Towards a new model for early warning signals for systemic financial fragility and near crises: an application to OECD countries

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Abstract

The prohibitive historic cost of crises, the cost of the recent three year financial crisis with output loss estimates in excess of USD10.0 trillion of 'opportunity loss' global GDP and direct write downs of USD3.4 trillion by agents, and the pursuant *structural* changes which have taken place in the global economy highlight the importance of early warning systems for fragility. Previously existing models had failed miserably to signal warnings for the 2007-2010 crisis and this failure could be partly attributed to the dependent and independent variable specifications and empirical model design as this research demonstrates. Using a signal extraction framework and looking at OECD countries over a 30 year period this paper attempts to identify a number of variables significant in predicting near-crises as a pre-cursor to full-fledged crises. These include growth in pension assets as an indicator for the development of liquidity bubbles, equity market dividend yields as a proxy for corporate balance sheet health, banking sector assets growth and relative size to GDP. We also study the development of asset price bubbles through an equity markets indicator and a house price indicator. Finally we also look at a banking sector funding stability indicator and liquidity indicator on a micro-level. Simultaneously, a dynamic research design improves on previous static set-ups and enhances the model predictive power and applicability to different time periods.

This paper shows that as early as 2004, clear signals were being given for a number of countries that vulnerabilities were building up with out-of-sample performance better than in-sample in terms of overall noise to signal ratios, showing a significant improvement compared to earlier work. EWS design has significant implications for financial stability and financial regulation.

Key words: financial crises, financial fragility, liquidity bubbles, early warning signals, financial stability, financial regulation.

Outline

1. Introduction

The recent crisis highlighted the **failure of former early warning signals models**, using a sample of 105 countries, covering the years 1979 to 2003, Davis & 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 miserably 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.* This paper attributes this failure partly to dependent variable and independent variable specification and model empirical design, all three areas which we attempt to improve on.

Commonly used **dependent variable specifications** in the past are ex-post measures of the cost of crises in the form of *direct bailout funds* or *indirect GDP* losses compared to its previous growth trajectory (Davis & Karim 2003). Caprio and Klingebiel (1996) find bailouts cost on average 10% of GDP, with some crises much more damaging like the Mexican Tequila Crisis (1994) which cost 20% of GDP, and the Jamaican crisis (1996) which cost 37% of GDP. According to the IMF, the past crisis of 2007 - 2010 had cumulative (indirect) output losses over 2008-2010 estimated at around 5% of global output (this amounts to around USD10.2 trillion if we apply the rate to IMF global output estimates), while direct bailout measures by governments have almost tallied a similar figure and direct write-downs by agents tallied some USD3.4 trillion. These collectively are equivalent to **40%** of global GDP in 2010.

However, given that there is a substantial body of literature that highlights the linkage between the build-up of financial fragility and crises, this motivated our research into the precursor to crises, namely the build-up of financial vulnerabilities. In their book *Crisis Economics* Roubini and Mihm (2010) consistently highlight the linkage between financial fragility, the build up of imbalances and systemic financial crises and conclude that financial crises would not result in system wide distress in the absence of financial fragility. While Gonzalez-Hermosillo (1999) and Jagtiani, Kolari, Lemieux & Shin (2003) prove that low capital adequacy and a fragile banking sector is a leading indicator of banking distress, signalling a high likelihood of near-term bank failure. Furthermore, Cihak & Shaeck (2007) confirm the importance of bank profitability for the detection of systemic banking problems. Therefore, a dependent variable specification which focuses on ex-ante prediction, on banking sector fragility, as measured by capital adequacy and banking sector profitability was intuitive to us. As a measure it is also both necessary and sufficient for the prediction of full- fledged crises, but not vice versa. This dependent variable could be viewed as a 'Near crisis'. By focusing on 'near crises', the model is calibrated to detect a pre-crisis and in turn would give policy makers more lead time to avert or at least minimize crises costs. This way the EWS would be credible and usable by policy makers, and thus effective. Also the specification of the dependent variable to signal near-crises, means that a lot of data which was not previously utilized in an EWS analysis will now be taken into account.

Focusing on **independent variable specifications**, these evolved in earlier literature over three generations of thought. The first generation (Kaminsky and Reinhart 1999 is an example) was based on macro weaknesses and relied on macro-economic indicators as explanatory variables such as real GDP growth, real exchange rates, current account balance, inflation, etc. Second generation was based on self-fulfilling prophecies and herding behaviour using explanatory variables such as changes in real interest rates or changes in interest rate spreads which could signal changes in agent expectations. These include work by Flood and Garber (1984) and Obstfeld (1986), and Claessens (1991). Finally, third generation such as Krugman (1999), Bris and Koskinen (2000) and Cabellero and Krishnamurthy (2000) was based on contagion and spill-overs from other countries or markets which used explanatory variables such as changes in capital flows, changes in trade flows, in addition to other variables. Thus independent variable use spanned across macro factors, micro factors, a combination of both, on an endogenous and exogenous level as the case may be.

The choice of independent variables for this paper was as such guided to include exogenous and endogenous variables representative of all three schools and across all the different classifications. 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), 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 specific **empirical model designs** used to predict crises fall into *four* categories: i) signals models; ii) logit/probit models; iii) Merton type models; and a less used class of models, iv) Binary recursive trees. In this paper we use a signal extraction methodology. Predominantly in earlier literature such as Kaminsky and Reinhart 1999 and Alessi & Detken 2008, the structure of the signal extraction model was based on a static threshold chosen for each independent variable determined on the basis of minimizing Type I and Type II errors in-sample for this variable or in other words minimizing the Noise-To-Signal Ratio (NSTR - which itself is another way of summarizing a trade-off between Type I and Type II errors) and assessing the probability of a crisis conditional a signal being issued. This paper improves on empirical design substantially with the choice of variable thresholds no longer static, but rather dynamic in the form of standard deviations from a chosen metric which in this case has been chosen as a long-run mean for a variable (this is somewhat similar to Borio and Drehmann (2009) who use gap analysis from a long term trend but for only two independent variables). By shifting the analysis to focus on standard deviations as opposed to absolute values, this model focuses on capturing volatility in a chosen variable, rather than thresholds chosen on the basis of output of a certain data period. This means that the model design as such is usable in different time periods and different states of the world.

One of the problems with earlier models is that repeated exercises for different time periods always resulted in different performance of a fixed set of indicator variables. This is because causes for crises change over time and also because static thresholds chosen for each variable to signal a crisis are by default linked to whichever data period they were calibrated to. This explains why in-sample performance of these models was much better than out-of-sample and why the old models failed to predict the last crisis. The design of our model to read deviations from a chosen benchmark means that the chosen variables are valid for the data period for which the model was designed and for other data periods as well, thus improving on **out-of-sample performance**, another major weakness in earlier models.

