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FLEWS: A Novel Forward Looking Early Warning System

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Abstract

Despite the prohibitive cost of financial crises, an effective early warning system of such events remains a challenge. In this paper we develop a novel forward-looking indicator of near-crisis (FLEWS), based upon measures of financial stability and using a wide set of economic and financial indicators to forecast crises or periods of heightened financial fragility. Based on a Signal Extraction methodology which allows for the identification of dynamic thresholds, our results show that our indicator performs well. As early as 2004 we identify clear signals of financial sector fragility, significantly before the outbreak of the global financial crisis. We argue that it is possible to develop early warning indicators of near-crises and that their prior identification might be of more value than forecasts of crisis since it will give policy makers more time to respond.

Keywords: Financial Crises; Financial Fragility; Early Warning Signals; Financial Stability; Financial Regulation.
JEL Codes: E58; G21; G28.

1 Introduction

While it is difficult to quantify the cost of the 2007-10 financial crisis precisely, it is fair to say that it is a cost that would have been best avoided. The global financial crisis was associated with cumulative (indirect) output losses of around 5% of global output over 2008 to 2010 – equivalent to around USD10.2 trillion if we apply the rate to IMF global output estimates (Laeven and Valencia, 2014). They also estimate that the direct bailout costs were around USD10.2 trillion, while direct write-downs by agents came to around USD3.4 trillion. Taken together these costs represent 40% of global GDP in 2010. Despite the fact that there is much to be gained from avoiding such events, crisis prediction remains a challenge.

In this paper, we develop a novel forward looking early warning system (FLEWS) and use an indicator of near-crisis based upon notions of financial fragility. Why the emphasis on an EWS for near-crises rather than actual crisis? A near-crisis variable is forward look-

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ing, as it aims to identify a period of heightened fragility. This should provide a useful framework to recognise key vulnerabilities and therefore allow policy makers to enact policies, which could pre-empt the likelihood of a crisis occurring.

We proxy the existence of a near-crisis based upon a composite indicator of the solvency and profitability of the banking sector, and changes in both. We then develop a framework for the identification of the key variables which proxy for potential vulnerabilities in the financial and real sectors. Building upon the extant literature, we incorporate a number of indicator variables. We look at real GDP growth, banking sector asset growth, the level of banking sector assets to GDP, development of asset price bubble indicators (a house price indicator and an equity capital markets indicator)[1].

We also include a dividend yield indicator as a proxy for the health of the corporate sector, a banking sector liquidity indicator and a banking sector funding indicator as micro structural indicators for the industry, and a pension funds to GDP indicator as a proxy for the development of liquidity bubbles. The use of pension fund assets to GDP as a proxy for macro liquidity and dividend yields as a proxy for corporate sector health is another contribution of this work, as far as the authors are aware these two variables have not been used in an EWS context before.

Building upon the work of Kaminsky and Reinhart (1999) and Alessi and Detken (2011), we make use of the Signal Extraction methodology. The Signal Extraction approach aims to transform each indicator variable into a binary variable by setting critical thresholds. If the indicator exceeds its specified threshold, the binary variable takes a value of one and zero otherwise. We augment the existing literature and identify the indicator thresholds using a dynamic approach, based upon the relationship between the variable and its past average. This advances the traditional statistical methods that rely on sample distribution. The key advantage of our approach is that the model design can be used in different time periods and different states of the world. In this regard, our approach is similar in spirit to that of Borio and Drehmann (2009), who use what they refer to as «gap analysis» to identify their indicator thresholds.

We apply the signal extraction methodology with dynamic thresholds to a dataset of 30 OECD countries over a 27-year period (1980-2007). Our results show that our choice of indicator variables performs well in predicting near-crises: as early as 2004 we identify clear signals of financial sector fragility (near crises), significantly before the outbreak of the global financial crisis in 2007. The performance in terms of noise-to-signal ratios of our approach compared to earlier work in this area is attributable both to the new dependent variable specification in addition to independent variable enhancements and dynamic model design.

The rest of this paper is organised as follows: in Section 2 we provide a brief review of the literature; in Section 3 we describe our methodology and data; we present our results in Section 4; and we conclude the paper in Section 5.

[1] While not all booms result in a crisis (Dell'Ariccia *et al.*, 2012), there is evidence that the longer the boom period, the faster the growth rate, the higher the likelihood that the boom will end in a crisis (Dell'Arriccia *et al.*, 2013). In addition, rapid growth in credit and asset prices (particularly in the housing market) is found to be related to increased vulnerabilities (Borio and Lowe, 2002; Cardarelli *et al.*, 2011).

2 A Brief Literature Review of the Signals Approach to EWSs

When developing an Early Warning System (EWS), researchers are faced with three issues. First, the definition or identification of past crises, that is, the need to pre-specify the dependent variable that one is seeking to explain. Second, they face a more familiar challenge, which is to identify the economic and/or financial market indicators that will form the basis of the signal from the EWS. Finally, there are a number of different models, or approaches that could be used as the framework for the EWS. Although a large body of existing work has been devoted to crisis identification and prediction, both theoretical predictions and empirical results remain ambiguous. This is partly due to the fact that the financial sector has evolved over time and so have financial crises and their determinants. Evidence shows that currency crises were prevalent during the 1980s whereas banking crises became more frequent in the 1990s and 2000s (Laeven and Valencia, 2008; Claessens and Kose, 2013).

