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 recent crisis highlighted the failure of former early warning signals models. This research attributes this partly to dependent variable specification, independent variable specification, model empirical design, and looking at models in isolation (different empirical methodologies and macro and micro applications). This research uses a traffic analysis matrix to synthesize the output of the different models, which are applied on a macro and micro level, while similarly attempting to improve on all the aforementioned in the individual applications. This approach results in significant improvement in out-of-sample results and lead-time compared to earlier work and a number of key insights for regulation and policymaking.

A dependent variable innovation compared to earlier literature in the component models of the traffic lights matrix lies in adopting an ex-ante near-crisis variable compared to an ex-post cost of crisis variable used before. This variable is applied in the macro and micro applications throughout. Near crises is a necessary and sufficient condition for prediction of full-fledged crises. Near crises always precede crises and then either develops into fully-fledged crises or they don’t.

The first paper applies a macro signal extraction framework and looks at the 30 OECD countries over a 30-year period (1979 to 2007). A number of variables were found to be significant in predicting near crises, including banking assets growth, banking assets to GDP, liquidity and a proxy for corporate sector health. The second paper is a macro application comprising a dynamic logit model and a macro Z-score model. The third paper is a Z-score methodology applied on a micro level to 139 banks. The micro application is an important extension in two ways. Systems that have more institutions under stress are scaled on a composite traffic light matrix as worse. The second extension is with regards to credit ratings or rankings within a system, whereby the micro application would allow regulators to do so.

Different models invariably have different output in some aspects and strengths and weaknesses. Signal extraction performed best in terms of Type I errors, the Logit model in terms of NTSR and the Z-score model in terms of Type II errors. The overlay of the micro model improves the traffic lights matrix substantially. These findings reinforce the need by regulators to use a suite of models and a holistic macroprudential approach in judging the build up of systemic vulnerabilities.

1. Chapter One: Introduction

1.1 Motivation

Any macro or financial system has a set of structural characteristics that contribute to a system's gross risk. These include household sector, corporate sector, financial sector, state sector and external sector resilience. Factors such as leverage, diversification, equity, capitalization and flows have a major impact on systemic risk. Bearing these in mind we need an EWS to detect imbalance or vulnerability at the time of build up or ex-ante to: (i) help reduce boom and bust cycles on a macro-level (an "activist" approach to regulation a la Goodhart et al.); (ii) ensure network absorption of crises rather than amplification (a micro "resilience" approach, Milne et al.). Thus the research question this dissertation addresses is how to design an EWS model / suite of models to inform regulatory oversight and action in OECD countries. This while attempting to outperform earlier literature in lead time, performance output of individual models and introducing a new holistic macroprudential approach to EWS in the form of a traffic lights matrix. In addition, the design and usability by regulators in terms of credibility and effectiveness of the system is observed to ensure the EWS will actually be used to provide insight for and inform policy making.

Previously existing EWS failed to predict the 2007-2010 crisis. This research attributes this partly to dependent variable specification, independent variable specification, model empirical design, and looking at models in isolation (different empirical methodologies and macro and micro applications), rather than holistically. This research also demonstrates that we need a range of dependent variable triggers for which results to be presented consistently to regulators to enable sound decision making. Or in other words, the inherent feedback loops between the choice of the regulator objective and the output of an EWS are relevant in adopting a holistic approach.

1.2 Dependent Variable Innovation

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 near crises or the time of the build-up of financial vulnerabilities. In their book, Crisis Economics, Roubini and Mihm (2010) consistently highlight the linkage between the build up of imbalances, financial fragility and systemic financial crises. They conclude that financial crises would not result in system wide distress in the absence of financial fragility. If financial fragility is a precursor to crisis, then the study of financial fragility or near-crises is a necessary and sufficient condition for the prediction of full-fledged crises, but not vice versa. Near-crises are episodes of fragility and low banking sector capitalization when the financial system has a poor ability to withstand shocks. Gonzalez-Hermosillo (1999) also endorses the view that fragility and low capital adequacy are leading indicators of banking distress, signaling a high likelihood of near-term failure. The cost of crises is prohibitive and earlier detection means policy makers have time to avert or at least minimize crisis cost. As such this research aims to improve on existing literature by focusing the analysis on near-crises, as a proven leading indicator for full-blown crises. In this respect, the dependent variable specification is modified to measure near-crises as opposed to the more commonly used ex-post measures characteristic of previous early warning signals research.

The dependent variable, near-crisis, is measured by capital adequacy and banking sector profitability. Focusing on near-crises means that a lot of data that was not previously utilized in an EWS analysis will now be taken into account.

Dependent Variable Specification

The dependent variable designed to capture changes to 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 capitalization of more than a certain number of basis points (delta capitalization as measured by capital/total assets);

2. Or an increase in its capitalization of more than a certain number of basis points (delta 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.

Commonly used ex-post measures lagged crises occurrence by anywhere from one to several years. These include measures such as identified in Davis and Karim (2003), who specify cost of earlier systemic crises as *direct bailout costs* of failed institutions and *indirect in terms of GDP costs* or opportunity losses in GDP compared to its previous growth trajectory. Caprio and Klingebiel (1996) find bailouts cost on average 10% of GDP, with some crises much more costly like the Mexican Tequila Crisis (1994) which cost 20% of GDP, and the Jamaican crisis (1996) at 37% of GDP. According to the IMF, the crisis of 2007 - 2010 had cumulative (indirect) output losses over 2008-2010 estimated at around 5% of global output (c. USD10.2 trillion), while direct bailout measures by governments have tallied a similar figure. Furthermore, both direct and indirect costs of the past crisis are still being realized on the back of further write-downs by institutions as asset quality and prices deteriorate and GDP growth continues to falter. The following paragraphs discuss some of the causes of the crisis and motivate this research on Early Warning Signals (EWS) given the significant costs of crises and their various other ramifications.

1.3 The role of EWS in the past and their failure to identify the last crisis

With indirect global output loss estimates in excess of USD10 trillion and direct write downs of USD3.4 trillion by agents up to the end of 2010; and more importantly the *structural* changes that have taken place in the global economy, which will unlikely revert to pre-crisis ways, the importance of early warning systems for fragility and crises is self-evident. Crises are an intuitive motivator for research on EWS, examples include the Latin American debt crisis in the 1980s and the Asian financial markets crisis of the late 1990s among many others. The recent crisis identified the need for further research and new approaches as earlier models simply failed to signal the warnings for the 2007-2010 crisis, and this failure could be partly attributed to the dependent variable specification as this research demonstrates. 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 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% respectively for the binary tree model.

The question of how to design empirical models to signal financial crises has been addressed in previous literature in three generations of models: first generation models based on macro weaknesses; second generation models based on self-fulfilling prophecies and herding behavior; and third generation models based on contagion and spillovers. These models initially used two main types of explanatory variables: macroeconomic indicators and microeconomic factors, followed by a number of integrated empirical models that took both types of explanatory variables into account. Models were developed to focus on ‘endogenous’ shocks and ‘exogenous’ shocks and either predicted individual bank failure or looked at systemic banking crises as a whole. The specific methodologies used by these models to predict crises fell 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. One of the major drawbacks of these models was the ex-post crisis definition for the dependent variable, as opposed to a near-crisis definition.

1.4 Research and key contribution

The failure of EWS models to predict the past crisis highlights several of their weaknesses in terms of: i) static model design, which is only valid in hindsight to the historical crisis period to which these models were calibrated; ii) dependent variable specification which identifies a crisis in terms of the cost of dealing with it and in turn lags its occurrence by one to several years; iii) explanatory variable choice which is dictated by the historical crisis period to which these models were calibrated; iv) poor model performance out-of-sample because of the static model design, the dependent variable specification, the choice of explanatory variables and explanatory variable specifications.