The **results of this paper** using a signal extraction methodology for the set of 30 OECD countries over a 30 year period show a number of variables to be significant in predicting near-crises. These include growth in pension assets (significant at the 5% level for the base case), an indicator for the development of liquidity bubbles which leads to financial sector pains. While equity market dividend yield was significant at the 10% level for the base case. This is a proxy for corporate balance sheet health on the premise that companies usually raise dividends, in line with the pecking order hypothesis as free cash flows to equity shareholders, after debt service, are available. Banking sector assets growth was also significant at the 10% significance level for the base case, indicating a strong relationship between the rapid growth of the banking sector and the development of vulnerabilities (positive coefficient). Micro banking sector funding and liquidity indicators also improve the overall predictive ability of the model.

The output model shows that as early as 2004, clear signals were being given for a number of countries that vulnerabilities were building up. The best in-sample model for the base case, is the 3-year rolling one standard deviation specification. Performance out-of-sample, is better than in-sample in terms of overall noise to signal ratios, with the range falling from 0.7 to 0.63 for the base case. Levels of Type I errors are also very low ranging from a high of 36% to a low of 0% - or no misses.

This paper proposes that we should focus on minimizing Type I error as the optimal regulator objective function as this is the most conservative approach and it would ensure continuous action to ensure a sound system as such. Although Type II errors might be more, however if the regulator objective is clearly formulated to be ‘having a healthy financial system and continually correcting imbalances as they develop’, then this is what the model will achieve. This objective is equivalent to ‘avoiding crises at all costs’.

The best out-of-sample model for the base case is the 10-year rolling one standard deviation specification which results in a noise-to-signal ratio of 0.6 and a Type I error of 0%. These results show a significant improvement compared to earlier work, for example the median NSTR in Borio & Drehmann (2009) applied to the same period 2004 – 2008, is 0.67 over the three year forecast horizon and the median Type I error is 30%. The outperformance also holds in comparison to KLR99, where Type I errors over a two year horizon range between 25% for the best individual indicator to 9% for the poorest individual indicator, whereas for this model, the corresponding figure is 4% to 0%. Using an adapted dependent variable specification for near crises has improved the performance of the model in terms of minimizing Type I errors over a three year period and NSTR out-of-sample. Furthermore out-of-sample performance, because of the dynamic set up of this model, is better than in-sample performance, a major improvement to previously existing models which worked well in-sample, but performed poorly out-of-sample as indicated by Davis and Karim (2008).

The remainder of this paper is organized as follows: section two is a brief literature review; section three elaborates on the empirical model design including dependent and independent variable specification; section four provides the data and descriptive statistics for the 30 OECD countries; and section five presents the empirical results.

2. Brief Literature Review

The signals approach was originally developed by Kaminsky and Reinhart (1999), who documented the incidence of currency, banking and twin crises (the occurrence of both) in a sample of 20 industrial and emerging countries, where crises are identified based on an index of market turbulence developed by Eichengreen et al (1995). They describe the behaviour of fifteen macroeconomic variables, each on a stand-alone basis in the 24 months period preceding and following a crisis compared to non-crisis times. A variable is deemed to signal a crisis any time it crosses a certain threshold. If the signal is then followed by a crisis in the following 24 months, it is viewed as correct, otherwise a false alarm. Thresholds were chosen to minimize the in-sample noise-to-signal ratio. The performance of each signal is evaluated based on three criteria: i) associated Type I and Type II error (probability of missing a crisis and probability of a false signal, respectively); ii) the noise-to-signal ratio (hereafter NSTR); and iii) the probability of a crisis occurring conditional on a signal being issued. The main findings of this paper were that problems in the banking sector typically precede a currency crisis, a currency crisis deepens the banking crisis and financial liberalization usually precedes banking crises. The evolution of these crises also suggests that crises occur as the economy enters a recession, following a prolonged boom in economic activity fuelled by credit, 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 crashes than other countries, the impact of exchange rate on banking crises may have been overemphasized.

In more recent research, Borio and Drehmann (2009) develop a composite index and use weights for indicators designed based on gaps from a long-term trend, they find that in-sample performance of these indicators is quite good, with a lead for crisis prediction varying between *one* and *four* years. 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 that can help identify assessments of the build-up of risks of future banking distress in the economy. They find that in-sample predictions of crisis average 77% with a lead time of 3 years, while out-of-sample performance falls to hover around 60%, for the same lead time. Predictive ability both in-sample and out-of-sample, drops considerably in the 1-year lead time analysis to as low as 30%. This seems to highlight that 2 years before a crisis occurs, it is already too late to act on preventing the crisis because the preconditions for the crisis have already been staged, as evidenced by these indicators seeing no further deterioration.

Alessi and Detken (2009), using a signal extraction model, find *out-of-sample performance of a set of global liquidity indicators* would have predicted the most recent wave of *asset price booms* (2005-2007). These include global private credit, long term nominal bond yield, housing investment, short-term nominal interest rate, real equity price index and real GDP. Table 1 presents a brief description of these papers.

Table 1: Signal Extraction Selected Papers

Authors	Year	Data	Factors & Main Findings
Kaminsky & Reinhart	1998, 1999	20 countries, identifying 76 episodes of currency crises and 26 banking crises, of these 18 episodes are twin crises, 1970-1995.	Find that these three factors are the most influential • Real exchange rate appreciation • Equity prices • Money multiplier However, they have a large Type I error, failing to issue a signal in 73%-79% of the observations during the 24 months preceding the crisis for twin crises and 12 months for banking crises.
Alessi & Detken	2008	1970 – 2007, 18 OECD countries.	Propose 18 real-time and financial indicators for costly asset price booms and find some specifications would have issued persistent warning signals prior to the current crisis. The most robust indicators were: global private credit, long term nominal bond yield, housing investment, short-term nominal interest rate, real equity price index and real GDP.
Borio, Drehmann	2009	1980-2003 and test out of sample 2004 – 2008	Test the behaviour of credit and asset prices (equity and property using gaps from a long-term trend) in the prediction of financial crises both in-sample and out-of-sample, with low noise-to-signal ratios over 1 and 3 year horizons.

Sources: As listed above.

From Table 1, a key drawback of signal extraction models is clear: across the different time periods and countries studied the explanatory variables chosen vary significantly over time and between country groupings. Kaminsky and Reinhart (1998) find that real exchange rate appreciation, equity prices and the money multiplier are significant variables in predicting crises, while Alessi and Detken (2008) find a set of 18 real time financial indicators to be significant, of which there is only one overlapping with Kaminsky and Reinhart, equity prices, the rest of the variables are different. Alessi and Detken (2008) main significant variables in predicting crises are global private credit, long term nominal bond yield, housing investment, short-term nominal interest rates, equity price indices and changes in real GDP. Finally, Borio and Drehmann (2009) find two indicators to be significant, these are again equity price indices, thus overlapping with Alessi and Detkin, and introducing house price indicators as a new variable.

Dependent Variable in Earlier Literature

Earlier literature (Caprio and Klingebiel 1996 and Demirguc-Kunt and Detragiache 1998) defines a crisis ex-post and after losses are realized and/or public scale nationalization or melt downs occurred – specifically:

a. Proportion of NPLs to total baking system assets is greater than 10%
b. Public bailout costs exceed 2% of GDP
c. Systemic crisis causes large scale nationalization
d. Extensive bank runs and/or emergency government intervention
e. All or most of banking capital is exhausted; and
f. Level of non-performing loans falls between 5% and 10% or less if subjectively deemed systemically significant.