Another reason for this ambiguity is the wide range of methods used for crisis definition and identification and the fact that the methods, or early warning systems (EWS) have also changed over time. Frankel and Saravelos (2012) and Chamon and Crowe (2012) present extensive reviews of the early warning indicators literature and identify a number of variables that are frequent crisis indicators, although they conclude ample room remains for further research into the effectiveness of early warning systems.

A considerable body of work has identified the relationship between full-blown economic crises and a prior build-up of financial fragility. Gonzalez-Hermosillo (1999) and Jagtiani *et al.* (2003) show that low capital adequacy and a fragile banking sector are leading indicators of banking distress, signalling a high likelihood of near-term bank failure. Furthermore, Čihák and Shaeck (2010) confirm the importance of bank profitability for the detection of systemic banking problems. And in their book *Crisis Economics*, Roubini and Mihm (2010) stress the linkage between financial fragility, that is, the build-up of imbalances and wider crises. They conclude that financial crises would not result in system wide distress in the absence of financial fragility. Given this, we favour a focus on a crisis variable based upon banking sector fragility, as measured by capital adequacy and banking sector profitability.

The second key step in EWS models relates to the development of a framework to identify the key variables which proxy for potential vulnerability in the financial and real sectors. The independent variables that have typically formed the basis of EWSs arguably comprise three related sets. Kaminsky and Reinhart (1999) (followed by many others) focus on variables that reflect macroeconomic weaknesses and so are based upon macroeconomic indicators such as real GDP growth, the current account balance, inflation, etc. Another set of variables focus on signals that might indicate crucial changes in agents' expectations, such as real interest rates or changes in interest rate spreads. Flood and Garber (1984), Obstfeld (1986), and Eichengreen *et al.* (1995) make use of such indicators. More recently, Shin (2013) focuses on banking system measures (comprising bank CDS spreads, implied volatility and bank liability aggregates among others) to identify vulnerabilities. Adrian *et al.* (2014) focus on leverage, maturity transformation, interconnectedness, complexity and the pricing of risk as key indicators of financial vulnerability and track these vulnerabilities within the banking sector (including the shadow banking sector) but also in the non-financial sector and asset markets.

Finally, Krugman (1999), Bris and Koskinen (2002), Caballero and Krishnamurthy (2001), Obstfeld *et al.* (2009) and Rose and Spiegel (2011) focus on contagion and spill-overs from other countries or markets such as changes in capital flows, changes in trade flows, in addition to other variables. Thus the set of independent variables used can include both macro and micro factors.

Having identified the dependent and independent variables the next step is to identify the modelling framework. The literature has made use of four modelling approaches, including *i*) signals models; *ii*) logit/probit models; *iii*) Merton type models; and *iv*) Binary recursive trees.

In their signal extraction models, Kaminsky and Reinhart (1999) find that real exchange rate appreciation, equity prices and money multiplier to be the most useful indicators. They argue that: problems in the banking sector typically precede a currency crisis; a currency crisis typically deepens the banking crisis; and that financial market liberalisation usually precedes banking crises. The evolution of these crises also suggests that crises occur as the economy enters a recession, following a period of prolonged or extended economic expansion fuelled by credit expansion and capital inflows at a time of currency overvaluation. However, because the sample was chosen to include only countries with fixed or heavily managed exchange rates which are usually more prone to currency crises, the impact of the exchange rate in this process may not be applicable to economies with floating rate regimes.

Using data comprised from 18 OECD countries for the sample period from 1970 to 2007, Alessi and Detken (2011), apply a signal extraction model using 18 real and financial indicators for costly asset price booms. The most useful indicators in their study were found to be: global private credit, long term nominal bond yield, housing investment, short-term nominal interest rate, real equity price index and real GDP. Their out-of-sample results would have predicted the most recent wave of asset price booms (2005-2007).

Borio and Drehmann (2009) analyse potential crisis indicators by monitoring their divergence from longer-term trends. They also examine in depth the choice of optimal indicators, indicator signal thresholds and optimal indicator weights. They find that it is possible to build relatively simple indicators comprising credit and asset prices, and in particular house prices, that can help to identify the build-up of risks of a future banking crisis. They find that in-sample predictions of crises (derived from data spanning 1980 to 2003) average 77% with a lead time of 3 years, while out-of-sample performance (derived from the period from 2004 to 2008) is around 60%, for the same lead time. The predictive ability of their indicators, both in-sample and out-of-sample, drops considerably in the 1-year lead time analysis to as low as 30%. This may be because 2 years before the start of a crisis the indicators do not change significantly enough, as the preconditions for the crisis are already embedded by this point.