The key contributions of this research improve on all weaknesses listed above as follows: i) a dynamic model design ensures that explanatory variables witnessing movements are the ones that ‘talk’ while others are ‘silent’, this way the model is relevant and usable for different crises and different time periods; ii) use of near crises as the dependent variable rather than a measure of ex-post damage, improves lead time by the duration it takes for losses to materialize and be quantified from the date a vulnerability develops, i.e. by one to three years at least; iii) use of near crises as the dependent variable also allows for a cleaner model as the explanatory variables are now predicting system vulnerability. While vulnerability may or may not develop into a full-fledged crisis in the absence of shocks, this design ensures no crisis will go undetected because the model is picking up on vulnerabilities or episodes of financial fragility – a precursor to crises; iv) choice of explanatory variables is based on an iterative process using this dynamic model design and as such ensures that the ones that remain in the robust final model are effective, predict vulnerabilities with sufficient lead time; v) by improving on design, dependent variable specification and explanatory variable calibration and choice, model performance out-of-sample improves substantially on earlier literature. In this research, the model is applied to OECD countries, but it could be also easily mapped to other geographic or geopolitical economic groupings. In summary, as the model improves on crisis definitions (dependent variable specification); explanatory variables choice, design and specification; methodology design, out-of-sample performance and lead-time of crisis signals, it is a credible and usable by alternative by policy makers for the prediction of systemic near-crises or fragility.

Finally, vi) Different models invariably have different output in some aspects and strengths and weaknesses. Signal extraction performed best in terms of Type I errors, the Logit model in terms of NTSR and the Z-score model in terms of Type II errors. The overlay of the micro model improves the traffic lights matrix substantially. These findings reinforce the need by regulators to use a suite of models and a holistic macroprudential approach in judging the build up of systemic vulnerabilities.

The structure of the dissertation is as follows:

Chapter Two provides an overview of the financial crisis of 2007 – 2010 and the motivation for this research on EWS and Chapter Three provides a detailed literature review for four distinct methodologies used in EWS models. This includes a history of financial crises in OECD countries over the past 30 years.

Chapter Four is a signal extraction application and forecast model for 30 OECD countries; Chapter Five is Macro-Applications of Near Crises in OECD countries, this includes a Logit/Probit application and a Z-Score (Merton type) application; Chapter Six is a micro-application to a set of 139 OECD banks in 11 OECD countries and it also presents some proposed rating implications based on this analysis.

Chapter Seven covers conclusions and policy implications. It synthesizes all the findings and gives an overview of Basle III and the proposed changes to existing regulation, macroprudential regulation tools and the use of EWS to guide their application. This chapter also discusses policy implications and recommendations drawn from the findings of this research for individual country regulators, OECD regulators, and other regulators in regional groupings that have different conditions.

2. Chapter Two: An Overview of the Financial Crisis of 2007 - 2010

2.1 Global financial sector structure pre-crisis and systemic hot spots

With a low interest rate environment for almost a decade, two main changes in financial player business models took place: a) a continuous search for yield and b) significant build-up of leverage, predominantly in unregulated shadow banking and opaque Over-the-Counter (OTC) derivatives markets. The notional outstanding amount of derivatives was more than 10 times the global GDP in 2008. Securitization grew to represent a larger portion in bank wholesale funding and credit extension, capturing a little under a third of outstanding credit in the US, mostly linked to the housing sector. Europe, in contrast, relied on securitization to a limited extent (6% of total outstanding credit), but held a disproportionate share of risk, owning more than 72% of Asset Backed Commercial Paper (ABCP) committed facilities globally. As the crisis unraveled, global banking sector capitalization collapsed to almost a third of what it was pre-crisis to USD2.6 trillion in March 2009.

The structural changes delineated in the previous paragraph led to the development of asset price bubbles, in both the housing and equity markets and to credit bubbles in the plain vanilla banking market and in the shadow banking system as illustrated. Poor governance, lack of credit risk transfer and poor funding structures also exacerbated the fragilities.

2.2 Non-Bank Financial Institutions: Insurance companies

Insurance companies heavily involved in the securitization market through the provision of credit enhancement (specifically in the US market which is comprised of 60% non-life activities versus only 40% of insurance activities related to life) guaranteed some USD2.4 trillion in asset-backed securities. When this market sub-segment began to collapse, a number of these companies lost their Triple-A status while insurance giant AIG had to be bailed out by the US government after booking losses to the tune of USD100 billion in 2008.

2.3 Other Non-bank financial institutions

Pension fund assets sustained estimated losses of USD3.2 trillion (out of USD25 trillion estimated total assets), while the USD2.0 trillion hedge fund industry saw 62 funds collapse. Data on private equity activity showed deals in the first half of 2009 falling to almost a quarter of what they were in the same period in 2008. Fannie Mae and Freddie Mac, US Government Sponsored Enterprises (GSEs), exposed to USD5.3 trillion of mortgage-related iNTSRuments, were taken over by the US government in September 2008. Structured Investment Vehicles (SIVs), a type of off-balance sheet special purpose entity (SPE) used by banks to raise cheap capital in the short-term money markets and seek yields in an opaque, unregulated manner, collectively held assets of USD300 billion at the beginning of 2007, of which less than USD50 billion was equity financed, and the majority were sponsored by US banks. Theoretically without recourse to their sponsors, these ended up being subsumed or fully merged with their sponsors as the crisis unraveled.

2.4 Roll-out of Basle II

Institutions adopting the new accord and the implementation of the various pillars meant that bigger banks with more sophisticated risk management systems and greater risk exposures ended up holding less capital. While the implementation of Pillar II supervisory tools to correct for that and level the playing field lagged considerably.

2.5 Governance issues

Governance issues specifically related to the US securitization market were that No-Income-No-Job (NINJA) loans, Adjusted Rate Mortgages (ARMs) and liar loans where borrowers self-certify their own submitted information sold at very low teaser rates. When the rates adjusted on the mortgages, linked to a Fed fund rate which was beginning to rise, these mortgages became unaffordable. Furthermore, the originate-and-distribute model failed on the back of poor incentives, mortgage brokers off-loaded mortgages to other financial sector players, they were compensated on the basis of volume rather than quality and had no link to a mortgage once it was off-loaded. Thus, the link between originating a mortgage and its sale to a financial institution was severed. The financial institution which then acquired these mortgages, pooled them into similar risk categories, based on data which was self-verified especially with later vintages where underwriting standards were lax, and then repackaged and sold it to the market (distributed the risk). However, at this level, the link again between acting as a distributor for a pool and bearing any associated losses should the pool perform worse than what it had been priced on the basis of, was also severed. Save for any portion retained by the distributing financial institution, it had no further liability for any losses.

2.6 No credit-risk transfer

There was no credit-risk transfer, neither between different market players (banks, insurance companies and investors), nor to vehicles set up by their sponsors. Banks were forced to take back around 95% of their own sponsored SIV assets, and held on-balance sheet pre-crisis around 40% of other SIVs of which they were not sponsors.

2.7 Weak capitalization, excessive leverage and skewed funding structures

Weak capitalization and excessive leverage are major culprits in increasing bank fragility. A decomposition analysis of US, Eurozone and UK banks return on equity (Saleh, 2010) - using on-balance sheet data from Bankscope - in 1996 and 2007 shows that the increase in banking sector return on equity (RoE) over the period was predominantly a pure leverage play, where ROE = return on assets (RoA) x leverage. Had this increase in leverage not taken place, banking return on equity would have been much lower due to increased competition and smaller spreads. This is especially true for the UK, which saw leverage increase from 18 times in 1996 to 28 times in 2007.

Saleh (2010) shows that as leverage normalizes to pre-crisis levels, and assuming pre-crisis levels to be 25 times, this would point to normalized post-crisis RoEs of around 14% across Europe, 12.1% for the US and 16.6% for the UK respectively. If more aggressive deleveraging is assumed to only 10 times, RoEs would fall to 6.6% in the US, 5.4% in Europe and 4.8% in the UK. This shows that the shift in the banking industry is structural, with real impact on business models, and not a transitory shock after which we will return to pre-crisis norms. Moreover, this simulation does not take into account increased regulatory burdens, whether in the form of systemic taxes or others. With lower profitability, it will take longer to build capital buffers. Basle III and ring fencing requirements in the UK will have a significant cost for institutions in terms of compliance and building the adequate systems to support its implementation. Cross subsidization of cost of capital across businesses will now also not be possible.

As shown in Saleh (2010), the funding structure of banks over the same period reflected some core shifts, while deposits and short-term funding continued to constitute a stable percentage of around two thirds of total balance sheet funding. The proportion of wholesale funding as a percentage of total deposits and short-term funding showed a massive shift, rising from 24% in the US in 1996, 7% in Europe and 29% in the UK to 40% and 19% in the US and Europe respectively in 2007 and a sizable 84% in the UK.