The following Table 2 presents the number of crises in line with the definition in earlier literature. In total we have 135 crisis episodes, out of 870 observations or 15.5%.

Table 2: Crises Definitions in Earlier Literature for OECD Countries (1980 – 2007)

Crises Definitions in Earlier Literature

		1979	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
1	Australia											1	1	1	1																4
2	Austria																														0
3	Belgium																														0
4	Canada					1	1	1																							3
5	Czech Republic																														0
6	Denmark									1	1	1	1	1	1																6
7	Finland													1	1	1	1														4
8	France																1	1													2
9	Germany																														0
10	Greece													1	1	1	1	1													5
11	Hungary																														0
12	Iceland			1				1	1			1				1															5
13	Ireland																														0
14	Italy			1									1	1	1	1	1	1													7
15	Japan														1	1	1	1	1	1	1	1	1	1	1			1			12
16	Korea																			1	1										2
17	Luxembourg																														0
18	Mexico			1	1	1	1	1	1	1	1	1	1	1			1	1	1	1	1	1	1								18
19	Netherlands																														0
20	Norway									1	1	1	1	1	1	1															7
21	New Zealand									1	1	1	1																		4
22	Poland			1								1	1	1	1	1	1	1													8
23	Portugal					1			1	1	1	1																			5
24	Slovakia																														0
25	Spain		1	1	1	1	1	1																							6
26	Sweden												1	1	1	1	1														5
27	Switzerland																														0
28	Turkey		1	1	1	1	1	1						1			1		1				1	1	1			1			13
29	UK						1							1	1			1												1	5
30	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%

Sources: Demirgüç-Kunt & Enrica Detragiache (2005), Kaminsky & Reinhart (1999), Caprio & Klingebiel (1996 and 2003) Reinhart & Rogoff (2008), Laeven & Valencia (2008).

3. Empirical Model Design

Methodology

The indicators are based on a signal extraction method, for each period, t, a signal, S, is calculated which takes the value of 1 ("on") if indicator variables exceed critical thresholds or is 0 ("off") otherwise. For a signal to be issued, critical thresholds which were usually calibrated statically have to be breached and aggregating the information issued by different indicators was a challenge. In line with Kaminsky, Lizondo and Reinhart (KLR) 1999, who were the creators of this methodology, among others and a later application by Borio and Drehmann (2009), we modify this approach by choosing dynamic thresholds measured in standard deviations to a benchmark and a signal monitor which summarizes the model output.

The decision rule for whether a variable is 'on', i.e. is a '1' or is 'off', i.e. is '0', for our chosen explanatory variables is based on whether it is a certain number of standard deviations away from a chosen benchmark. The benchmark was calculated for three cases as the mean of a 3-year, 5-year and 10-year period of the variable in question. These '0' and '1' indicators for each independent variable and for each case are then summarized using the 'SIGNAL MONITOR' for each country for each year. The number of standard deviations to trigger a signal is currently calibrated to read '1' or is 'On' if two of the nine variables modelled are 'On'. Thus the crisis prediction process is on two levels: predicting aberrations in the individual variables by being too 'far' from a rolling mean, and then 'translating' or 'summarizing' this into a crisis predictor.

The use of standard deviations from a mean is an innovation partly inspired by Borio and Drehmann's (2009) gap analysis, but with methodological changes in the number of variables and how the output is summarized and evaluated. The selection of the number of standard deviations that turns the fluctuation in an economic time series into a signal is subject to a trade-off. If the cut-off is chosen too 'tight' (a small number of standard deviations) it is likely to signal a lot of crises, including false ones. This compares to KLR where a low absolute is chosen that would increase the number of false signals, i.e. result in Type II errors. On the other hand, if the threshold is too high, or set at a large number of standard deviations, it would result in Type I errors, missing a crisis when there is one in the making. This compares to KLR where a high absolute threshold was chosen.

There is no consensus approach to choosing the size of a threshold. Kaminsky and Reinhart (1996), choose the size of the optimal threshold for each variable by selecting the value that minimizes the in-sample noise-to-signal ratio, ω, that is computed in their application as follows:

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

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 NSTR calculation for this paper is calculated in the same way, with the difference that now both are functions of the chosen *deviation* threshold.

Dependent and Explanatory Variables

Dependent Variable

This paper uses an adapted definition focusing on near-crises, where each country is identified as having a near-crisis or not based on a composite indicator of the solvency and profitability of the banking sector and changes in both thereof. By using this definition of near-crises as opposed to an *ex-post metric* of losses as a percentage of GDP or NPL levels which identify crises at a stage which is too late for policy makers to take any action to actually prevent a crisis – this adapted near-crisis definition would by default lead to a longer lead period for the signals issued as they will point to imbalance and/or fragility build-up.

Dependent Variable Specification, Unbundling and Calibrations

The dependent variable designed to capture changes to bank solvency and profitability or periods of 'near-crisis is composed of four components as follows:

1. For any given year for any country, if it saw a decrease in its banking sector capitalization of more than a certain number of basis points (delta banking sector capitalization as measured by capital/total assets);

2. Or an increase in its banking sector capitalization of more than a certain number of basis points* (delta banking sector capitalization as measured by capital/total assets);

3. Or if its net income before provisions as a percentage of average balance sheet falls by more than a number of basis points (delta NI before provisions/average balance sheet);

4. Or if its net income before provisions as a percentage of average balance sheet is less than a certain number of basis points;

this country is deemed to be facing a near-crisis or a period of heightened fragility.

The reason the profitability metrics were included as separate components, is 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 we could potentially be faced with an inflated balance sheet or capital base or both.

Notes

*The use of component two as part of the dependent variable specification was tested separately as an explanatory variable based on the intuition that banks would potentially increase their capital *ex-ante* in anticipation of taking on more risk in future. However, when calibrated as such the model performance for the 12 unbundled runs (3 cases plus one consolidated times 3 dependent variable specifications unbundled) deteriorated drastically across the board. Which led the authors to another potential reasoning, which is that banks increase capital only if they know they have already taken on more risk, so this is a 'post' or dependent variable. This variable proxies the asymmetry in 'realizing' the impact of increased risk explicitly on the assets side (i.e. that 'booking' the risk happens with a lag after the action of risk taking has occurred). The increase in capital/total assets is then the mirror image to the decrease metric, where the assets are booked and capital is catching up. We are grateful to Professors Alistair Milne and Steve Thomas of Cass Business School for their comments on this particular point.