Using a sample of 105 countries, covering the years 1979 to 2003, Davis and Karim (2008) apply macro EWS models, using signal extraction, Logit and binary recursive tree methodologies, to US and UK data to test for out-of-sample performance (whether a crisis was correctly called) from 2000-2007. They find that for the US, both models fail with a probability of a crisis occurring in 2007 of 1% for the Logit model and 0.6% for the binary tree model. For the UK, the results were similar, with the Logit probability of a crisis at 3.4% in 2007 and 0.6% for the binary tree model. Barrell *et al.* (2010) develop and EWS which demonstrates that banking sector indicators (capitalisation and liquidity), alongside real house price growth, are important crisis determinants in OECD countries. A number of applications have used Merton type approaches on an aggregate level to calculate Z-scores and distance to default measures. Tieman and Maechler (2009), adopt this «superbank» approach, which aggregates all players on one «pseudo» balance sheet. They focus on the short-run feedback effect from market-based indicators of financial sector risk to the real economy through the credit channel, and estimate this effect on an economy-wide (macro) level. A somewhat similar application, but with a focus on creating a new financial stability quantifiable metric is made by Čihák (2007) who presents an integrated measure of financial stability which he calls «systemic loss». The author looks at the financial system as if it is a «portfolio» of financial institutions» and considers the whole «distribution» of systemic losses of this aggregate portfolio, over one period. An earlier paper by Blejer and Schumacher (1998), uses a similar assessment of a distribution of losses of a financial system as a whole, but in a value-at-risk (VaR) type set-up, with regards to currency crises, by constructing a VaR metric for central banks and concludes that this is a useful monitor of sovereign risk. The analysis covers 29 countries, including 12 in which a systemic banking crisis started during the period of study according to Caprio and Klingebiel (2003). The main findings are that the indicators used do point to increased instability and using the Loss Given Default (LGD) and correlations across failures into account improves the measurement (reduces the noise-to-signal ratio).

3 Data and Methodology

3.1 Crisis Identification: Defining the Dependent Variable

One of the crucial components of this type of analysis is the identification of a «*crisis*». However, crises come in many shapes and sizes. By analysing the impact of various crises Caprio and Klingebiel (1996) and Demirgüç-Kunt and Detragiache (1998) define crises with reference to the following metrics, either in isolation or in combination, when:

i) the proportion of NPLs to total baking system assets exceeds 10%;

ii) public bailout costs exceed 2% of GDP;

iii) large scale nationalisation is required;

iv) extensive bank runs and/or emergency government intervention is required

v) all, or most of bank capital is exhausted; and when

vi) the level of non-performing loans falls between 5% and 10% or less if subjectively deemed systemically significant.

In Table 1 we present the number of crises that occurred in our sample of nearly 30 years, between 1980 and 2007, where a 1 indicates a crisis as defined by the earlier lit-

Table 1: Crises Identification in Earlier Literature for OECD Countries (1980-2007). This Table presents the number of crises that occurred in our sample of nearly 30 years, between 1980 and 2007, where a 1 indicates a crisis as defined by Demirgüç-Kunt and Detragiache (2005), Kaminsky and Reinhart (1999), Caprio and Klingebiel (1996 and 2003) Reinhart and Rogoff (2008), Laeven and Valencia (2008)

	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	Total
Australia										1	1	1	1																4
Austria																													0
Belgium																													0
Canada				1	1	1																							3
Czech Republic																													0
Denmark								1	1	1	1	1	1																6
Finland												1	1	1	1														4
France															1	1													2
Germany																													0
Greece												1	1	1	1	1													5
Hungary																													0
Iceland		1				1	1			1				1															5
Ireland																													0
Italy		1									1	1	1	1	1	1													7
Japan													1	1	1	1	1	1	1	1	1	1	1			1			12
Korea																		1	1										2
Luxembourg																													0
Mexico		1	1	1	1	1	1	1	1	1	1	1			1	1	1	1	1	1	1								18
Netherlands																													0
Norway								1	1	1	1	1	1	1															7
New Zealand								1	1	1	1																		4
Poland		1								1	1	1	1	1	1	1													8
Portugal				1			1	1	1	1																			5
Slovakia																													0
Spain	1	1	1	1	1	1																							6
Sweden											1	1	1	1	1														5
Switzerland																													0
Turkey	1	1	1	1	1	1						1			1		1				1	1	1			1			13
UK					1							1	1			1												1	5
US	1	1	1	1	1	1	1	1	1	1	1	1	1															1	14
Total	3	7	4	6	6	6	4	6	6	9	9	12	11	8	9	7	3	3	3	2	3	2	2	0	0	2	0	2	135
Total Observations																													870
%																													15.5%

Table 2: Near-Crises Identification by Criteria. This table illustrates criteria for the identification of a near-crisis, based upon a composite indicator of the solvency and profitability of the banking sector and changes in both

Criteria	w = 50bps; x = 50bps y = −50bps; z = 5bps	w = 10bps; x = 10bps y = −10bps; z = 1bp	w = 100bps; x = 100bps y = −100bps; z = 10bps
Decrease in banking sector capitalization more than w%	91	222	45
Increase in banking sector capitalization of more than x%;	115	265	62
Net Income before provisions / Average Balance Sheet falls by y%	36	131	12
Net Income before provisions / Average Balance Sheet is less than z%	19	22	18
Sub-Total	261	640	137
Less: Double counting between the four rules	29	131	10
Net	232	509	127
% of Total Observations	27%	59%	15%

erature outlined above. In total the table shows that there were 135 crisis episodes, out of 870 observations or 15.5%.