2.8 Global imbalances: systemic significance of the US

The reason the crisis was not a localized US event is the systemic significance of the US. In global equity capital markets in 2008, it represented 20% of total global equity market capitalization of USD59.8 trillion, in global market share of securitizations, greater than 50%, and in banking sector capitalization (12% pre-crisis, 14% post-crisis). In terms of global insurance industry share, the US represented around a third of total premiums. Finally, share of non-bank financial institutions and SIVs activities in the financial markets and money market funding as a percentage of total deposits and short-term funding showed the US having 40% of the total capitalization of these markets. This sheds light on why and how the spillovers were transmitted and were of this magnitude.

2.9 Systemic and institutional crisis cost

Davis and Karim (2003) identify cost of systemic crises as both direct bailouts cost and indirect in terms of GDP costs. Caprio and Klingebiel (1996) find bailouts cost on average 10% of GDP, with some crises much more costly like the Mexican Tequila Crisis (1994) which cost 20% of GDP and the Jamaican crisis (1996) which had a toll equivalent to 37% of GDP. According to an update from the IMF, world growth is projected to fall to a mere 0.5% percent, the lowest rate since World War II, with significant financial strains remaining acute. Cumulative (indirect) output losses over 2008-10 are projected at around 5% of global output (USD10.2 trillion if we apply the rate to IMF global output estimates). Direct measures by governments up to 2010 were estimated at around USD10 trillion or more. While, the IMF's total estimate of direct losses in the form of write-downs was revised significantly upwards in April 2009 to USD4.0 trillion (from USD1.45 trillion in April 2008 and USD945 million in January 2008) and down again in October 2009 to USD3.4 trillion. Actual losses globally realized up to first half of 2010 by financial institutions amounted to USD1.9 trillion (compared USD760 billion in September 2008, of which USD580 billion were by banks). Thus, in total the last crisis cost around a hefty 40% of global GDP in 2010.

Demirgüç-Kunt and Detragiache (2005) identify the impact of banking crises with respect to the real economy in the form of a credit crunch hypothesis where markets are starved for credit following a crisis resulting in output losses. This has found strong empirical support in Lindgren et al (1996), Kaminsky and Reinhart (1999) and Eichengreen and Rose (1998). They find that more financially dependent sectors lose about 1% of growth in each crisis year compared to less financially dependent sectors. A study by Demirgüç-Kunt, Detragiache and Gupta (2000) finds that growth of both deposits and credit slows down substantially and banks reallocate their asset portfolio away from loans. This seems to be applicable to the current crisis. Thus, both theory and empirical findings indicate that in times of financial stress, banks prefer cash instruments and reserves to traditional extension of credit and other products to the market. The sharp drop in the ratio of interbank lending to total bank reserves in the US and the drastic fall in loan multiplier (loans divided by bank reserves) over January 1999-May 2009 are evidence of this.

2.10 Asset Price Bubbles: Real Estate

There are three key indicator sets of house price evolution: house price appreciation year on year, house prices to disposable income ratio and house prices to rent ratio. Using 1992 as the base year with an index value of 100, there are a few OECD countries which have seen drops in house prices in real and nominal terms: Japan, Germany, Switzerland and Korea, the latter saw a drop only in real terms but not in nominal terms. At the other end of the spectrum Ireland for example has seen the largest increase in real estate prices, at 436% in nominal terms and 233% in real terms. There's a clear link here to the real estate-related non-performing loans in Ireland with lending to developers capturing two thirds of GNP, usually without collateral.

Based on this simple index, economies which saw house prices rise by more than 200% very well may have experienced a bubble. These include Australia, the UK, Denmark, New Zealand, Spain, Norway, the Netherlands and Ireland.

2.11 Regulatory regimes and response to the crisis

This crisis has triggered much debate as to which regulatory regimes were the most effective: how they dealt with past crises, what actions were taken, the set of policy tools and the impact of these on losses realized and on the speed of crisis unraveling and its resolution. Preliminary empirical results by Nier (2009) classify the losses associated with each main type of regulatory regime - single-integrated regulator (SIR) versus twin peaks (TP) - in Europe. He finds greater losses associated with the SIR model. The single-integrated regulator model has one regulator overseeing market regulation (commercial banks, mutual funds and pension funds and insurance companies) and the central bank overseeing lender of last resort (LOLR) activities and payments oversight. Examples of SIR-type models are the UK (before 2011), Denmark, Norway, Sweden and Switzerland among others. TP models have the central bank overseeing systemic risk, including LOLR and payment systems and all potentially systemic institutions and another regulatory body handling regulation of financial services. Examples of TP type systems include the UK (after 2011), Netherlands, Bulgaria and South Africa, France, Italy, Portugal and Spain. According to Nier (2009), SIRs have on average lost the equivalent of 3% of total outstanding credit, compared to TP systems, which lost only 0.5%. In terms of value, SIRs collectively lost USD126.4 billion and TPs USD39.6 billion.

Regulatory policy response to the crisis has been far reaching, from direct intervention in the financial sector through capital injections, purchase of assets, central bank provision of liquidity and guarantees, in addition to traditional coordinated monetary action and fiscal stimulus and measures which have not been used in recent history such as quantitative easing. For the latter, the Federal Reserve had announced in March 2009 some USD1.2 trillion for quantitative easing, while the Bank of England had initially announced an outlay of GBP75 billion, which was later raised to GBP175 billion and to GBP275 billion in October 2011. The measures listed have collectively ranged from less than 1% of GDP to almost 20% in the UK. Central bank balance sheets in the US, the UK and Europe ballooned, exhibiting growth of around 250%, 220% and a third on the low-end as of 2010, respectively.

2.12 Fiscal overhang as a consequence of necessary policy action

The IMF estimates fiscal stimulus in G-20 countries in 2009 to be around 1.5% of GDP, while overall fiscal balance in advanced economies was estimated to have deteriorated by 3.25% to -7% percent of GDP in 2009. The US has announced a stimulus package to the tune of 2% of GDP in 2009 and for a total of 4.6% until 2011 (or USD787 billion).

The increase in government debt is forecast to have significant crowding-out effects: for every 10% of increase in government debt, global GDP is forecast to drop by 1.3% (1.2% in the US). Furthermore, fiscal deterioration in advanced economies poses an additional threat to future global growth, as these very same nations have to deal with the effects of a rapidly ageing population and the consequences on pension funding deficits, among others. The first nation to show serious threats to its fiscal position was Greece in October 2009 which has a forecast public debt of GDP for 2010 of 120%, with concerns about the fiscal stability of Portugal (90% of GDP), Spain (68% of GDP) and Italy (130% of GDP). Thus far the IMF has pledged USD1.1 trillion to help developing countries weather the crisis, while a European Financial Stability Fund (EFSF) has been set up by Eurozone countries with an initial capitalization of Euro 500 billion.

2.13 Regulatory challenges, proposed changes and critique

The IMF identified a set of upcoming policy challenges ahead that will need to be addressed. These include policies to a) secure a backdrop for economic recovery, b) strengthen the banking sector and promote resumption of lending, c) revive securitization markets, d) prevent crises in emerging markets in Europe which remain vulnerable to deleveraging, e) ensure orderly disengagement or exit strategies for regulators, and f) manage the recent transfer of private risks to sovereign balance sheets. It proposes the following priorities for reform: a) restoring market discipline; b) addressing fiscal risks caused by financial institutions (the idea of a 'systemic tax'); c) living wills; d) a macroprudential approach to policy making; e) integrating the oversight of Large and Complex Financial Institutions (LCFIs) into the global financial market. However, the road map for regulation in the near term is challenging due to a number of reasons, most important of which is that banking sectors and indeed individual institutions are too big to fail. A snapshot of the current size of the banking sectors in a number of countries and indeed the size of selected banks relative to the GDP of their host countries shows bank assets to GDP range from a high of more than 800% in Switzerland, more than 400% in the UK, to a low of 100% in the US (excluding Fannie Mae and Freddie Mac and other key quasi banking players, this ratio however goes up to 230% of these are included).

