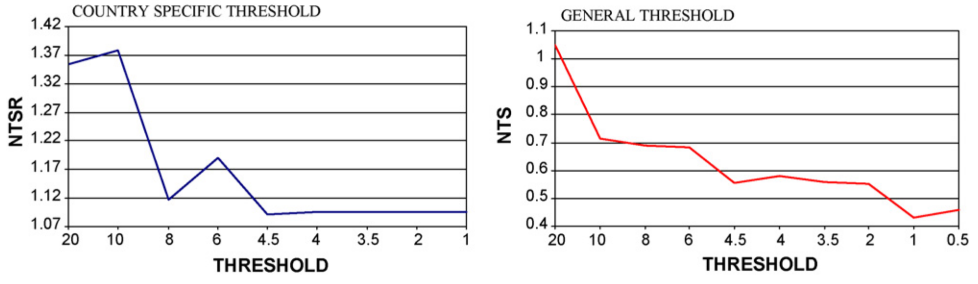
[24] We therefore abandon the KR99 variable list which is more focused on detecting balance of payments difficulties.

Table 9
Comparison of in-sample predictive ability for general and country-specific thresholds

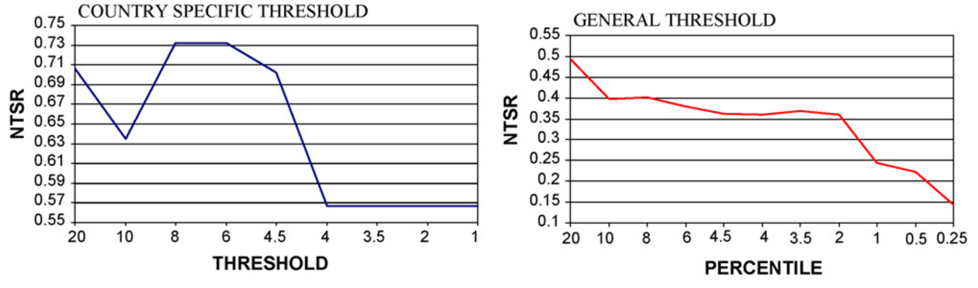
	Real GDP growth		Terms of trade	
	Country specific	General	Country specific	General
Optimal percentile	8	4	10	8
NTSR	0.5904	0.2701	0.7370	1.0284
% crisis correct	12	10	15	7
% no crisis correct	93	97	89	93
% total correct	81	84	76	78
	Real interest rate		Depreciation	
	Country specific	General	Country specific	General
Optimal percentile	4.5	1	4	2.5
NTSR	1.0917	0.4309	0.5667	0.1436
% crisis correct	7	2	6	1
% no crisis correct	92	99	96	100
% total correct	80	85	82	84
	Inflation		Budget surplus	
	Country specific	General	Country specific	General
Optimal percentile	6	4	6	4
NTSR	0.9373	0.5509	0.7113	0.8084
% crisis correct	9	6	12	4
% no crisis correct	92	97	91	97
% total correct	79	83	79	82
	M2/Reserves		Credit/GDP	
	Country specific	General	Country specific	General
Optimal percentile	20	1	8	2
NTSR	0.8598	0.3246	1.1318	0.4251
% crisis correct	23	2	8	4
% no crisis correct	80	99	91	98
% total correct	71	84	78	83



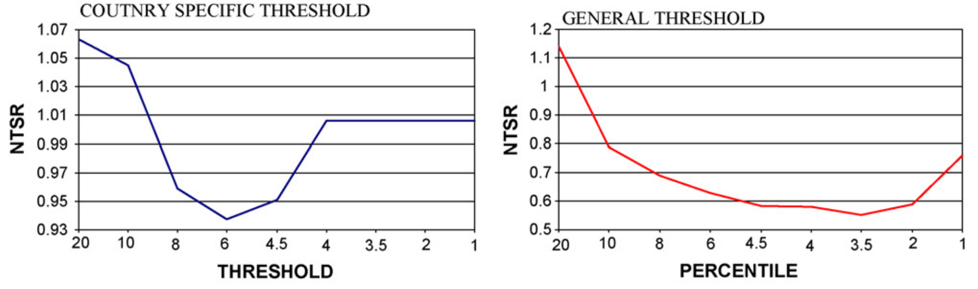
Graph 2. Terms of trade.