Three cases were considered for the dependent variable calibration as follows:

1. Base Case: changes in banking sector capitalization of more than 0.5% (delta banking sector capitalization); net income before provisions as a percentage of average balance sheet falls by 50 bps (delta NI before provisions/average balance sheet); or net income before provisions as a percentage of average balance sheet is less than 5 bps (0.05% absolute threshold), a country is deemed to be facing a banking near-crisis.
2. High Change Dynamic Threshold: changes in banking sector capitalization of more than 1.0% (delta banking sector capitalization); net income before provisions as a percentage of average balance sheet falls by 100 bps (delta NI before provisions/average balance sheet); or net income before provisions as a percentage of average balance sheet is less than 10 bps (0.10% absolute threshold), a country is deemed to be facing a banking near-crisis.
3. Low Change Dynamic Threshold: changes in banking sector capitalization of more than 0.10% (delta banking sector capitalization); net income before provisions as a percentage of average balance sheet falls by 10 bps (delta NI before provisions/average balance sheet); or net income before provisions as a percentage of average balance sheet is less than 1 bps (0.01% absolute threshold), a country is deemed to be facing a banking near-crisis. This is explained more in details in the following Table 3.

Table 3: Unbundling of Near-Crises Definitions by Criteria and Consolidated

No.	Criteria	High Change Dynamic Threshold 100 bps, 100 bps, -100, and 10 bps	Base Case 50 bps, 50 bps, -50bps and 5 bps	Low Change Dynamic Threshold 10 bps, 10 bps, -10bps and 1 bps
1	Decrease in banking sector capitalization	45	91	222
2	Increase in banking sector capitalization	62	115	265
3	Net Income before provisions/Average Balance sheet falls	12	36	131
4	Net Income before provisions/Average Balance sheet is less than	18	19	22
Sub-total		**137**	**261**	**640**
Less Double counting between the four rules		10	29	131
Net		**127**	**232**	**509**
% of Total Observations		**15%**	**27%**	**59%**

*Case calibration is for rules 1 through 4 in order.

Source: Authors' calculation.

As table 3 shows, for the base case, the most dominant factor is banking capitalization in line with earlier literature, with 206 out of 232 'near crisis' observations being captured by this. The other two factors which look at the link between income statement returns and the balance sheet capture only 55 out of the 232 'near crisis'. This is because if a bank is realizing poor or negative returns it should have already been liquidated or merged – so these criteria capture the 'zombies' still in the system so to speak, which by default should be very few. Please note that there were 29 incidences where more than one criterion captured a 'near crisis' and the double counting was eliminated.

The use of profitability metrics is to capture any 'hidden' factors in asset quality or bank operations, which are not evident on the surface just looking at solvency, but are manifested in very low and/or sizable drops in profitability. The duration of a near-crisis is one year/ each vulnerability spot is viewed separately.

The High Change Dynamic Threshold and the Low Change Dynamic Threshold scenarios both show very low incidence (15%) and very high incidence (59%), of systemic crises respectively and resulted in poorly performing models for the 12 runs when tested.

The number of 'near-crises' for the base case, by country and year are 232 observations out of 870 or 27% as per the following Table 4. The new model proposed identifies a greater number of 'near-crisis' as compared to full fledged crises identified in earlier literature. This makes sense given that not all near-crises would necessarily grow to become crises. But from the perspective of a regulator, this paper puts forward the argument that regulators should always be concerned with predicting the 'near crises' and working on the conditions within their purview to prevent them from developing into crises.

Table 4: Near-Crises / Vulnerability Spots Identified for OECD Countries (1980 – 2007)- Base Case*

		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
1	Australia	0	0	0	0	0	0	0	0	0	1	1	0	1	0	1	0	1	0	0	1	0	0	1	0	0	0	0	1	8
2	Austria	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	1	4
3	Belgium	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	3
4	Canada	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
5	Czech Rep	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	14
6	Denmark	0	0	0	1	1	1	0	0	1	0	1	1	1	1	1	0	0	0	0	0	1	1	0	0	0	0	1	1	13
7	Finland	0	0	0	0	0	0	0	0	1	0	1	1	1	1	1	1	1	0	0	0	0	1	0	1	1	0	0	1	12
8	France	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	3
9	Germany	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	Greece	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	0	0	1	0	0	0	0	5
11	Hungary	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	1	1	1	1	7
12	Iceland	1	1	1	1	1	1	1	0	1	0	0	1	1	1	0	1	1	1	1	1	1	1	1	0	1	1	1	0	22
13	Ireland	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	1	1	0	1	0	0	5
14	Italy	0	0	0	0	1	0	1	1	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	6
15	Japan	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	1	0	1	1	0	0	1	1	1	0	1	1	10
16	Korea	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	1	1	1	1	1	1	1	0	0	1	1	0	0	11
17	Luxembou	0	0	0	1	1	1	1	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	1	0	0	0	0	0	7
18	Mexico	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	1	0	1	1	6
19	Netherlan	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	3
20	Norway	0	0	1	0	0	0	1	1	0	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	10
21	New Zeala	0	0	0	0	0	0	0	0	0	0	1	1	1	1	0	0	1	1	0	0	0	0	1	1	0	0	1	0	9
22	Poland	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	1	1	0	0	0	1	1	0	0	0	1	0	7
23	Portugal	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	1	1	0	0	0	1	6
24	Slovakia	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	0	1	1	1	1	1	0	10
25	Spain	0	0	1	1	0	0	0	0	1	0	0	1	0	1	0	1	0	0	0	0	1	0	0	0	0	1	1	0	9
26	Sweden	1	0	0	1	0	0	0	0	0	1	1	1	1	1	1	0	1	0	0	0	0	0	0	0	1	1	1	0	12
27	Switzerlan	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	1	0	1	0	0	0	0	0	0	0	4
28	Turkey	0	0	0	0	0	0	1	0	1	0	1	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	12
29	UK	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	1	1	1	1	6
30	US	1	0	0	1	1	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	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**
% Crises																														**27%**

*As per the rules explained. Source: Author's calculation.

The advantage of this definition of near-crises over previous literature is that we gain at least a couple of years by doing this based on the underlying assumption that a well capitalized and profitable banking sector can better withstand any shock. Also this way the EWS has a pre-emptive built in component because it will always ensure a minimum level of 'sector health' as it continuously corrects for 'near-crises'.

The correlation between the predicted total near crises by country in the base case model and full-fledged crises in earlier literature is very high at 0.98, which supports the premise on which the new dependent variable specification was designed. While Table 5, presents the binary (logit) regression output between the definition of crises in earlier literature and the new definition presented in the base case. This shows 'near-crises' as predicting 'crises' with a coefficient of 0.61, significant at the 1% level. The model's MacFadden's R^2 is quite low however, at only 1% and the residuals suffer from heteroskedasticity with kurtosis at 4.4 (normal distribution at around 3). Thus this relationship could be further investigated in future research.

Table 5: Binary Regression Results between 'Crisis' Definitions in Earlier Literature and 'Near Crises' OECD Countries (1980 – 2007)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-1.858582	0.118728	-15.65417	0.0000
NEAR_CRISES	0.616869	0.197187	3.128350	0.0018

McFadden R-squared	0.012818	Mean dependent var	0.159524
S.D. dependent var	0.366382	S.E. of regression	0.364416
Akaike info criterion	0.871269	Sum squared resid	111.2856

Schwarz criterion	0.882539	Log likelihood	-363.9331
Hannan-Quinn criter.	0.875589	Restr. log likelihood	-368.6587
LR statistic	9.451245	Avg. log likelihood	-0.433254
Prob(LR statistic)	0.002110		

Source: Author's calculation.