2.14 Selected proposed regulatory changes

The Basle Committee on Banking Supervision (BCBS) and the International Association of Deposit Insurers (IADI) proposed changes to restore the level and quality of bank capital in 2009. These are summarized in the following: a) higher (and better quality) risk-weighted capital requirements, b) countercyclical credit loss provisioning, c) formal liquidity and leverage ratios, d) mandatory capital insurance or contingent capital, e) convertible capital, f) subordinated debt issuance frequency, g) prefunding of deposit insurance, and h) capital charges linked to systemic risk.

A number of 'super' or 'uber' regulators were also set up in 2009, including the European Systemic Risk Board (ESRB) to oversee systemic risk at a European level, while in the US these powers were delegated to the Federal Reserve. The mandate of the ESRB is the macroprudential oversight of the financial system within the European Union. The ESRB aims to prevent and mitigate systemic risks within the European financial system in order to prevent financial distress in the European Union. It is also charged with issuing risk warnings, giving recommendations on measures and follow-up on implementation.

2.15 Macroprudential analysis and early warning systems for fragility and crises

The De Larosière Report recommended that a global EWS needs to be put in place, with all the regulatory implications thereof on a national and cross-border level. This research shows that this EWS must be guided in design by a meta-theory that takes into account: procyclicality and boundary problems playing on the national and cross-border levels; the trade-off of various regulator objectives; the need for both macroprudential and microprudential analysis and the interaction between them; some degree of built-in countercyclicality as in the Spanish model; and strengthening risk-based supervision by enabling national and cross-border regulators to reduce systemic net risk.

This research also shows that the EWS has to be effective, not just the coNTSRuct of a large magnitude and political weight. Its effectiveness must be continuously challenged, covering a basic checklist of minimum requirements needed for a robust EWS. These include: pre-crisis sanctions on undercapitalized institutions, that it be usable by policy makers and effective in identifying stress indicators with sufficient lead time; that it is credible and simple enough to be understood by policy makers at all levels.

Each crisis will unravel differently, but could have similarities to previous crises, will have different triggers or similar ones to its predecessors. As such the best way to prevent a crisis is to ensure that the ‘system’ is as healthy as possible by attacking imbalances before they accumulate, and recognizing that you cannot predict crises with certainty or their timing. A suite of models will only help capture imbalance build-up and as such is necessary as a starting point, however it is nowhere near sufficient and must be approached as just one of a set of decision packages to be used.

3. Chapter Three: Literature Review

3.1 Introduction on Crises Literature

The design of empirical models to signal financial crises on a systemic level and bank failure on an individual institution level has been addressed in the past mainly over three generations of models. First generation models based on macro weaknesses; second generation models based on self-fulfilling prophecies and herding behavior; and third generation type models based on contagion and spillovers, triggered by boom-bust cycles. Another strand of research, is classified as fourth generation models, they aim to identify the features of the institutional environment that set the stage for the build-up of macroeconomic imbalances, which in turn led to banking problems. These models initially used two main types of explanatory variables: macroeconomic indicators as key explanatory variables and microeconomic factors, followed by a number of integrated empirical models which took both types of explanatory variables into account. Models were developed to focus on ‘endogenous’ type shocks and ‘exogenous’ type shocks and either predicted individual bank failure, with applications on bank ratings, or looked at systemic banking crises as a whole. The specific methodologies used by these models to predict crises fell 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. One of the major drawbacks of these models was the ex-post crisis definition for the dependent variable, as opposed to a near-crisis definition in the case of a systemic crisis or in the case of an individual bank, bank failure as opposed to a ‘close-to-failure’ metric.

3.2. Signal Extraction

3.2.1 Overview

The signals approach was originally developed by Kaminsky and Reinhart (1999), focusing on ‘twin crises’ phenomenon, simultaneous occurrence of currency and banking crises. A wide body of literature has utilized signals models for predicting exchange rate crises on the basis of inconsistent macro policies or the development of macro weaknesses (first generation models) and has developed further to second generation models where speculative attacks with self-fulfilling prophecies or herding behavior both playing a large role in causing crises. A third generation of models of external crisis using the signaling approach were developed by Krugman (1999), Bris and Koskinen (2000) and Cabellero and Krishnamurthy (2000) based on the notion of 'contagion' where the occurrence of a crisis in one country or region increases the likelihood of a similar crisis elsewhere. As illustrated by Masson (1998), three related contagion channels can be identified to represent this paradigm: 'monsoonal trade effects', 'spill over effects' and 'pure contagion effects'. Sachs, Tornell and Velasco (1996) explore a methodology for analyzing crises that focuses on the depth rather than the likelihood of the crisis using a crisis index, which in approach is similar to signal extraction, but to 'predict' or evaluate crisis 'depth', rather than its 'occurrence'.

Kaminsky and Reinhart (1999) documented the incidence of both currency and banking and twin crises 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). 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, as such the impact of exchange rate on banking crises may have been overemphasized. They describe the behavior of fifteen macroeconomic variables 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 NTSR); 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.

Cihak and Shaeck (2007), apply a logit model, a duration model and non-parametric tests akin to signal extraction to a dataset of 2,600 banks in more than 100 countries over the period from 1994-2004. Similar to signal extraction, non-parametric tests do not impose distributional assumptions upon the data and as such inferences from them are considered to be more robust. They find that capital adequacy, return on equity, Non-Performing Loans (NPLs) to Gross loans and more importantly NPLS net of provisions to capital are useful signaling indicators of individual bank fragility or of a bank being 'close-to-failure'. They use static thresholds for the indicators and find that for the ratio of NPLS net of provisions to capital, more than 66% of all failures are called correctly (Type I error of 34%) at a low static threshold cut-off for this variable of 10%.

Lo Duca and Peltonen (2012) cover a set of 28 emerging market and advanced economies with quarterly data between 1990 Q1 and 2009 Q4, developing a framework for assessing systemic risks and for predicting systemic events. They use a financial stress index for identifying the starting date of systemic financial crises and combine both domestic and global indicators of macro-financial vulnerabilities to predict crises. The paper shows that combining indicators of domestic and global macro-financial vulnerabilities substantially improves the models' ability to forecast systemic financial crises with good out-of-sample performance.

3.2.2. Innovation and Contribution to Model Design

The structure of the signal extraction model as explained above shows that: a) static thresholds for each variable were chosen; and b) these static thresholds were determined on the basis of minimizing Type I and Type II errors in-sample, minimizing the NTSR (which itself is another way of summarizing a trade-off between Type I and Type II errors) and in some cases assessing the probability of a crisis conditional a signal being issued. This research improves on these two points substantially. For the choice of variable thresholds: these are no longer static, but rather dynamic in the form of standard deviations from a chosen metric (this is somewhat similar to Borio and Drehmann (2009) who use gap analysis from a long term trend but for only two variables), which in this case has been chosen as a long-run mean for a variable. 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 does not only improve on out-of-sample performance, but also is usable in different time periods and different states of the world. One of the problems with earlier models is that repeated exercises with different data periods always resulted in different performance of indicator variables for crises because causes for crises change over time and because the thresholds chosen for each variable to signal a crisis are by default linked to whichever data period the model was calibrated to. Furthermore, for the choice of variables itself, each data period seemed to dictate a different set of variables, because their performance in-sample showed they were significant in predicting crises for that specific data period studied. The design of the 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. Finally, the design of the model to signal crises, means that a lot of data on near-crises was not utilized in the analysis – something which this model also improves upon by the innovative dependent variable specification. Table 3.1 further illustrates these points by highlighting some of the major studies and their findings.

For example, taking the choice of explanatory variables, Table 3.1 shows that across the different time periods and countries studied the indicator variables chosen vary significantly over time and between country groupings. This is also true for looking at the causes of financial crises in general and individual bank distress in specific. This is attributable to the static set up of the models. By using a dynamic set-up, this would ensure the continuity in use of variables and the ability to add new variables as they become systemically significant and more importantly the changing states of the economy would not render the model invalid.

An illustration of the changes between different studies of the variables identified as significant to predicting crises because of model design is shown as an example by Kaminsky and Reinhart (1998) finding 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. While, 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. On an individual bank level, Cihak and Shaeck (2007), find capital adequacy, the level of NPLs to gross loans, NPLs net of provisions to capital and RoE to be significant variables in predicting failure.