In this paper we use an alternative, though not too dissimilar definition of crisis, so that we pick up a near-crisis. The existence of a near-crisis is based upon a composite indicator of the solvency and profitability of the banking sector and changes in both. The criteria for the identification of a near-crisis are illustrated in Table 2. By using this definition of near-crises as opposed to an *ex post metric* of losses as a percentage of GDP or NPL levels etc., – and which therefore identify crises at a stage which is too late for policy makers to take any action – our adapted near-crisis definition allows for a longer lead period for the indicators pointing to financial imbalances and/or a build-up of fragility.

Our indicator is composed of four components. We define a country as facing a near-crisis or a period of heightened fragility if, in any one year:

i) there is a decrease in banking sector capitalisation of more than 0.50%; or

ii) there is an increase in banking sector capitalisation of more than 0.50%; or

iii) net income before provisions as a percentage of average balance sheet falls by 0.50%; or

iv) net income before provisions as a percentage of average balance sheet is less than 0.05%.

We include the profitability metrics as separate components to capture any over statement of capital or hidden non-performing loans. If these two metrics are really poor, while the former two seem robust, then the country's banking sector might have an inflated balance sheet or capital base, or both. Table 2 shows that according to criteria *i*) and *ii*) we identify 206 near-crisis years. The other two definitions, which look at the link between income statement returns and the balance sheet, identify 55 near-crises. The number is lower because if a bank is realising poor or negative returns it may well have already been liquidated or merged – so these criteria capture the «zombie banks» that are still in the system which, by default, should be relatively few. There were also 29 incidences where more than one criterion captured a near-crisis. When we account for this double-counting, we identify 232 near-crises, representing 27% of the total number of country/year observations.

Table 3: Near-Crises for OECD Countries (1980-2007)

	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	Total
Australia										1	1		1		1		1			1			1					1	8
Austria								1								1											1	1	4
Belgium		1												1														1	3
Canada									1																				1
Czech Republic														1	1	1	1	1	1	1	1	1	1	1	1		1	1	14
Denmark				1	1	1			1		1	1	1	1	1						1	1					1	1	13
Finland									1		1	1	1	1	1	1	1					1		1	1			1	12
France									1											1						1			3
Germany																													0
Greece																		1	1	1	1			1					5
Hungary																					1	1	1		1	1	1	1	7
Iceland	1	1	1	1	1	1	1		1			1	1	1		1	1	1	1	1	1	1	1		1	1	1		22
Ireland																1		1					1	1		1			5
Italy					1		1	1				1		1														1	6
Japan														1	1		1		1	1			1	1	1		1	1	10
Korea											1				1	1	1	1	1	1	1	1			1	1			11
Luxembourg				1	1	1	1							1						1			1						7
Mexico																					1		1	1	1		1	1	6
Netherlands																										1	1	1	3
Norway			1				1	1		1	1	1	1	1	1	1													10
New Zealand											1	1	1	1			1	1					1	1			1		9
Poland														1	1		1	1				1	1				1		7
Portugal																		1	1	1			1	1				1	6
Slovakia																	1	1	1	1	1		1	1	1	1	1		10
Spain			1	1					1			1		1		1					1					1	1		9
Sweden	1			1						1	1	1	1	1	1		1								1	1	1		12
Switzerland														1				1	1		1								4
Turkey							1		1		1									1	1	1	1	1	1	1	1	1	12
UK																		1					1		1	1	1	1	6
US	1			1	1							1	1	1											1				7
Total	3	2	3	6	5	3	5	3	7	3	8	9	8	15	9	8	10	11	8	11	11	8	14	10	12	11	15	14	232
Total Observations																													870
%																													27%

Table 4: Binary Regression Results between «Crisis» Definitions in Earlier Literature and Near-Crises OECD Countries (1980-2007). This Table 4 presents the binary (logit) regression output between the definition of crises given in Table 1 and the definition of near-crisis in Table 3

Variable	Coefficient	Std. Error	Prob.
Constant	−1.858582	0.118728	0.0000
NEAR_CRISES	0.616869	0.197187	0.0018

McFadden R-Squared	0.012818	Mean Dep Var	0.159524
S.D. independent variable	0.366382	S.E. of regression	0.364416
Akaike information criterion	0.871269	Sum squared residuals	111.2856
Schwarz criterion	0.882539	Log Likelihood	−363.9331
Hannan-Quinn	0.875589	Restr. Log Likelihood	−368.6587
LR Stat	9.451245		
Prob (LR Stat)	0.002110		
Avg. Log Likelihood	−0.433254		