The explanatory variables

Based on analysis of earlier literature and fundamental analysis, narrowing down the universe to the data set which is available for the 30 year period under study- from a long list of 30 variables, nine were chosen after proving significant in 'explaining' the dependent crisis variable in an OLS model. These nine variables and their definitions are presented in the following table.

Table 6: Explanatory Variables

Acronym	Variable	Explanation / Rationale for Use	Data Source
BAG	Banking Sector Asset Growth (BAG)	The faster the growth of banking sector assets, the more vulnerable the system could become as the quality of lending decisions is affected. (Expected sign: Positive)	OECD database, growth calculated YoY, end of year balance.
BAGDP	Banking Sector Assets to GDP (BAGDP)	The greater the proportion of banking sector assets to GDP, the more vulnerable the financial system is to any shock in the sector. (Expected sign: Positive)	Banking Sector Assets as above, Nominal GDP from IMF WEO database.
HPI	House Price Indicator (HPI)	The greater the appreciation in house prices, the more likely asset bubbles are to develop and the more likely this would negatively impact the financial sector. (Expected sign: Positive or negative depending on the impact on agents and initial conditions)	OECD database, real appreciation in house prices YoY.
PENS	Pension Fund Assets to GDP (PENS)	Pension funds are large liquidity providers in their markets, therefore the changes in how much they hold as a percentage of GDP indicate how much liquidity they are providing to the system. Increases could result in more funds poured into the stock markets and real estate (contributing to crises by bubble development) and drops could mean sale of these assets contributing to bubble deflation and losses by other agents, resulting in crises if substantial. (Expected sign: Positive or Negative depending on which economic agents are affected and initial conditions).	OECD database, pension assets as a % of GDP.

EMKTDY	Equity Capital Markets Dividend Yield (EMKTDY)	This is a proxy for corporate leverage, in most cases, companies only increase their dividend when they have free cash flows to equity shareholders, after they have made their debt service and interest repayments from free cash flows to the firm as a whole. Rising dividend yields should indicate healthier corporate balance sheets, and lower crisis probability. (Expected sign: Negative)	World Federation of Stock Exchanges (WFE)
EMI	Equity Market Index (EMI)	This is a proxy for stock market appreciation, with an expected positive sign. The more price appreciation, the greater the possibility that a bubble could be forming.	World Federation of Stock Exchanges (WFE)
DRGDP	Change in Real GDP (DRGDP)	Growth in real GDP provides agents with the conditions in which they can flourish, build their balance sheets and retained earnings from higher profits, it results in a boost in capital investment. However, growth in real GDP could also result in the development of credit and asset price bubbles, thus depending on a country's position in the cycle, it can affect the probability of a crisis arising in either way. Expected sign: Positive or Negative.	WEO database.
LIQ	Liquidity Indicator	The proportion of securities to total assets held by the financial system as a whole indicates the availability of short term liquidity in the system in the time of crisis. If there is too much liquidity, it could trigger the development of bubbles. If there is too little liquidity, this may lead to solvency issues. Expected sign: positive or negative.	OECD database, authors' calculation.
FUN	Funding Indicator	The ratio of loans to deposits indicates how much of a banks' loan books are funded by deposits, and how much are funded from external sources. The greater the proportion funded from external sources, the larger the banking system's exposure to changes in market conditions. Expected sign: positive or negative (positive if above 100%, negative if less than 100%).	OECD database, authors' calculation.

Empirical OLS Model Used to Verify Choice of Variables

These nine explanatory variables were used to estimate an OLS regression to verify their choice as components of the signal indicator, for each of the 30 countries. The models were compared by assessing: i) Information criterion (Akaike, Schwarz and Hannan-Quinn); and ii) adjusted R^2. The OLS regression model is as follows:

$\text{Crisis}_i = C + aDRGDP_i + bHPI_i + cMEMI_i + cBAG_i + dBAGDP_i + ePENS_i + fEMKTDY_i + gLIQ + hFUN + E_i$

The best model according to the criteria is presented in the table below.

Table 7: OLS Model

Variable	Coefficient	Std Error	t-Stat	Prob
C	-0.1641	0.4293	-0.3823	0.7034
DRGDP	4.8779	4.6713	1.0442	0.3001
HPI	-1.0048	1.1245	-0.8897	0.3768
DEMI	0.3799	0.3356	1.1321	0.2616
CAB	0.9902	1.0886	0.9096	0.3663
BAG	1.3807	0.7651	1.8056	0.0756
BAGDP	0.0458	0.0449	1.0184	0.3121
PENS	-0.3243	0.1646	-1.9704	0.0529
EMKTDY	-4.5277	2.6076	-1.7363	0.0870
LIQ	0.8912	1.3224	0.6739	0.5026
FUN	0.0917	0.2322	0.3951	0.6940
Observations	79			
R-Squared	**27.2%**			
Adjusted R-Squared	**16.5%**			
Prob (F-Stat)	**1.1%**			

Source: Authors Calculations.

The model's adjusted R^2, or its explanatory power adjusted for the number of variables incorporated is 16.5%, i.e. it explains 16.5% of the results. The overall significance of the model however, as indicated by the F-Statistic is 1.1%, indicating the model is significant at the 1% level. The model also provides the smallest information criteria values among the models estimated using various runs with different variable combinations from the universe of 30 possible independent variables.

Growth in pension assets is positive and significant at the 5% level, and equity market dividend yield is positive and significant at the 10% level. The former is an indicator for the development of liquidity bubbles which leads to financial sector pains. The latter is a proxy for corporate balance sheet health on the premise that companies usually raise dividends, in line with the pecking order hypothesis, after meeting all other cash flow needs and when they believe the coming years will be better and also as excess free cash flows to equity shareholders, after debt service, are available.

Banking sector assets growth is also significant at the 10% significance level, indicating a strong relationship between rapid growth of the banking sector and the development of vulnerabilities (positive coefficient).

Other variables not significant at the 10% level but are included in the model as they have correct signs and help improve substantially the overall forecasting ability of the model are House Price Indicators, mean equity market price rises over a rolling period, a sector micro liquidity indicator and a sector micro funding indicator.

4. Data and Descriptive Statistics of Country Universe

OECD comprises: Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Japan, Korea, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovakia, Spain, Sweden, Switzerland, Turkey, United Kingdom and the US. Collectively, these countries captured 75% of global nominal GDP in 2007 (60% on a purchasing-power-parity adjusted basis) and had a total population of 1.2 billion, 18% of total global population, respectively. OECD data on banking activity is available for 30 years, back to 1979 for on-balance sheet activities. The data period spans 30 years from 1980 to 2009 with 9 explanatory variables for the 30 OECD countries (this translates into approximately 8,000 observations).