Note however, if these studies had been calibrated to predict near-crises, and also in a dynamic framework as proposed by the signals extraction model in this research, the divergence in explanatory variables and their significance across different data periods and countries would not have been as pronounced and the model would have been temporally consistent (across different time periods) and geographically consistent (in that only relevant variables would 'talk' for each country as they would be the ones which saw deviations from a long run mean, whereas non-relevant factors would be silent). More importantly this research integrates macro and aggregated micro variables on a system level, whereas previous research mainly focused on either one set or the other.

Table 3.1: Signal Extraction Selected Papers

Authors	Year	Data	Factors and Main Findings
Kaminsky and Reinhart (Systemic Crises)	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 27%-21% of the observations during the 24 months preceding the crisis for twin crises and 12 months for banking crises.
Alessi and Detken (Systemic Crises)	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 (Systemic Crises)	2009	1980-2003 and test out of sample 2004 – 2008	Test the behavior 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.
Cihak and Shaeck (Individual Banks)	2007	1994 – 2004, 2,600 banks in more than 100 countries (with 51 banking crises episodes during)	Find capital adequacy, return on equity, NPLs to Gross Loans, NPLs net of provisions to capital useful in signaling problems in individual banks. NPLs net of provisions correctly calls failure 66% of the time.

Sources: As listed above.

3.2.3 Disadvantages of the Signals Approach

Disadvantages of the signals approach include that it only considers each variable in isolation and there is no clear methodology for aggregating the information provided by each indicator on a stand-alone basis. Another disadvantage is that the model does not provide a platform to address conflicting signals, i.e. one indicator signaling a crisis and others not. Furthermore, the model in the static set up focuses only on whether a threshold has been crossed or not, and ignores other useful information content in assessing fragility which might be in the data. Also, as such, the model is backward looking. To address some of the disadvantages of the signals approach, Kaminsky (1999) develops a composite index, constructed as the number of indicators that cross the threshold at any given time. Alternatively, also a weighted variant could be used where each indicator is weighted by its signal-to-noise ratio (the percentage of correct signals issued to the percentage of false signals, this contrasts to the NTSR defined earlier).

Borio and Drehmann (2009), also 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% (Type I error of 23%) with a lead time of 3 years, while out-of-sample performance falls to hover around 60% (Type I error of 40%), 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% (Type I error of 70%). This could be an indication 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.

On an individual bank level, Cihak and Shaeck (2007) look at each explanatory variable independently, however they try to funnel the variables by their effectiveness in signaling failure and conclude with a small number of variables useful in predicting individual bank failure.

3.2.4 Innovation and contribution in addressing the disadvantages of previous models as listed above

As the signals extraction model in this research is calibrated to predict near-crises, it does capture all the necessary information in fragility build-up. Also, while each variable under the new model design proposed is still considered independently, the use of a dynamic threshold ensures that only a relevant variable to crisis prediction is taken into account when looking at which variables forecast a near-crisis. This is because any variable which has not changed significantly as per the defined objective function of the model, will not trigger a signal by default and therefore the variables which do, are relevant - only the contributors to near-crises will issue signals, or talk while other variables will be silent or not issue any signals. Also, another disadvantage of signal extraction models in earlier literature was that a static model throws away a lot of information content on fragility which might be in the data, a dynamic model, focusing on near-crises, ensures that this information is taken into account because all comparisons are relative to a chosen benchmark of change. Furthermore, one other disadvantage of earlier design models are that they are backward looking, calibrated on historical data and thresholds determined on the basis of the critical levels of these variables in the past. By using a dynamic design, this ensures that the model is forward looking because it is calibrated to signal crises based on future changes to a chosen benchmark ex-ante not a static level chosen ex-poste.

Also, the use of weighted indices of signal indicators, while it did address some of the problems with static, backward looking benchmarks, is not sufficient to make them forward looking, on the contrary, what they did is in effect improve the fit of the signal extraction model to the data period studied (signal extraction model criticisms include this particular issue of over-fitting to a certain data period). By using a dynamic model, this criticism is not applicable and it still does not prevent a regulator from assigning different weights to variables at a later stage based on their expertise and/or objective function, but they will be doing it again on a dynamic basis, because they are choosing a weight for a degree of variability of a variable, not a static threshold. Another major problem with models in the past and indeed as severely highlighted by the last financial crisis is their blind use and lack of understanding of their limitations. By leaving room for regulator input on variables and focusing on near-crises, this forces regulators to look at the variables in a more dynamic manner and ensures the incorporation of a qualitative human element, which does not preclude also weightings being determined by other models used in other parts of the regulatory function (eg. Output of models used by different departments within the Bank of England for example, could be used as an input to an EWS, and similarly within other institutions to ensure maximum utilization of available resources and expertise across departments).

Finally, as previous research focused on either macro variables or micro variables, while very few studies have been conducted using an integrated approach, this research provides a significant improvement in the use of macro and aggregated micro variables in its design.

3.3. Logit/Probit Models

3.3.1Overview

Logit models use a logistic specification and enable the study of covariates of banking crises, developed by Demirgüç-Kunt and Detragiache (1998). In this paper, Demirgüç-Kunt and Detragiache use a large sample (45 to 65 variables based on the specification of the regression) of developing and developed countries during 1980-1994 and find that crises tend to erupt when the macroeconomic environment is weak, especially when growth is low and inflation is high. Also high real interest rates and vulnerability to balance of payments crises plays a role. They also find that countries with an explicit deposit insurance scheme and with weak law enforcement were also particularly at risk.

This approach assumes that the probability that a crisis occurs is a function of a vector of explanatory variables and its output, although in the form of a probability, is transformed into binary mode through a decision rule. Either a country is experiencing a crisis or not (determined by what threshold probability is given in the decision rule to label a country as having a crisis). Another variant by the same authors uses the forecast probabilities under two frameworks:

Framework 1: the regulator wants to know whether there is enough fragility to take action. The forecast probability of a crisis is used to determine the optimal trade-off between taking action when there is no crisis against the costs of doing nothing when there is a real crisis.

Framework 2: the regulator wants to simply rate the fragility of the banking system, depending on the rating, different courses of action may follow. This emphasizes one of the main advantages of the Logit model, that its non-linear and incorporates several variables simultaneously, granting flexibility in output evaluation as compared to other models.

When the authors apply the monitoring frameworks to six crisis episodes in Jamaica, Indonesia, Korea, Malaysia, Philippines and Thailand - the results are mixed, however. This highlights one of the main weaknesses of existing econometric analysis tools of systemic banking crises in having limited success in out-of-sample prediction accuracy. This could be partly due to the fact that coefficients derived from in-sample estimation are of limited use outside sample and that new crises are different from past crises. Another limitation is also that banking crises are rare events, so in-sample estimates are based on relatively few data points.

Probit models are used to estimate the contribution that each explanatory variable makes to the probability that financial distress/failure will occur. Another variant, discriminant Analysis techniques allow for the identification of those explanatory variables which signal the presence of financial failure with the highest probability. These were used by Worrell, Cherebin and Polius-Mounsey (2001) and by Polius and Sahely (2003).

Mulder, Perrelli and Rocha (2002), using a Probit model, test balance sheet explanations of external crises in emerging markets and the role of standards in these crises with the main findings that corporate sector balance sheets have a very significant impact on both the likelihood and depth of crisis caused by external shocks. The authors use a set of indicators which they call the Lawson Indicators (named after the former UK Chancellor of the Exchequer) covering: corporate balance sheet indicators (degree of financial leverage, maturity structure of debt financing, availability of liquidity, profitability and cash flow of a company); macroeconomic balance sheet and institutional indicators (extent of foreign currency financing by corporates and revenues) and legal indicators (creditor rights, shareholder rights, the ability to enforce contracts, accounting standards, and the origin of the legal regime). They use a parametric probit model to which they add the Lawson indicators. They find that using their indicator set in addition to the macroeconomic variables results in a much higher degree of accuracy, calling on average more than 80% of the crisis in-sample (Type I error of 20%, compared to 30% on average to Kaminsky and Reinhart 2005 for example), however with a high degree of false alarms ranging from around 30% to over 50% for different cut-off probabilities (30% false alarms for the higher probability threshold of 50% and 50% false alarms for the lower probability threshold of 25%, respectively).