Table 2 also shows the results of two alternative definitions of near-crisis based on alternative definitions of fragility. When we set the definitions of variables *i*) to *iv*) to be equal to «more than 10bps», «more than 10bps», «a fall of 10bps» and «less than 1bp» respectively then 59% of the sample years are identified as near-crises. Conversely when we increase the limits of variables *i*) to *iv*) to be equal to «more than 10bps», «more than 100bps», «a fall of 100bps» and «less than 10bp» then only 15% of the sample years are identified as being near-crisis. There is of course no correct way to set these definitions of near-crisis, however we find that the correlation between the predicted total near-crises by country when the near-crisis levels are set at 0.50%, 0.50%, −0.50% and 0.05%, as presented in Table 3 and the fully-fledged crises as defined in the literature (Table 1) is very high at 62%.

Table 3 identifies in which country and in which year each near-crises occur according to our criteria. There are more near-crises than actual crisis, as defined in Table 1. This is not surprising since not all near-crises will develop into a fully-fledged crisis either because other factors help to alleviate any fragility, or if regulators act to avert the possible crisis.

Table 4 presents the binary (logit) regression output between the definition of crises given in Table 1 and our definition of near-crisis in Table 3. The results of the regression analysis show that near-crises predict actual crises with a coefficient of 0.61, a result that is statistically significant at the 1% level. The results presented in this paper are based upon the near-crisis definition as presented in Table 2[2].

We argue that our proposed near-crisis definition should prove useful from the point of view of regulators since it gives them the opportunity to act to reduce the likelihood of an actual crisis. Averting a near-crisis is likely to be much less expensive than the costs associated to dealing with the aftermath of a full crisis.

Having defined the near-crisis dependent variable, we now move on to consider the independent variables that we use to develop an early warning system for such near-crises.

[2] The results based on the two alternative definitions of «near crisis» are available on request from the authors.

3.2 Defining the Independent Variables

Based on the extant literature (reviewed in Section 2) and taking in to consideration data availability over our chosen sample period of 1980 to 2007, we chose nine indicator variables[3]. We use two macroeconomic variables in our indicator group. The first is the *Change in Real GDP Growth* (DRGDP). Economic growth, as represented by growth in GDP, provides all groups of economic agents with the conditions to expand activity further. Households confidence grows as employment grows which can be accompanied by a reduction in household savings rates and an increase consumption; corporations feel confident as profits rise, and so investment spending increases; and governments embark on ambitious spending plans on the assumption that the increase in tax take will be permanent, and so on. However, «*unsustainable*» economic growth may be created by credit and asset price bubbles, which can ultimately lead to a financial crisis when the good times end. The second variable is the *Current Account Balance* (CAB) to GDP which captures the impact of the magnitude and direction of short term flows with the rest of the world on the financial system, a deterioration puts pressure on the domestic financial system and vice versa. We collected real GDP data for the countries in our sample from the IMF WEO database.

We also chose to include two variables based on total bank sector assets. The first, *Banking Sector Asset Growth* (BAG), is intended to capture the risks that arise from rapid growth banking sector assets; arguably, the faster this growth the more vulnerable the system could become to a deterioration in the average quality of loans. We collected this variable from the OECD database, and calculate its year on year growth. The second variable based on bank sector assets is *Banking Sector Assets to GDP* (BAGDP); arguably the greater the proportion of banking sector assets to GDP the less capable the economy is to deal with a shock from the financial system and therefore the more likely any shock will be to turn into a full blown crisis (think about the recent case of Ireland). The nominal GDP data for this variable was collected from the IMF's WEO database.

We next construct two variables based upon the assets of other parts of the economy. First, using the OECD database we calculate the annual, *Real Appreciation in House Prices* (HPI) for each economy in our sample, on the grounds that a sharp appreciation in house prices can lead to an associated rapid increase in bank lending, given that the value of available collateral is rising. This can lead to dire consequences ultimately (think the UK house price bubble in the late 1980s, Japan's property bubble in the 1980s and 1990s and the US house price bubble in the 2000s – amongst many other examples). Using the same OECD database, we also calculate the proportion of *Pension Fund Assets to GDP* (PENS), as major asset owners pension funds can sometimes have a big impact on markets and in particular on their liquidity. For example, a switch from equity orientated portfolios to credit portfolios could reduce credit spreads and have an impact on the borrowing decisions of economic agents which could lead to a credit bubble. The

[3] Variable definitions and data sources are detailed in Appendix table A1.