This data set is obtained from OECD, IMF, World Bank, World Federation of Exchanges and national central banks. In this sample there were 232 years of systemic vulnerabilities for the base case as per the definition explained earlier, out of 870 usable observations. Innovation and contribution to data sources includes the use of World Federation of Exchanges data on dividend yields as a proxy for corporate sector health and using data on fluctuations in pension assets which have not been used before in the literature. Table 8 shows the nine variables chosen for this paper and their descriptive statistics. It shows the mean growth in real GDP for OECD countries over the study period to be 2.9%, with a standard deviation of 2.7% and a slight skew to the left of 0.5 (normal distribution skewness is approximately zero), and almost normal kurtosis, or no fat tails, with kurtosis at 3.46 (normal distribution is approximately three).

Table 8: Data Descriptive Statistics*

Acronym	DRGDP	HPI	DEMI	CAB	BAG	BAGDP	PENS	EMKTDY	LIQ	FUN	SIGNAL Monitor
Long-Name	Delta Real GDP in %	House Price Indicator %	Delta Equity Market Index %	Current Account Balance %	Banking Sector Asset Growth	Banking Sector Assets to GDP	Pension Fund Assets to GDP	Equity Capital Markets Dividend Yield	Liquidity Indicator	Funding Indicator	Signal Monitor
Definition	Change in Real GDP YoY	Real appreciation in House Prices YoY	Change in eqity capital markt index YoY	Current Account balance to GDP %	Change in banking sector assets YoY %	Banking Sector Assets to GDP %	Pension Fund Assets to GDP	Equity Capital Markets Dividend Yield %	Securities / T. Assets	Loans to Deposits Ratio	Model Output based on ex-ante decision rule
No. Of Observations	825	246	691	811	613	649	243	287	481	481	840
Mean	2.87%	3.79%	18.83%	-0.70%	13.03%	328.36%	36.18%	3.43%	18.65%	105.08%	34.29%
SD	2.7%	6.0%	45.0%	5.0%	15.3%	655.4%	45.9%	2.9%	6.5%	28.7%	47.5%
Skewness	- 0.5	0.4	5.9	0.2	3.5	3.5	2.9	4.0	0.1	0.6	0.7
Kurtosis	3.5	0.7	57.0	1.7	16.1	11.1	19.2	20.8	-0.8	0.7	-1.6

**Signal Monitor for the Base Case Dependent Variable Specification, 10 year - 1 SD calibration.*

Source: Authors' calculation.

The mean of the signal monitor for the base case 10-year rolling mean, 1 SD specification, over the study period was 34.3% (i.e 30% of the time a signal was issued based on the decision rule for the current calibration of any two signals of the nine pointing to a crisis, this 'Signal Monitor' reads 1, otherwise it is 0). The standard deviation of the series is 47.5% and a skew to the right of 0.7 (normal distribution skewness is approximately zero), and fat tails with kurtosis at negative 1.6 (normal distribution is approximately three). *These statistics endorse the use of the SIGNAL MONITOR as a summary indicator, because its resulting distribution is close to normal given a small skew and slightly negative kurtosis.*

5. Empirical Results

Setting Up the Independent Variable Indicator Signals

For each of the nine variables, a signal is issued if it crosses a threshold theta, ϴ, which is defined in terms of number of standard deviations from a 3-year, 5-year and 10-year rolling mean for that variable.

$$S_t = \begin{cases} 1 \;\; if \; V_1 > \Theta_1 \\ 0 \; else \end{cases}$$

In the first run, Theta$_1$, θ_1 is calibrated at one-standard deviation from a three year rolling mean. This is done for each variable, for each country, for each year. The following table below shows the calibration of Theta$_1$ to Theta$_9$: θ_1 , $\theta_2, \theta_3, \theta_4, \theta_5, \theta_6, \theta_7$, θ_8, θ_9.

Table 9: Calibration of Signal Triggers

Run	Acronym	Rolling Mean Period	No. Of Standard Deviations (Signal Trigger)
Theta$_1$	θ_1	3 Years	One
Theta$_2$	θ_2	3 Years	Two
Theta$_3$	θ_3	3 Years	Three
Theta$_4$	θ_4	5 Years	One
Theta$_5$	θ_5	5 Years	Two
Theta$_6$	θ_6	5 Years	Three
Theta$_7$	θ_7	10 Years	One
Theta$_8$	θ_8	10 Years	Two
Theta$_9$	θ_9	10 Years	Three

Source: Authors' Calculations.

These runs where replicated for each of the unbundled four component dependent variable calibrations, for a total of *144 iterations*. Independent variable thresholds set at more than one standard deviation (i.e for Theta$_2$ and Theta$_3$, Theta$_5$ and Theta$_6$ and Theta$_8$ and Theta$_9$) resulted in almost no triggers. This means that if standard deviation is calculated on the basis of a volatile series, the signal is effectively *'understated' or 'muted'*, and an adjusted measure of standard deviation or an adjusted signal for volatile series should be investigated or alternatively the dynamic measure should be something other than standard deviation.

Forecasts and Model Performance
Crisis Signal Forecasts

Crisis signal forecasts for each of the 144 iterations is summarized based on the Signal Monitor, which is currently calibrated to forecast a crisis if two out of the nine indicators signal a crisis (other calibrations, whether they be linear, weighted could be adjusted to reflect the regulator's views on contributors to fragility). In-sample forecasts are the reading of the Signal Monitor for the same year. Out of sample forecasts are the signal monitor reading of the year t-1.

A summary is presented below in Table 10 which shows the outputs for $Theta_1$,$Theta_4$ and $Theta_7$ (Θ_1, Θ_4 and Θ_7), by country, for the base case dependent variable scenario, using *one standard deviation* from a 3-year rolling mean, a 5-year rolling mean and a 10-year rolling mean, respectively. As can be seen, the output model shows that as early as 2004, clear signals were being given for a number of countries that vulnerabilities were building up.

Table 10: Signal Extraction Forecasts for $Theta_1$,$Theta_4$ and $Theta_7$ (Θ_1, Θ_4 and Θ_7) – Base Case Dependent Variable