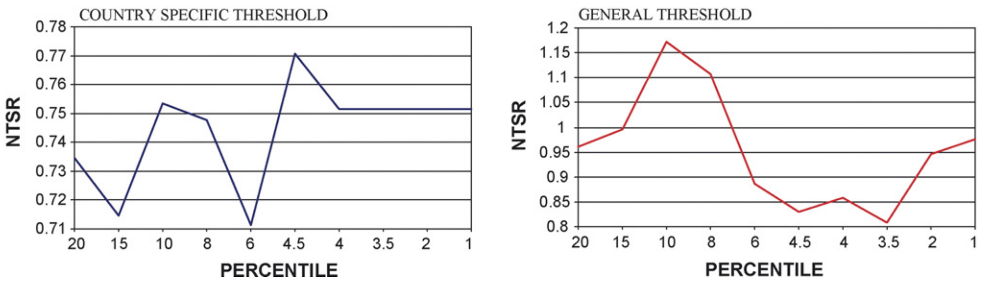
Graph 3. Real interest rate.



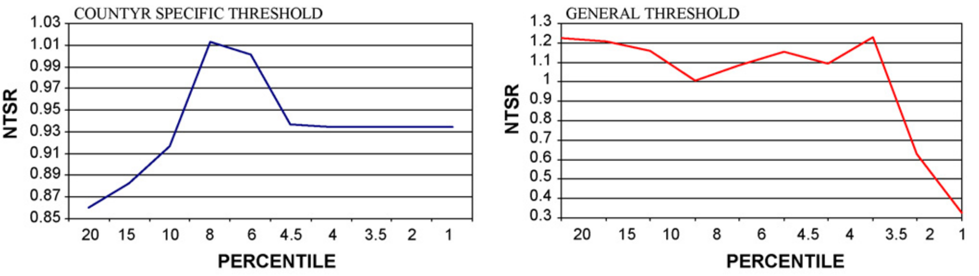
Graph 4. Depreciation.



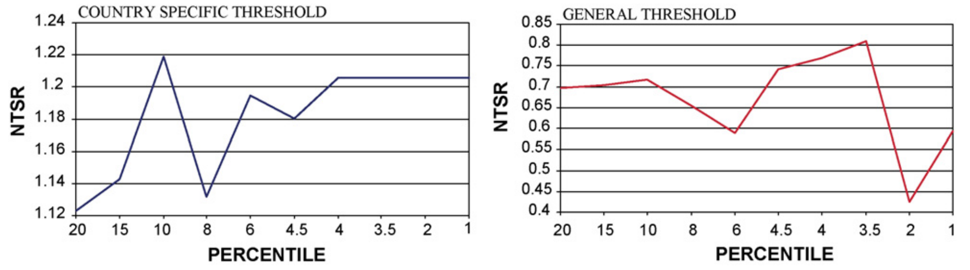
Graph 5. Inflation.



Graph 6. Budget balance.



Graph 7. M2/Reserves.



Graph 8. Credit/GDP ratio.

identify the best threshold, which relies on country-specific information but which generates a single threshold that is applied to the whole panel of countries. Hence both the KR99 and our approaches result in a panel-based EWS, but the threshold construction differs.