Table 5: Descriptive Statistics of indicator variables. This table illustrates the descriptive statistics for the ten early warning indicator variables. DRGDP = Delta Real GDP; HPI = House Price Indicator; DEMI = Delta Equity Market Index; CAB = Current Account Balance; BAG = Banking Sector Asset Growth; BAGDP = Banking Sector Assets to GDP; PENS = Pension Fund Assets; EMKDTY = Equity Capital Markets Dividend Yield; LIQ = Liquidity Indicator (Securities/Total Assets); FUN = Funding Indicator (Loans/Deposits)

	DRGDP Delta Real GDP (%)	HPI House Price Indicator (%)	DEMI Delta Equity Market Index (%)	CAB Current Account Balance (%)	BAG Banking Sector Asset Growth (YoY %)	BAGDP Banking Sector Assets to GDP (%)	PENS Pension Fund Assets to GDP (%)	EMKTDY Equity Capital Markets Dividend Yield (%)	LIQ Liquidity Indicator (Securities/ T. Assets)	FUN Funding Indicator (Loans to Deposits Ratio)
No. of Observations	825	246	691	811	613	649	243	287	481	481
Mean	2.9%	3.8%	18.8%	–0.70%	13.03%	328.4%	36.2%	3.43%	18.65%	105.08%
SD	2.7%	6.0%	45.0%	5.0%	15.30%	655.4%	45.9%	2.90%	6.50%	28.70%
Skewness	0.5	0.4	5.9	0.2	3.5	3.5	2.9	4.0	0.1	0.6
Kurtosis	3.5	0.7	57.0	1.7	16.1	11.1	19.2	20.8	–0.8	0.7

larger the assets of this sector of the financial community, the larger is the potential for it to destabilise the wider financial markets.

Another, arguably more obvious, indicator of the health of a financial system is the ratio of loans to deposits which indicates how much of a banks' loan books are funded by deposits, and how much are funded from external sources; this is proxied by an indicator of *Funding* (FUN); the greater the proportion funded from external sources, the larger the banking system's exposure to changes in market conditions. We calculated this variable for each country in our sample using data from the OECD. From the same database we also use a measure of *Liquidity* (LIQ), which we define as the proportion of securities to total assets held by the financial system (since «securities» can be traded in secondary markets as opposed to loans which are more difficult to trade in such markets). Either too little or too much liquidity (as it is defined here) could leave the balance sheet exposed to financial market shocks, which could in turn trigger a financial crisis, as sudden changes in liquidity levels can cause the most stress.

The last two variables that we include are derived directly from the capital markets and are not country specific. The first of these variables is «the» *Equity Market Dividend Yield* (EMKTDY), as defined by the World Federation of Stock Exchanges. We use this as a proxy for the corporate sector health as represented by listed companies on the equity market. A rapid increase in the dividend yield is likely to have been brought by increasing dividends paid out by companies as their profitability increases and they are confident this will persist (dividend stickiness), this also could imply companies are better credits because they have higher cash flows. Finally, in a similar vein we use the an actual *Equity Market Index* (EMI), calculated by the World Federation of Stock Exchanges to capture more directly equity market bubbles.

Table 5 shows descriptive statistics for the ten early warning indicator variables. It shows, for example, that the mean growth in real GDP for OECD countries over the study period was 2.90%, with a standard deviation of 2.7% and a slight skew to the left of 0.5, and almost normal kurtosis, or no fat tails, with kurtosis at 3.46.

3.3 Dynamic Signal Extraction Approach

The signals approach to crisis identification was originally developed by Kaminsky and Reinhart (1999). Their approach involved describing the behaviour of fifteen macroeconomic variables, each on a stand-alone basis in the 24-month period preceding and following a crisis compared to their behaviour outside of a crisis period[4]. The methodology involves identifying a threshold for the indicator variable which, when crossed, is taken as a sign of potential crisis. If this crisis signal is then followed by a crisis in the following *h* forecasting periods (the crisis window), it is viewed as providing a correct signal, otherwise it is viewed as a false alarm or noise. Thresholds were chosen to minimise the in-sample noise-to-signal ratio, that is the ratio of incorrect signals to correct signals. The performance of each variable is evaluated based on three criteria: *i*) associated Type I and Type II errors – the probability of missing a crisis (Type I) and the probability of a false signal (Type II), respectively); *ii*) the noise-to-signal ratio (hereafter NTSR); and *iii*) the probability of a crisis occurring conditional on a signal being issued. The NTSR is given as follows:

$$\omega = \frac{\beta}{1-\alpha} \tag{1}$$

where α is the size of the type I error and β is the size of the type II error, and where both are functions of the chosen variable threshold. The choice of a relatively low threshold can lead to too many signals (Type II error) while a relatively high threshold can lead to increased probability of missing crisis (Type I error). Arguably, Type II errors are less important to policymakers, as the cost of prompt corrective actions are generally lower than the costs of financial crises (Fuertes and Kalotychou, 2007). In addition, «false alarms» are not necessarily mistakes if policy actions undertaken during period of increased fragility were successful in mitigating or avoiding crises.