	Signal Monitor Theta 1						Signal Monitor Theta 4						Signal Monitor Theta 7					
	In-Sample			Out-of-Sample			In-Sample			Out-of-Sample			In-Sample			Out-of-Sample		
Country	2005	2006	2007	2005	2006	2007	2005	2006	2007	2005	2006	2007	2005	2006	2007	2005	2006	2007
Australia	0	1	1	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1
Austria	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Belgium	1	0	0	1	1	0	1	1	1	1	1	1	1	0	1	1	1	0
Canada	1	1	0	1	1	1	1	1	1	0	1	1	0	1	1	0	0	1
Czech Republic	1	0	1	0	1	0	1	1	1	1	1	1	1	1	1	1	1	1
Denmark	1	0	0	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1
Finland	0	0	0	1	0	0	1	1	0	1	1	1	1	1	1	1	1	1
France	1	0	0	1	1	0	1	1	0	0	1	1	1	1	1	0	1	1
Germany	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Greece	1	0	1	1	1	0	1	0	1	1	1	0	0	0	1	0	0	0
Hungary	0	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1
Iceland	1	0	0	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1
Ireland	1	1	0	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1
Italy	1	0	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1
Japan	0	1	1	1	0	1	1	1	1	1	1	1	0	1	1	1	0	1
Korea	1	1	0	0	1	1	1	1	1	1	1	1	1	1	1	0	1	1
Luxembourg	1	1	0	0	1	1	1	1	0	0	1	1	0	0	0	0	0	0
Mexico	0	1	0	1	0	1	0	1	0	1	0	1	1	1	1	1	1	1
Netherlands	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1
Norway	1	1	0	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1
New Zealand	0	1	1	1	0	1	0	1	1	1	0	1	0	1	1	1	0	1
Poland	1	1	0	1	1	1	1	1	1	1	1	1	0	1	1	0	0	1
Portugal	0	0	1	0	0	0	0	1	1	0	0	1	0	1	1	0	0	1
Slovakia	1	1	1	0	1	1	1	1	1	0	1	1	1	1	1	1	1	1
Spain	1	0	1	1	1	0	1	0	1	1	1	0	1	1	1	1	1	1
Sweden	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Switzerland	1	1	0	1	1	1	1	1	0	1	1	1	1	1	1	0	1	1
Turkey	0	0	1	1	0	0	0	0	1	0	0	0	0	0	1	1	0	0
UK	1	0	1	1	1	0	1	1	1	1	1	1	1	1	1	0	1	1
US	0	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1
Total	21	18	16	24	21	18	26	27	22	24	26	27	22	26	29	21	22	26

Source: Authors' calculations.

While Table 11 shows the Summary Consolidated Runs for the three dependent variable cases: namely the base case, high change dynamic threshold and low change dynamic threshold scenarios.

Table 11: Signal Extraction Forecasts for $Theta_1$,$Theta_4$ and $Theta_7$ (θ_1, θ_4 and θ_7) – Summary Consolidated Runs for Dependent Variable Cases

Base Case **50 bps, 50 bps, -50bps and 5 bps**					
Theta 1					
Noise-To-Signal Summary	1-Year Horizon			2-Year Horizon*	3-Year Horizon**
	2005	**2006**	**2007**		
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**
Theta 4					
Noise-To-Signal Summary	1-Year Horizon			2-Year Horizon*	3-Year Horizon**
	2005	**2006**	**2007**		
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**
Theta 7					
Noise-To-Signal Summary	1-Year Horizon			2-Year Horizon*	3-Year Horizon**
	2005	**2006**	**2007**		
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**

High Change Dynamic Threshold **100 bps, 100 bps, -100, and 10 bps**					
Theta 1					
Noise-To-Signal Summary	1-Year Horizon			2-Year Horizon*	3-Year Horizon**
	2005	**2006**	**2007**		
In-Sample					
Type I %	20%	20%	25%	10%	0%
Type II %	360%	360%	188%	260%	156%
Noise-To-Signal Ratio	**4.50**	**4.50**	**2.50**	**2.89**	**1.56**
Out-of-Sample					
Type I %	0%	80%	50%	0%	0%
Type II %	400%	420%	225%	270%	150%
Noise-To-Signal Ratio	**4.00**	**21.00**	**4.50**	**2.70**	**1.50**
Theta 4					
Noise-To-Signal Summary	1-Year Horizon			2-Year Horizon*	3-Year Horizon**
	2005	**2006**	**2007**		
In-Sample					
Type I %	20%	20%	25%	10%	0%
Type II %	440%	460%	213%	290%	161%
Noise-To-Signal Ratio	**5.50**	**5.75**	**2.83**	**3.22**	**1.61**
Out-of-Sample					
Type I %	20%	40%	13%	10%	6%
Type II %	420%	460%	250%	280%	156%
Noise-To-Signal Ratio	**5.25**	**7.67**	**2.86**	**3.11**	**1.65**
Theta 7					
Noise-To-Signal Summary	1-Year Horizon			2-Year Horizon*	3-Year Horizon**
	2005	**2006**	**2007**		
In-Sample					
Type I %	20%	20%	0%	10%	0%
Type II %	380%	460%	263%	280%	161%
Noise-To-Signal Ratio	**4.75**	**5.75**	**2.63**	**3.11**	**1.61**
Out-of-Sample					
Type I %	20%	40%	25%	0%	0%
Type II %	420%	400%	263%	240%	133%
Noise-To-Signal Ratio	**5.25**	**6.67**	**3.50**	**2.40**	**1.33**

Low Change Dynamic Threshold **10 bps, 10 bps, -10bps and 1 bps**					
Theta 1					
Noise-To-Signal Summary	1-Year Horizon			2-Year Horizon*	3-Year Horizon**
	2005	**2006**	**2007**		
In-Sample					
Type I %	22%	28%	24%	4%	0%
Type II %	17%	16%	8%	40%	34%
Noise-To-Signal Ratio	**0.22**	**0.22**	**0.11**	**0.41**	**0.34**
Out-of-Sample					
Type I %	17%	28%	32%	2%	0%
Type II %	26%	16%	20%	44%	29%
Noise-To-Signal Ratio	**0.32**	**0.22**	**0.29**	**0.45**	**0.29**
Theta 4					
Noise-To-Signal Summary	1-Year Horizon			2-Year Horizon*	3-Year Horizon**
	2005	**2006**	**2007**		
In-Sample					
Type I %	13%	12%	20%	2%	0%
Type II %	26%	20%	12%	52%	38%
Noise-To-Signal Ratio	**0.30**	**0.23**	**0.15**	**0.53**	**0.38**
Out-of-Sample					
Type I %	22%	12%	12%	4%	3%
Type II %	30%	16%	20%	50%	36%
Noise-To-Signal Ratio	**0.39**	**0.18**	**0.23**	**0.52**	**0.37**
Theta 7					
Noise-To-Signal Summary	1-Year Horizon			2-Year Horizon*	3-Year Horizon**
	2005	**2006**	**2007**		
In-Sample					
Type I %	26%	12%	0%	4%	0%
Type II %	26%	20%	16%	48%	37%
Noise-To-Signal Ratio	**0.35**	**0.23**	**0.16**	**0.50**	**0.37**
Out-of-Sample					
Type I %	22%	20%	12%	8%	5%
Type II %	30%	12%	20%	48%	32%
Noise-To-Signal Ratio	**0.39**	**0.15**	**0.23**	**0.52**	**0.33**

Source: Authors' calculations.

Noise-to-Signal Ratios and Forecast Performance (In-Sample and Out-of-Sample)

The model performance for $Theta_1$,$Theta_4$ and $Theta_7$ (Θ_1, Θ_4 and Θ_7), or one standard deviation from a 3-year rolling mean, a 5-year rolling mean and a 10-year rolling mean, respectively for the base case is summarized below. The 1-year NSTR is calculated based on whether a crisis was correctly called in the year following the forecast. However, measuring NSTR this way would result in an attempt to also predict crisis timing, which according to (Borio & Drehmann 2009) is not feasible. What if a crisis occurs after 1 year and 2 months from a signal being issued? Or 1 year and 3 months? In this case the NSTR would be indicating a false signal, whereas it is not true, predicting the timing however was what was not possible. The NSTR over a two year horizon, measures how correct the model was in signalling crises in the 24 months period after a crisis occurs, this is in line with Kaminsky and Reinhart (1999). This paper chooses to focus on the three year horizon, i.e. the ability of a signal to predict a crisis in the three years following a signal being issued. By using this focus, from the regulatory perspective, this means that the signal being evaluated could signal a crisis as early as 3 to 4 years before a crisis occurs.