The results show there is a big difference between country-specific and general thresholds and that as a result, the optimal percentile differs widely. Using a country-specific optimisation procedure results in a higher percentage of crises being predicted compared to the generalised threshold method. However, the general threshold procedure is better at calling non-crisis episodes, so that there are a higher chance of Type I errors with the general method and conversely, a higher chance of Type II errors with the specific method. Given that there is a high ratio of non-crisis to crisis observations in the sample, overall the general procedure performs better in terms of total correct predictions. As a result, the general threshold virtually always gives a lower NTSR to the specific threshold where values below one indicate the variables are informative.

In terms of individual leading indicator performance, the best predictors of crisis appear to be real GDP growth and changes in the terms of trade. This is consistent with the panel logit results. M2/Reserves and budget surpluses are also better than other indicators at calling crises.

Although we follow the Kaminsky and Reinhart (1999) procedure, we are unable to compare most of our indicator performances with theirs since they conducted their estimations for a different sample of countries and different time frames, using mostly different indicators on a monthly basis.[25] However, comparison of indicators common to our study and theirs (real interest rates and domestic credit/GDP) shows our indicators are considerably worse at calling banking crises

[25] Kaminsky and Reinhart (1999) base their study on 20 small open economies with a fixed exchange rate or a crawling peg over a period 1970–1995. Their sample contained 26 banking crises, 19 of which were twinned. Because they were investigating balance of payments crises as well as twin crises, the variables they used were predominantly different to ours which are based on the DD05 study.

correctly compared to theirs. For Kaminsky and Reinhart (1999), real interest rates are able to call 100% of crises correctly whilst domestic credit/GDP is able to call 50% of crises correctly. However the authors do not mention their indicators' ability to call non-crisis periods correctly or the level of Type II errors that arise with such high prediction rates.

Overall our results suggest there may be policy implications for the selection of the optimisation procedure. Policy makers who place emphasis on crisis avoidance may utilise the country-specific approach. However the results also imply that a country-specific Signal Extraction Model, where thresholds are derived from historic data for a single country, is likely to incorporate more information when selecting the optimal threshold. Much of this heterogeneity is averaged away when deriving global thresholds. We next turn to investigate whether combining indicators changes the trade-off between Type I and Type II indicators for our dataset.

3.7. Developing the signal extraction approach: composite indicators

Borio and Lowe (2002) developed the Kaminsky and Reinhart (1999) procedure by constructing composite indicators[26] to extract signals of banking crisis. Their approach is to select indicators which a priori are thought to contain information for banking crisis prediction. They then aggregate these variables to generate a composite signal whereby the indicator is switched on if all constituent variables cross their respective thresholds simultaneously. Selection of optimal composite thresholds is achieved by a grid search to identify the minimum NTSR. However, the noteworthy difference to the KR99 approach is that the Borio and Lowe (2002) method implicitly gives more weight to Type II errors, since they consider the failure to predict crises outweighs the costs of unnecessary intervention. Their more stringent requirement that all individual indicators in the composite must cross their thresholds for the composite to signal, means when a crisis is called it is more likely to happen; the probability of a Type I error is reduced at the cost of higher levels of Type II errors.

In this section we also generate composite indicators but our method differs from Borio and Lowe (2002). We do not impose a requirement that all indicators within the composite must cross their thresholds for the composite to signal. Rather, we construct a composite indicator in the manner of Kaminsky (1999) which may signal crisis even if some of the individual indicators have not crossed their thresholds. Although we do not assign any weights to Type I or Type II errors, we do construct composites based on the general and specific methodologies followed in Section 3.4. Since these two approaches have been shown to favour Type I and Type II errors differently, we wish to see if this behaviour persists when we construct composites. We also investigate whether creating composite indicators affects the informational content of the indicator.

Kaminsky (1999) constructs the composite (C) by weighting each component variable by the inverse of its noise-to-signal ratio (Eq. (5)), where S_j^t is the signal for variable j at time t and ω^j is the noise-to-signal ratio for variable j.

$$C = \sum_{t=1}^{T} \frac{S_j^t}{\omega^j} \tag{5}$$

The Kaminsky (1999) criterion for inclusion in the composite is that the variable must generate a noise-to-signal ratio of less than one since this implies the variable contains a higher proportion

[26] They actually focus on the accumulation of risk by integrating different variables' departures from trend into one composite variable.