Cihak and Shaeck (2007), apply a logit model to a dataset of 2,600 banks in more than 100 countries over the period from 1994-2004. They find that several bank ratios are useful signaling indicators of individual bank fragility or of a bank being close-to-failure, especially return on equity, and selected macro indicators in line with previous literature, such as credit to the private sector, credit growth, the ratio of M2 to international reserves (to capture the impact of capital flows) are also very useful. Their results show a Type I error of between 11% to 27% across four different specifications of the model, while Type II errors range between a low of 41% to a high of 61% in some specifications.

Pogyhosyan and Cihak (2009), use a logit model based on a database of individual bank distress across the EU-25 countries from 1996 to 2008, covering 5,708 banks, and identify a set of indicators and thresholds to differentiate between sound banks and banks which are vulnerable or close-to-failure, which they call banks at risk. They identify 79 distress events for 54 banks. In this study the determinants of bank distress are based on CAMELs, with the key explanatory variables of each category being capital adequacy, asset quality, cost-to-income ratio and return on equity plus a liquidity indicator, in addition to a market discipline variable and a contagion dummy. They find all variables to be significant, with the exception of managerial quality and liquidity. The model used has strong predictive ability with a pseudo R2 for the base case of 48.5%. For a 10% cut-off probability, the model had a Type I error of 44% and a negligible Type II error, (less than 0.1%).

Bussiere (2013), in an application to currency crises in 27 countries over a 7 year period, uses a dynamic logit model to identify how early in advance each explanatory variable sends a warning signal. He finds some indicators to signal a crisis in the very short run while others signal a crisis at more distant horizons. He also shows that state dependence matters, albeit mostly in the short run. The results have important implications for crisis prevention in terms of the timeliness and usefulness of the envisaged policy response. The results presented have important policy implications. First, state dependence suggests that vigilance must not decrease after a first crisis has happened as it may be followed by another crisis soon after. It suggests also that the true cost of a crisis may be underestimated, because letting a crisis happens increases the probability that a future crisis happens too. The second policy implication stems from the results obtained with a more flexible lags structure than previously estimated in the literature: some indicators signal crises in the very short run, which calls for a particularly quick policy response. This is the case of the short-term debt to reserves liquidity ratio and of financial contagion. This calls for heightened vigilance for policy makers when such variables are on the rise.

3.3.2 Innovation and Contribution to Model Design

As is the case with Signal Extraction, Logit models have failed in reliably calling crises in the past and thus motivate new research in the subject. The main challenges are similar to the signal extraction application: firstly we need to identify a crisis or a banking failure at a pre-crisis time, namely the build-up of imbalances or financial fragility. Secondly, the EWS has to be effective in identifying the stress indicators with sufficient lead time and be credible and usable by policy makers. The Logit application herein improves on: crisis definitions (dependent variable specification); explanatory variables choice and design; methodology, out-of-sample performance and lead time of crisis signals. The main difference is that for the Logit model, the output is a probability of a crisis occurring, and hence it is possible to map this on to a spectrum where episodes are labeled in terms of their degree of severity as a) vulnerability spots; b) near crises; and c) full-fledged crises in contrast to the signals approach where the output is a binary indicator.

The key innovation in dependent variable design in the Logit application uses the same adapted crisis definition as for the signal extraction application, where each country is identified as having a 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 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 definition would by default lead to a longer lead period for spotting imbalances and/or fragility build-up.

The structure of the Logit model as explained above shows that variable selection was determined by its impact on overall Logit model performance. This research improves on this point by having the variable universe drawn from the signal extraction universe and funneling this to the variables which are meaningful in the Logit application. By shifting the analysis to focus on variables already proven to have an impact on crises in a dynamic rather than static set up, we avoid the static threshold problem of previous Logit specifications. This means that the model design as such should not only improve on out-of-sample performance, but would also be usable in different time periods and different states of the world. One of the problems with earlier models is that repeated exercises with different data periods always resulted in different performance of indicator variables for crises because causes for crises change over time and because the thresholds chosen for each variable to signal a crisis are by default linked to whichever data period the model was calibrated to.

Furthermore, for the choice of variables itself, each data period seemed to dictate a different set of variables, because their performance in-sample showed they were significant in predicting crises for that specific data period studied. The design of the model to funnel only variables from a universe based on 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. Finally, the design of the model to signal crises, means that a lot of data on near-crises was not utilized in the analysis – something which this model also improves upon by the innovative dependent variable specification. Table 3.2 further illustrates these points by highlighting some of the major studies and their findings.

For example, taking the choice of explanatory variables, Table 3.2 shows that across the different time periods and countries studied the indicator variables chosen vary significantly over time and between country groupings. This is attributable to the static way of choosing variables into the model. By using a dynamic set-up, this would ensure the continuity in use of variables and the ability to add new variables as they become systemically significant and more importantly the changing states of the economy would not render the model invalid. An illustration of the changes between different studies of the variables identified as significant to predicting crises because of model design is shown as an example by Demirgüç-Kunt and Detragiache (1998, 2005) finding that real GDP, real interest rates, budget deficit, private credit to GDP and GDP/capita as significant variables in predicting crises, while Eichengreen and Rose (1998) overlap in two variables, but also find short term debt to be a significant indicator. Eichengreen and Arteta (2000) find another set of significant variables in predicting crises are rapid domestic credit growth, large bank liabilities relative to reserves, and deposit rate decontrol, despite having a high data period overlap with DandD (1998). Finally, Cihak and Shaeck (2007) and Pogyhosyan and Cihak (2009), find CAMELs based indicators, especially relating to capital adequacy, asset quality and return on equity to be significant explanatory variables, without any overlap with the aforementioned studies.

Table 3.2: Logit Selected Papers

Authors	Model Used	Year	Data	Factors and Main Findings
Demirgüç-Kunt and Detragiache	Multivariate Logit	1998, 2005	94 countries, 77 crises occurred, 1980 to 2002.	• Real GDP growth, • real interest rates and • real GDP per capita • Budget deficit • Private credit/GDP Around 70% of the time the model predicted crisis occurrence correctly. Forecasted data perform poorly in predicting crisis, using the same coefficients obtained from real data.
Caprio and Klingebiel	Multivariate logit	2003	117 crises in 93 countries, 1970 to 2002	Defines systemic banking crises as episodes during which most or all bank capital was exhausted. The listing of crises used by these authors has been used as a reference by almost all academic researchers after this paper.
Cihak and Shaeck	Logit, duration analysis and non-Parametric	2007	2,600 banks in more than 100 countries over the period from 1994-2004	They find that several bank ratios are useful signaling indicators of a bank being 'close-to-failure', especially return on equity, and selected macro indicators in line with previous literature, such as credit to the private sector, credit growth, the ratio of M2 to international reserves (to capture the impact of capital flows) are also very useful. Their results show a Type I error of between 11% to 27% across four different specifications of the model, while Type II errors range between a low of 41% to a high of 61% in some specifications.
Poghosyan and Cihak	Logit	2009	EU-25 countries from 1996 to 2008, covering 5,708 banks, 79 distress events for 54 banks.	Determinants of bank distress are based on CAMELs - capital adequacy, asset quality, cost-to-income ratio and return on equity plus a liquidity indicator, in addition to a market discipline variable and a contagion dummy. They find all variables to be significant, with the exception of managerial quality and liquidity. The model used has a pseudo R2 for the base case of

				48.5%. For a 10% cut-off probability, the model had a Type I error of 44% and a negligible Type II error, (less than 0.1%).
Eichengreen and Rose	Multivariate probit	1998	105 developing countries, 1975-1992	Main findings: higher crisis probability if higher interest rates, low growth, more short-term debt.
Glick and Hutchison	Multivariate probit	1999	90 industrial and developing countries, 1975 - 1997	Main findings: twin crisis are more common in emerging markets, especially in the presence of financial liberalization. Banking crises are a good leading indicator of currency crises, the opposite is not true.
Eichengreen and Arteta	Probit	2000	75 countries, 78 crises, 1975 – 1997.	Authors apply the results in previous empirical literature to emerging market crises to check the robustness of explanatory variables. Factors which they found to be robust are: • Rapid domestic credit growth • Large bank liabilities relative to reserves • Deposit rate decontrol. Factors which the authors find not to be robust include the relationship between exchange rate regimes and banking crises, deposit insurance and weak institutional frameworks.
Davis and Karim	Multivariate Logit and Signal Extraction	2008	1979 – 2003, 105 countries, 72 to 102 systemic crisis depending on the definition used.	The authors replicate the Demirgüç-Kunt and Detragiache (2005) study and Caprio and Klingebiel (2003) study. They find that logit is the most suitable approach for EWS while signal extraction is more suited for single-country EWS and that the same variables with some transformations are better predictors of crises, than the earlier set in the original papers.