In this paper, the use of dynamic thresholds, measured in terms of a certain number of standard deviations away from a variable's long term average allows us to incorporate the variables' short term volatility and minimise NTSR. More specifically, we use the set of variables described in Section 3.2 as potential near-crisis indicators. The signal from each of these variables is based upon its relationship to a «critical threshold». For each period, t, a signal, S, is generated by each variable if the variable breaches its threshold. This signal is then taken as an indication of a crisis in the literature, though here it is taken as an indication of near-crisis. The calibration of the thresholds is therefore a crucial aspect of this methodology. Our approach is similar in spirit to that of Borio and Drehmann (2009) who choose dynamic thresholds based upon one-sided rolling Hodrick-Prescott filters. We also identify thresholds using a dynamic approach but which we base upon a simpler and more transparent approach. We calculate indicator thresholds based upon the rolling average and standard deviations of the indicator variables.

We calculate these statistics using three sample periods, 3-year, 5-year and 10-year period of the variable in question. The selection of the number of standard deviations that

[4] Kaminsky and Reinhart (1999) based their identification of a crisis on a definition developed by Eichengreen *et al.* (1995) based upon an index of «market turbulence».

turns the fluctuation in an economic time series into a signal is subject to a trade-off. If the cut-off is too «tight» (a small number of standard deviations) it is likely to signal a lot of crises, including false ones. On the other hand, if the threshold is too high, that is set at a large number of standard deviations, it would result in a large number of Type I errors, that is, the indicator would miss many of our near-crises.

To identify the threshold for each indicator, that is, the choice of a one, two or three standard deviation threshold we used the following process. For the first year in our sample, year t, we take the rolling means and standard deviations of each indicator variable, calculated over t-n to t-1, for each country and identify those variables that are more than one, two and three standard deviations away from their mean. In these instances, the variable is potentially indicating that a crisis is likely. We then calculate the NTSR for each variable (as presented in equation (1)) to determine whether to use the one, two or three standard deviation threshold, that is, we choose that standard deviation threshold for each variable, where the NTSR is lowest. In all cases the one standard deviation threshold produced the lowest NTSR.

3.4 Creating the Forward Looking Early Warning Signal (FLEWS)

Once the thresholds have been established for each of the ten variables, a signal is issued if it crosses its threshold, Θ_k:

$$S_t = \begin{cases} 1 \; if \; V_i > \Theta_k \\ 0 \; else \end{cases} \tag{2}$$

where V_i is the i[th] indicator variable, the subscript k, indicates whether the threshold was calculated using a 3-year, 5-year or 10-year rolling mean and standard deviation for that variable.

In the event that two or more of these indicators for any county in year t are signalling a near-crisis we create a variable that we refer to as the «*Forward Looking Early Warning Signal*» (FLEWS) which takes the value of 1 for any country in that year, for which two or more of the indicators are indicating a crisis. In all those years where none or only one of the country's indicators are indicating a crisis, the FLEWS for those countries has a value of zero. We then roll this process forward to $t + 1$ and so on, until we have derived an FLEWS for each country for the full sample period from 1980 to 2007, for the different calibrations. The FLEWS is therefore comprised of a series of zeros and ones over the sample, where the zeros indicate no potential crisis and the ones indicate the possibility of a near-crisis.

4 Signal Extraction Results

In this section we present the empirical results obtained using the methodology described in Section 3. The FLEWS is calibrated to «forecast» a near-crisis if two out of the ten indicators breach their threshold. We conduct both in-sample and out-of-sample

Table 6: Signal Extraction Results. This table presents the summary of Type 1 and Type 2 errors, along with the associated NTSRs in- and out-of-sample, for each of the three years leading up to the financial crisis of 2008/2009. The thresholds for the indicators in Panel A are calculated using a three year rolling window; in Panel B are based upon a five-year rolling window, and in Panel C are based upon a ten-year rolling window

Noise-to-Signal Summary	2005	2006	2007	2-Year Horizon	3-Year Horizon
Panel A: Three year threshold calculation window					
In-Sample					
Type I %	18%	33%	21%	4%	0%
Type II %	118%	80%	71%	92%	70%
Noise-to-Signal Ratio	1.44	1.20	0.91	0.96	0.70
Out-of-Sample					
Type I %	9%	33%	36%	0%	0%
Type II %	136%	80%	93%	96%	63%
Noise-to-Signal Ratio	1.50	1.20	1.44	0.96	0.63
Panel B: Five year threshold calculation window					
In-Sample					
Type I %	9%	13%	21%	4%	0%
Type II %	145%	93%	86%	108%	73%
Noise-to-Signal Ratio	1.60	1.08	1.09	1.12	0.73
Out-of-Sample					
Type I %	18%	20%	7%	4%	3%
Type II %	145%	93%	100%	104%	70%
Noise-to-Signal Ratio	1.78	1.17	1.08	1.08	0.72
Panel C: Ten year threshold calculation window					
In-Sample					
Type I %	9%	7%	0%	4%	0%
Type II %	118%	87%	107%	108%	73%
Noise-to-Signal Ratio	1.30	0.93	1.07	1.12	0.73
Out-of-Sample					
Type I %	9%	27%	14%	0%	0%
Type II %	136%	80%	107%	92%	60%
Noise-to-Signal Ratio	1.50	1.09	1.25	0.92	0.60

analysis of the FLEWS. The in-sample forecasts look at the relationship between the FLEWS and the indicator of near-crisis in the same year, so if the FLEWS is «on» in a year when our dependent variable is indicating a near-crisis then the FLEWS has correctly identified the near-crisis. We also test the out-of-sample properties of the FLEWS. In this case, if the FLEWS is «on» in year $t - 1$, and the dependent variable is «on» in year t then the FLEWS has correctly «anticipated» the near-crisis.