Table 10
Variables qualifying for the composite indicator

0.5 NTSR cut-off	0.75 NTSR cut-off	
General	General	Country specific
Real GDP growth	Real GDP growth	Real GDP growth
Real interest rate	Real interest rate	Terms of trade
Depreciation	Depreciation	Depreciation
M2/Reserves	M2/Reserves	Budget balance
Domestic credit/GDP	Domestic credit/GDP	
	Inflation	

Table 11
Comparison of in-sample predictive ability of composite indicators using general and country-specific thresholds

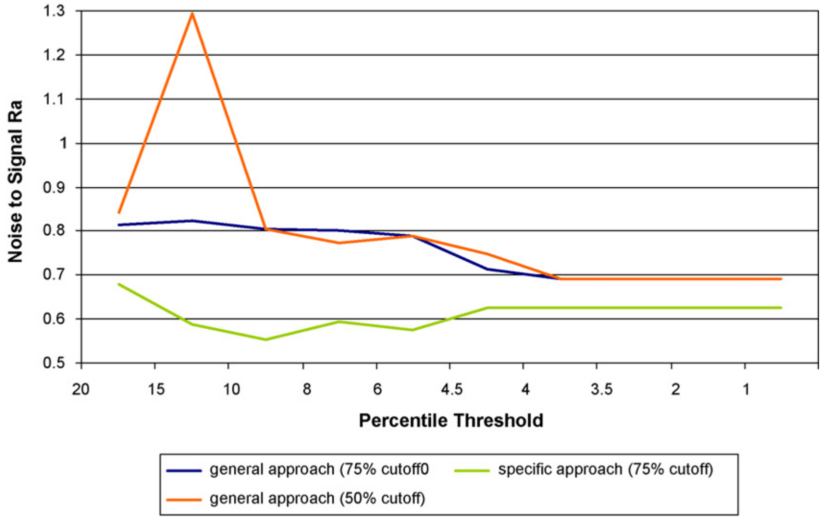
	50 NTSR cut-off	75 NTSR cut-off	
	General	General	Country specific
Optimal percentile	4	4	10
NTSR	0.6911	0.6911	0.5541
% crisis correct	7	7	15
% no crisis correct	95	95	88
% total correct	82	82	77

of information than noise. In our case, we set stronger criteria; we first construct a composite indicator using variables that have a noise-to-signal ratio of 0.5 or less and then we construct composites using variables where the ratio is 0.75 or less. Table 10 lists the indicators that qualify for each composite; for the 0.5 cut-off, none of the variables qualify using the country-specific approach and we are left with a composite based on the general threshold approach. For the 0.75 cut-off we construct two composites based on the general and country-specific approaches.

Table 11 and Graph 9 show the results for the general and specific approaches based on the different cut-offs for the NTSRs. In Section 3.4, we showed the trade-off between Type I and Type II errors when selecting between the general and country-specific threshold approach, where the general (specific) approach reduced Type II errors (Type I errors) at the cost of higher Type I (Type II) errors. A comparison of the general and specific methods for the composite indicator based on the NTSR ≤ 0.75 shows that this trade-off persists even if composite indicators are constructed. Hence the general approach continues to weight Type II errors more heavily whilst the specific approach remains better for policy makers wishing to avoid unnecessary intervention costs.

In terms of percentage of crises correctly called, both composites based on the general approach outperform six of the eight indicators used in Section 3.4. On the other hand, the ability to call non-crisis periods correctly is drastically reduced since the general composite underperforms against seven of the eight indicators. Similarly, the composite based on the country-specific method outperforms six of the single variables at calling crises but underperforms all except one in its ability to call non-crisis periods correctly.