Sources: As listed above.

3.3.3 Disadvantages of the Logit Approach

The Logit model forecasts in the static set up are highly dependent on initial conditions, with poor initial conditions resulting in an overstated probability of crisis and vice versa. Also variable specifications in the past were based on static set ups. In addition, this model by construct is backward looking as in the static signals approach. In order to evaluate out-of-sample performance, Demirgüç-Kunt and Detragiache in their extension paper in 2000, use the coefficients estimated from the multivariate logit model and forecasts of the right-hand-side variables drawn from professional forecasters or international institutions. Finally, the cut-off probabilities for the various states of 'crises' are linked to the distribution of outcomes and are subject to a heuristic decision rule for the final classification.

3.3.4 Innovation and Contribution in addressing the disadvantages of previous models as listed above

The innovation and contribution in addressing the disadvantages of previously used models are similar to the signals approach. These predominantly relate to the dependent variable innovation and the dynamic model set up. These two contributions improve on out-of-sample performance, signal lead time and render the model forward looking. While at the level of the explanatory variables, the mesh of macro and aggregated micro variables is an approach adopted on a limited scale in previous literature and adds a number of useful insights.

3.4. Merton Type Applications

3.4.1 Overview

This approach has been mainly used to study individual bank failure, with empirical studies dating back to the 1970s, mainly relying on bank balance sheet and market information to explain and forecast the failure of individual institutions. These include studies with variations of a Merton type, options based model to predict expected number of defaults (END) Z-scores or distance to default (DD) for financial institutions or sovereigns and credit migrations (recent studies include Gropp, Vesala and Vulpes 2004, Fuertes and Kalotychou 2006 and Savona and Vezzoli, 2008, Tieman and Maechler 2009, among others).

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 (this approach was also adopted by the Central Bank of Egypt's Macro-Prudential Unit for some of its stress-testing exercises). 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 and on an individual (micro) bank level. Their sample includes seven countries: France, Germany, Italy, Spain, Sweden, Switzerland, and the United Kingdom, and focuses on the largest banks in each of these countries (a total of 26 banks) over the period covered 1991–2007, the authors find that although there is considerable variation across indicators, in both cases, the period 2004 to mid-2007 is characterized by low risk, as reflected by (almost) uniformly high DD indicators or, conversely, low Expected Default Frequencies (EDFs).

A somewhat similar application, but with a focus on creating a new financial stability quantifiable metric is made by Martin Cihak (2007) who presents an integrated measure of financial stability which he calls 'systemic loss'. The author looks at the financial system as if it's a 'portfolio' of financial institutions' and considers the whole 'distribution' of systemic losses of this aggregate portfolio, over one period. He proposes that systemic loss measurement should be based on i) probability of default; ii) loss given default; and iii) correlation of defaults across institutions. 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).

Gropp, Vesala and Vulpes (2004), using a Merton type approach, analyze the ability of equity and bond market signals as leading indicators in a sample of EU banks. They find both indicators are good leading metrics of fragility, with distance to default exhibiting lead times of 6 to 18 months, while bond spreads signal values close to problems only. In a related study, Krainer and Lopez (2004), find that stock returns and equity-based default probabilities are useful indicators for US bank supervisors. The authors develop a model of supervisory ratings that combines supervisory and equity market information and find that their model forecasts supervisory rating changes by up to four quarters. Finally, an application to Estonia by Chen, Funke and Mannasoo (2006) attempts to predict bank fragility from market prices through the use of a Merton type approach and find that market indicators are moderately useful for anticipating future financial distress and rating changes.

The following table, adapted from Cihak (2007), presents a summary of the different Merton type applications to predict banking and systemic crises and the advantages and drawbacks of each sub-set.

Table 3.3: Merton Type Methods for Crises Prediction and the Advantages and Disadvantages of Each

Indicator	Advantages	Disadvantages
DD or Z-Score (or probability of Default)	Easy to calculate from individual institutions' or for a portfolio, for DDs, Z-scores, or PDs.	• Does not reflect contagion (correlation across failures if average of individual institutions). • Does not reflect LGD of individual institutions, even though can be partially addressed by weighting. • DD requires liquid market in financial institutions iNTSRuments used to back out the metric if market data is used.
First-to-default and nth-to-default indicator	• Clear theoretical underpinnings for the nth to default indicator	• Does not fully reflect differences in LGD in different institutions. • FTD looks at individual vs systemic risk.
Expected number of defaults (END) indicator	• Relatively easy to interpret.	• Does not reflect different LGDs in institutions. • Difficult to calculate as its not a closed form expression • Focuses only on central tendency of the distribution. • Depends on total number of institutions
Distribution of systemic loss	• Captures differences in LGD in institutions • Captures correlation across bank failures • Focuses only on central tendencies	• May be difficult to calculate in some cases; no closed-form expression.

Source: Adapted from Cihak (2007).

3.4.2 Innovation and Contribution to Model Design

This research contributes to the existing body of literature in two ways. First, the design of the Z-score macro application, looking at the aggregate balance sheet of the financial system to calculate system Z-scores has been utilized rarely in earlier literature. Second, the innovation in the way the Z-score is calculated, by focusing on equity to total assets plus profit before tax and provisions to average assets, and also using the volatility of the latter for the denominator as opposed to ROA, the resulting Z-score is much more indicative. This is because equity to total assets is a 'clean' and 'standard' measure of capitalization across countries and financial systems and banks, not subject to different classifications of prudential rules for calculation of capital adequacy. Also the returns calculation before taxes and provisions, normalizes for the tax regime differences and the provisioning differences across different time periods. Where usually provisioning is used as an earnings smoothing tool by management. This return measure is akin to operating profit to total assets, and as such also improves on lead time, as changes to operating profit usually precede hits to income statement lines after further deductions. On the micro-level, the calculation improvements of the Z-score are also applicable and as such render the scores more comparable compared to previous works across countries and banks. The transition matrices are also more reliable based on the Z-scores calculated this way. Finally, book equity is used for the calculation of capital adequacy, this is on the premise of banking book equity being a proxy for market equity given bank balance sheets are the closest to fair value compared to all other industrial or service players given its nature. While simultaneously it normalizes for periods of abnormal market volatility, especially around crisis and distress episodes.

3.4.3 Disadvantages of Merton Type Applications

In general, Merton type models are subject to the same set of basic assumptions required for the functioning of options pricing and asset pricing models. We assume no information asymmetries, liquid markets with no frictions, rational investors, among many others. However, in reality, these assumptions do not hold either consistently or at all in some cases and are affected by the level of market efficiency or indeed also by periods of irrational behavior by investors. On the macro level, another disadvantage is that the aggregated analysis ignores correlations between institutions which may decrease or increase the total risk of a system. On a micro-level, differences in liquidity between different bank stocks would have an impact on the outcome of the Z-score model calculated using market data.

3.4.4 Innovation and Contribution in addressing the disadvantages of Merton Type Applications

Given the research design herein, as book values are used, we avoid all the disadvantages related to violation of Merton basic pricing assumptions. The underlying premise is that a bank's balance sheet is sufficiently close to fair value and the long run value of book equity should approximate the long run market cap. The improved calculation of the Z-score is more comparable across countries and banks, which was not the case in earlier literature. Finally for the micro-application, the universe of banks studied is much larger than previous studies using Merton type applications. The micro paper also proposes a new rating paradigm based on our particular application which could be more stable, forward looking and highly useful for both regulators and market participants.