In Panel A of Table 6 we present the summary of Type 1 and Type 2 errors, along with the associated NTSRs in- and out-of-sample for each of the three years leading up to the financial crisis of 2008/2009. The thresholds for the indicators in Panel A were calculated using a three year rolling window. For example, the in-sample noise to signal ratio for 2005 is estimated to be 1.44, while the out-of-sample equivalent is 1.50, where the thresholds for the individual indicator variables were calculated using a three year estimation window. However, Borio and Drehmann (2009) argue that precise crisis (or near-crisis in our case) prediction is difficult. For example, what if the FLEWS forecasts a crisis in year t, but the crisis doesn't occur until the second month of year t + 1? In this case the FLEWS would be judged to have emitted a «false» signal. To deal with this potential issue, we also calculate two and three-year horizon forecasts. In the case of the two year in-sample forecast, we test whether the FLEWS in 2005 is able to «forecast» a near-crisis in years 2005 and 2006. The three year in-sample forecast looks at the occurrence of a near-crisis over 2005, 2006 and/or 2007, based on the FLEWS in 2005, and so on. For example, Panel A of Table 6 shows that the in-sample NTSR falls from 0.96 for the two year forecast horizon to 0.70 for the three-year horizon. Finally, Table 6 is comprised of three panels. Panels B and C differ from Panel A only with regard to the estimation window for the indicator threshold calculations. The results in Panel B are based upon a five-year estimation window, while the results in Panel C are based upon a ten year window.

When we focus on panel A, we can see that the in-sample NTSR falls from 1.44 to 0.91 as we move from 2005 to 2007, and from 1.5 to 1.44 out of sample. A similar decline is seen when we consider Panels B and C. The in- and out-of-sample results for the two-year horizon are fairly similar in each of the panels. Arguably the most impressive results are found when we consider the three-year horizon. For example, the out-of-sample NTSRs for Panels A, B and C are 0.63, 0.72 and 0.60 respectively. These results compare well with those of Borio and Drehmann (2009) who apply their analysis to the same period, 2004 to 2008. Their NTSR median result is 0.67 over the three year forecast horizon with an associated median Type I error of 50%. Over a two-year horizon Kaminsky and Reinhart (1999) achieve Type I errors between 9% for the best individual indicator to 25% for the poorest individual indicator; as Table 6 shows, the corresponding figures for our model are 4% to 0% (see column headed «2-year horizon»).

In summary, our model outperforms compared to earlier work in dependent variable specification, independent variable specification, methodology, forecasting performance out-of-sample and usability by regulators due to the longer lead time and room for utilisation of their specific country experience in model calibration.

5 Conclusion

In this paper we have developed a system that might be adopted by regulators and policy makers as a way of pre-empting crises. Instead of focussing on actual crises – as defined by the existing literature – we focus instead on a definition of near-crisis. Our near- crisis definition is based upon measures of financial market fragility. Such fragility is often either the catalyst for a fully-fledged economic crisis, or serves to exacerbate a crisis. A near-crisis variable has one key advantage in being an *ex ante* definition of a crisis, the identification of which should provide policy makers with a greater opportunity for corrective action and therefore help design policy actions aimed at reducing the build-up of systemic risk.

Given that the post crisis costs will almost certainly be higher than any pre-crisis preventative measures, we feel that this is an appropriate focus for any Early Warning mechanism.

Using a wide set of indicator variables, we show how a dynamic signal extraction methodology can be harnessed to develop a mechanism for forecasting near-crises. Given the likely pre- and post-crisis asymmetric costs alluded to above we also feel that the focus of modelling work in this area should be the minimisation of Type 1 errors. There will of course be costs associated with responding to a «false» early warning of an impending

Appendix Table A1: Variable Definitions and Sources

Variable	Definition	Source
Macroeconomic Variables		
DRGDP	Change in Real GDP Growth	IMF WEO database
CAB	Current Account Balance to GDP	IMF WEO database
Banking Sector Variables		
BAG	Banking Sector Asset Growth	OECD database
BAGDP	Banking Sector Assets to GDP	IMF WEO and OECD databases
FUN	Funding (banking sector)	OECD database
LIQ	Liquidity (banking sector)	OECD database
Other Sectors Variables		
HPI	Real Appreciation in House Prices	OECD database
PENS	Pension Fund Assets to GDP	OECD database
Capital Markets Variables		
EMKTDY	Equity Market Dividend Yield	World Federation of Stock Exchanges
EMI	Equity Market Index	World Federation of Stock Exchanges

crisis, but in the long-term strengthening the stability of a financial system is likely to be more beneficial than allowing it to weaken to the point of crisis.

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