The composite method therefore appears to improve crisis prediction whether a country-specific or general threshold approach is used but this occurs at the cost of higher Type II errors. As a result, the overall percentage observations correctly called deteriorates with both types of composite so that they outperform only one univariate indicator in this respect. The composite



Graph 9. Comparison of noise-to-signal ratios for composite indicators.

approach raises Type II errors across the board and the general approach has a lower chance of Type II errors than the specific approach. Hence, we would expect the composite method to change the NTSR based on the general approach more than it changes the specific approach NTSR. The results confirm this since both the general composites are equalised at a NTSR of 0.69 which is higher than virtually all the NTSRs for single indicators based on the same approach.

Conversely, the specific threshold approach which already yields low Type I errors benefits from the composite method so that the composite specific threshold approach lowers the NTSR below that of virtually all the univariate indicators with the same methodology. Graph 9 shows that there is a difference in optimal percentile thresholds between the general and country-specific approaches at the 4th percentile and the 10th percentile, respectively. However using different values for the NTSR (0.5 and 0.75) as a criterion for individual indicator acceptance into the composite makes no difference to the optimal threshold or the optimal NTSR.

To summarise, creating a composite indicator increases the likelihood of correctly calling crises compared to the univariate approach but raises the chances of false alarms. Although the general approach benefits in terms of crisis prediction, it is penalised by the higher level of Type II errors and the NTSR is correspondingly higher than when single variables act as signallers using the same approach. The gains in crisis identification from using a composite approach conform to the findings of Borio and Lowe (2002) although these authors found efficiency increased due to a reduction in Type II errors.

3.8. Comparison of the signal extraction and multivariate logit models

On the basis of in-sample predictive ability, the multivariate logit model outperforms the signal extraction approach in terms of the percentage of crises correctly predicted. Even the best leading indicator in the signal extraction approach (M2/Reserves) is able to call only 23% of crises correctly, whereas our dynamic multivariate models (regressions 5 and 6) are able to call an average of 32% of crises, despite us setting our cut-off probability much higher than DD05 and well over 90% of crises using their 0.05 probability.

Berg and Pattillo (1999) who conducted a comparison of multivariate probit and signal extraction EWS for currency crisis prediction also found the multivariate approach outperformed the univariate method. With the signal extraction approach, every indicator misses a substantial number of crises. Berg and Pattillo (1999) suggest this is because the signal extraction process assumes that a threshold for a variable is a discrete value and that whenever this is crossed, a crisis becomes impending. In actual fact, as Graphs 1–8 show, the NTSRs "jump" between thresholds so that there is no smooth relationship between threshold and crisis probability, something that Berg et al. (2004) also note. If the NTSR jumps at different threshold for different countries, then using cross-country data to derive a common threshold may not be fruitful; the threshold that minimises the NTSR will fall on either side of the individual optimal thresholds for most countries. In this case, the percentage of crises correctly called will be sub-optimal compared to where threshold are analysed for individual countries (but on the other hand, this would not be feasible for countries that have not had a banking crisis, and could be vulnerable to structural change).

The multivariate logit on the other hand, assumes a specific smooth non-linear form for the relationship between crisis probability and variable behaviour. As the results suggest, this may be closer to the truth of banking crises, especially once dynamics are taken into account and given that a large number of crisis episodes across many countries are being assessed simultaneously for both models. On the other hand, Berg et al. (2004) found that out-of-sample prediction was better with the K&R signal approach than with a multivariate probit approach[27] although the comparison was done for currency crises only.

Even if indicators are aggregated to a composite, the percentages of crises predicted do not match the dynamic multivariate logit models, although percentage crisis prediction improves. An alternative approach to ours would be the Borio and Lowe (2002) methodology where individual variable thresholds are jointly evaluated. In this sense, a composite indicator's ability to predict crises is more comparable to the multivariate logit model than the univariate signal extraction procedure so the two procedures could be compared on the same dataset. This is a subject of further research for banking crisis prediction.