Performance in-sample shows small Type I errors ranging from 0% to 3%. The noise-to-signal ratio range, improves significantly to 0.7 from 1.6 times, over the three year forecast horizon as compared to the one year horizon, as the range of false alarms falls from 145% to 70%. *The best in-sample model, is the 3-year rolling one standard deviation specification.*

Performance out-of-sample, is better than in-sample, in terms of overall noise to signal ratios, with the range falling from 1.6 to 0.6 over the three year forecast horizon as compared to the one year horizon. Levels of Type I errors are also very low ranging from a high of 36% to a low of 0% - or no misses. These results show a significant improvement compared to earlier work, for example the median NSTR in Borio & Drehmann (2009) applied to the same period 2004 – 2008, is 0.67 over the three year forecast horizon and the median Type I error is 70%. The outperformance also holds in comparison to KLR99, where Type I errors over a two year horizon range between 75% for the best individual indicator to 91% for the poorest individual indicator, whereas for this model, the corresponding figure is 4% to 0%. *The best out-of-sample model is the 10-year rolling one standard deviation specification.*

Comparing the base case with the High Change Dynamic dependent variable specification and the low change dynamic threshold dependent variable specification shows that the best performing calibration is the base case calibration, which has an overall crisis incidence of 27%. Although the low change dynamic threshold seems to have better noise to signal indicators – it has an overall crisis incidence of almost 60%, which would render any model used by regulators invalid as it would be calling ‘crisis’ two thirds of the time and will lose all credibility.

Comparison between Model Results for the base case using 'Near-Crises' as the Dependent Variable and 'Crises' as per the Definition in Earlier Literature

To evaluate the model performance had it been calibrated using the crises definitions in earlier literature as opposed to a 'near-crises' definition as proposed by this research, a run using the crises definition in earlier literature was done for the base case. The results are presented in the following table.

Table 12: Summary Noise-to-Signal Ratios, Type I and Type II Errors, In-Sample, Out-of-Sample

a) Model Output for 'Near Crises'

Base Case 50 bps, 50 bps, -50bps and 5 bps					
Theta 1					
Noise-To-Signal Summary	1-Year Horizon			2-Year Horizon*	3-Year Horizon**
	2005	**2006**	**2007**		
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**
Theta 4					
Noise-To-Signal Summary	1-Year Horizon			2-Year Horizon*	3-Year Horizon**
	2005	**2006**	**2007**		
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**
Theta 7					
Noise-To-Signal Summary	1-Year Horizon			2-Year Horizon*	3-Year Horizon**
	2005	**2006**	**2007**		
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**

b) Model Output for 'Crises' /Earlier Literature

Base Case 50 bps, 50 bps, -50bps and 5 bps					
Theta 1					
Noise-To-Signal Summary	1-Year Horizon			2-Year Horizon*	3-Year Horizon**
	2005	**2006**	**2007**		
In-Sample					
Type I %	100%	N/M	0%	50%	0%
Type II %	1100%	N/M	950%	1350%	725%
Noise-To-Signal Ratio	**N/M**	**N/M**	**9.50**	**27.00**	**7.3**
Out-of-Sample					
Type I %	0%	N/M	50%	0%	0%
Type II %	1150%	N/M	1050%	1300%	650%
Noise-To-Signal Ratio	**11.50**	**N/M**	**21.00**	**13.00**	**6.50**
Theta 4					
Noise-To-Signal Summary	1-Year Horizon			2-Year Horizon*	3-Year Horizon**
	2005	**2006**	**2007**		
In-Sample					
Type I %	50%	N/M	0%	50%	0%
Type II %	1250%	N/M	1050%	1450%	725%
Noise-To-Signal Ratio	**25.00**	**N/M**	**10.50**	**29.00**	**7.25**
Out-of-Sample					
Type I %	50%	N/M	0%	50%	25%
Type II %	1200%	N/M	1250%	1400%	700%
Noise-To-Signal Ratio	**24.00**	**N/M**	**12.50**	**28.00**	**9.33**
Theta 7					
Noise-To-Signal Summary	1-Year Horizon			2-Year Horizon*	3-Year Horizon**
	2005	**2006**	**2007**		
In-Sample					
Type I %	100%	N/M	0%	50%	0%
Type II %	1150%	N/M	1350%	1350%	725%
Noise-To-Signal Ratio	**N/M**	**N/M**	**13.50**	**27.00**	**7.25**
Out-of-Sample					
Type I %	0%	N/M	0%	0%	0%
Type II %	1150%	N/M	1250%	1200%	600%
Noise-To-Signal Ratio	**11.50**	**N/M**	**12.50**	**12.00**	**6.00**

Source: Authors' calculations.

This shows clearly that the model with the new dependent variable specification outperforms substantially the model with the old dependent or crisis variable specification. This outperformance is across Type I and Type

II errors as well as overall Noise-To-Signal-Ratios (NSTRs). For example the median NSTR in Borio & Drehmann (2009) applied to the same period 2004 – 2008 referred to earlier, is 0.67 over the three year forecast horizon and the median Type I error is 70%.

For the three-year rolling mean, 1SD specification (Theta1), the new model has Type I errors of 4% for the 2-year forecast horizon Vs Type I error of 50% for the specification with the old dependent crises definitions and an NSTR of 0.96 for the new definition versus 27 for the old definition, in sample. Out of sample, NSTR for the new model is 0.96 for the 2-year horizon and 0.63 for the 3-year horizon, versus 13.0 for the old definition and 6.5, respectively.

For the five-year rolling mean, 1SD specification (Theta 4), the new model has Type I errors of 4% for the 2-year forecast horizon Vs Type I error of 50% for the specification with the old dependent crises definitions and an NSTR of 1.12 for the new definition versus 29 for the old definition, in sample. Out of sample, NSTR for the new model is 1.08 for the 2-year horizon and 0.72 for the 3-year horizon, versus 28.0 for the old definition and 9.33, respectively.

For the ten-year rolling mean, 1SD specification (Theta 7), the new model has Type I errors of 4% for the 2-year forecast horizon Vs Type I error of 50% for the specification with the old dependent crises definitions and an NSTR of 1.12 for the new definition versus 27 for the old definition, in sample. Out of sample, NSTR for the new model is 0.92 for the 2-year horizon and 0.60 for the 3-year horizon, versus 12.0 for the old definition and 6.0, respectively.

Thus, the comparison between the two sets of definitions also confirms the out-performance of the 10 year horizon model with near crises definitions.

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 utilization of their specific country experience in model calibration.

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