4. Conclusion

A comparison of the multinomial logit and signal extraction procedures shows that real GDP growth and terms of trade are robust leading indicators of banking crisis for our comprehensive sample. Results for other variables are mixed in terms of robustness and as comparison with the DD05 model shows, results vary according to the dataset used and the banking crisis definition adopted. Moreover, given the same dataset we show that the choice of estimation techniques makes a difference in terms of indicator performance and crisis prediction. Where a multinomial logit is used, transformations which take into account cross-country heterogeneity may improve model specification since the use of logit prevents fixed effects estimation. Where a signal extraction procedure is used, optimising thresholds country by country improves ability to correctly predict crises. Creating composite indicators may further improve crisis prediction. Hence the use of the multinomial logit model may be better suited to a global EWS whereas the signal extraction approach may be better suited to country-specific EWS.

We also show that dynamics of banking crises are an extremely important consideration when designing an EWS, since procyclical variables may have an independent effect on banking crisis

[27] The probit model was developed by the Developing Countries Statistical Division in the IMF.

and a joint effect with institutional factors. In such cases the sequencing of institutional reforms and procyclical movements in credit and real GDP growth become important. Using contemporaneous data for all variables ignores the build up of financial instability that arises from the procyclical behaviour of many indicators. Once we took theory into account and used the data to incorporate a more realistic story of crisis, indicator significance improved. Despite a much higher probability threshold than the DD05 study, our logit model was able to call a significant proportion of crises correctly.

Testing for out-of-sample predictive ability, we found the model which is able to classify the highest number of observations correctly is very good at predicting non-crisis episodes. More importantly, it is also able to detect increased vulnerability to crisis. By artificially generating out-of-sample data, we show on average the model is a good predictor of observations although there may be deviations from what the model predicts and what actually materialises.

As noted, international financial institutions do not employ an EWS specifically for banking crisis. However, given the ongoing liberalisation of emerging market financial sectors as well as the changing nature of banking risks as more economies move into market and securitised banking phases, the use of EWS for crisis prevention is more necessary than ever. As we have shown, it is important to consider the policy maker's objectives when designing predictive models since there is a trade-off between correctly calling crises and false alarms. In this sense our study confirms that EWS for banking crises are a necessary but not sufficient tool for predicting further crisis episodes, since a generalised global model cannot be a substitute for country-specific macroprudential surveillance.

Appendix A. Country list

Algeria	India	Switzerland
Antigua/Barbuda	Indonesia	Syria
Argentina	Ireland	Tanzania
Australia	Israel	Thailand
Austria	Italy	Togo
Bahamas	Jamaica	Trinidad and Tobago
Bahrain	Japan	Tunisia
Bangladesh	Jordan	Turkey
Barbados	Kenya	Uganda
Belgium	Korea	UK
Bolivia	Laos	Ukraine
Botswana	Lebanon	Uruguay
Brazil	Madagascar	USA
Burundi	Malaysia	Venezuela
Cameroon	Mali	Vietnam
Canada	Mauritius	Zambia
Chile	Mexico	Zimbabwe
Colombia	Mozambique	
Congo	Myanmar	
Costa Rica	Nepal	
Cyprus	Netherlands	
Czech Republic	New Zealand	
Denmark	Nicaragua	
Dominica	Niger	
Dominican republic	Nigeria	
Ecuador	Norway	

Egypt	Panama
El Salvador	Papua New Guinea
Equatorial Guinea	Paraguay
Ethiopia	Peru
Finland	Philippines
France	Poland
Germany	Portugal
Ghana	Romania
Greece	Russia
Grenada	Senegal
Guatemala	Seychelles
Guinea Bissau	Sierra Leone
Guyana	Singapore
Haiti	South Africa
Honduras	Spain
Hong Kong	Sri Lanka
Hungary	Swaziland
Iceland	Sweden

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