3.5. Other Methodologies

3.5.1 Overview

Other approaches include binary recursive trees (BRTs) and network models. The BRT approach analyses a sample of data to reveal a particular value of the explanatory variable that best explains the dependent variable. So for example if the level of real GDP is the explanatory variable being tested, BRT would identify the exact threshold level of GDP growth that separates crises from tranquil periods. The observations would then be split into two branches based on the level of GDP, and if low GDP is believed to result in more banking crises, then the low GDP branch should show a clustering of failures as such. And then another 'splitter' explanatory variable is chosen for the next tree node and so on. This approach has been used in a limited number of studies including Davis and Karim (2008) and Duttagupta and Cashin (2008) for banking crises, Ghosh and Ghosh (2002) for currency crises and Manasse and Roubini (2005) and Manasse et al. (2003) for sovereign debt crises.

Duttagupta and Cashin (2008) analyze banking crises in 50 emerging market and developing countries over the period from 1990 – 2005, comprising 127 annual crisis observations and 38 crisis episodes, identifying key indicators and their threshold values at which vulnerability to banking crises increases. They identify three conditions to be crisis inductive: very high inflation; highly dollarized bank deposits combined with nominal depreciation or low liquidity and low bank profitability. These factors point to foreign currency risk, poor financial soundness and macroeconomic instability being key triggers to banking crises. They also find that their results survive under alternative robustness checks endorsing BRT as an approach for monitoring banking system vulnerabilities. The authors cite as one of the advantages of a BRT model are that it considers a combination of vulnerabilities rather than deterioration of a unique factor. It also recognizes that economic indicators may have a nonlinear impact on the probability of a crisis. The model identifies five key variables as the most important determinants of banking crises: nominal depreciation, bank profitability, inflation, liability dollarization and bank liquidity. It also identifies three types of environments which are conducive to crises: macroeconomic instability, low bank profitability and high foreign exchange risk. The out-of-sample performance of the model, however, varies in correctly calling crises from 33% in 2001, 50% in 2002 and 66% in 2003 (for a total of 20 crises which occurred from 2001 to 2003).

A similar analysis for US banks, but of network structure nature rather than a binary mode, on a much more limited sample and for a short time horizon, was developed by Jagtiani, Kolari, Lemieux and Shin (2003) in the form of a non-parametric Trait-Recognition-Analysis (TRA). The analysis is closely associated with neural network models used in science for the prediction of earthquakes and oil exploration, and seeks to exploit information contained in complex interactions of the independent variable set. A unique aspect of the TRA is that variable interactions could be formed to be consistent with the logic of a financial analyst, rather than simple cross products of variables.

The drawbacks of TRA models are the required hands-on manipulation by researchers to create and input cut-off points for traits and selecting the minimum and maximum percentage definitions of features. Also no statistical measures of significance are produced by the TRA analysis. On the other hand, the TRA has an advantage over other techniques in that it generates a list of good and bad traits that may well be useful to bank supervisors in better understanding a bank's strength and weaknesses.

3.5.2 Focus on other Recent Research

There are four recent papers, however, which are forward looking in terms of the research focus and deserve special attention as such. These cover a) leverage, liquidity creation and off-balance sheet activity; b) multiple indicator models (MIMIC); c) multiple indicator models with contagion effects; and d) modelling of feedback loops to the real sector.

3.5.2.1 Leverage, Liquidity Creation and Off-Balance Sheet Activity: Berger and Bouwman (2008), find interesting patterns for liquidity creation around financial crisis by agents. Their main findings can be summarized as follows: first, prior to financial crises, there seems to have been a significant build-up or drop-off of abnormal liquidity creation. Second, banking and market-related crises are different. The authors suggest a possible dark side of bank liquidity creation and show that the causality may also be reversed in the sense that too much liquidity creation may lead to financial fragility.

3.5.2.2 Multiple Indicator Multiple Cause Models (MIMIC)

Rose and Spiegel (2009), model the causes of the financial crisis together with its manifestations, using a Multiple Indicator Multiple Cause (MIMIC) model (basically a set-up of two equations, with two vectors and an iterative algorithm to allow explicit modelling of a measurement error around a key variable, in this case the authors specified it as the incidence and severity of the crisis variable) conducted on a cross-section of 107 countries; focusing on national causes and consequences of the crisis and ignoring cross-country contagion effects. The authors replicate this paper adding channels of contagion through both financial and real sector exposures.

3.5.2.3 Modelling of Feedback Loops to the Real Sector and in Stress-Testing

Tieman and Maechler (2009), using a Merton-Type approach, estimate the magnitude of key effects on the real economy from financial sector stress. 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. The analysis includes adopting a superbank approach, which aggregates all players on one pseudo balance sheet (this approach was adopted by the Central Bank of Egypt's Macro-Prudential Unit for some of its stress-testing exercises as early as 2007). The authors also conduct the same analysis on the level of individual large banks and find significant feedback effects.

The sample includes seven countries: France, Germany, Italy, Spain, Sweden, Switzerland, and the United Kingdom, and focuses on the largest banks in each of these countries (a total of 26 banks). The period covered is 1991–2007, over which they perform regression analysis on quarterly data. For each country, the authors first constructs several economy-wide and bank-specific financial sector risk variables. These variables are all based either on a simple Merton-type distance-to-default (DD) model, or on Moody's KMV expected default frequency (EDF). In both cases an economy-wide risk measure is constructed by averaging the DDs and EDFs of individual large banks in the specific country. The authors find that although there is considerable variation across indicators, in both cases, the period 2004 to mid-2007 is characterized by low risk, as reflected by (almost) uniformly high DD indicators or, conversely, low EDFs.

The authors find that reductions in credit growth as a result of financial sector fragility are substantial. Between July and end 2007, the increased financial sector risk as perceived by the market, would lead real credit growth to decrease by 0.4 percentage point in real terms in the countries in the sample. Set against an average real credit growth of 4.4 percent over the period 1991–2006, this implies a decrease of some 10 percent. When taking account of further turmoil in the first half of 2008, i.e., looking out of sample at the impact over the period July 2007–July 2008, using estimated coefficients, the total impact on real credit growth amounts to a decrease of 32 percent. Similar effects are found for GDP with the increase in financial fragility over the period July 2007 to July 2008 possibly having a negative impact on GDP growth of over 1 percentage point on average, ranging up to 2.5 percentage points for specific countries.

3.5.3 Innovation and contribution in addressing the disadvantages of previous models as listed above

As this research uses a dependent variable definition that is calibrated to predict near-crises, it does capture all the necessary information in fragility build-up. The variables under the new empirical model designs used for each paper that rely upon dynamic thresholds and are the relevant variables in crisis and failure prediction. This is because any variables that did not change significantly as per the defined objective function of each of the applications, will not trigger a signal and the variables that did change significantly will.

Also, another disadvantage of models in earlier literature was that being designed to predict full fledged crises as opposed to near crises or failure of a bank throws away a lot of information content on fragility which might be in the data, a dynamic model, focusing on near-crises or near-failure, ensures that this information is taken into account because all comparisons are relative to a chosen benchmark of change.

Furthermore, one other disadvantage of earlier design models are that they are backward looking, calibrated on historical data and thresholds determined on the basis of the ‘critical’ levels of these variables in the past. By using a dynamic design, this ensures that the model is forward looking because it is calibrated based on future changes to a chosen benchmark ex-ante not a static level chosen ex-poste. By using a dynamic model, it still does not prevent a regulator from assigning different weights to variables at a later stage based on their expertise and/or objective function, but they will be doing it again on a dynamic basis, because they are choosing a weight for a degree of variability of a variable, not a static threshold.

Finally, this research proposes a new rating paradigm in the last application. While the building blocks of a holistic traffic light analysis or risk heat map, an innovation not included in any previous literature, to be used by regulators, are clearly demonstrated. This was a major problem with models in the past and indeed as severely highlighted by the last financial crisis is their blind use and lack of understanding of their limitations. By leaving room for regulator input on variables and focusing on near-crises, this forces regulators to look at the variables in a more dynamic manner and ensures the incorporation of a qualitative human element, which does not preclude also weightings being determined by other models used in other parts of the regulatory function (eg. Output of models used by different departments or think tanks for example, could be used as an input to an EWS, and similarly within other institutions to ensure maximum utilization of available resources and expertise across departments).

Thus, to conclude this section, the use of a traffic lights or risk heat map approach, with input form a suite of models and continuous monitoring of the system by regulators and indeed the markets is proven throughout as such.

3.6. 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 banking 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 3.4 presents the number of crises in line with the definition in earlier literature. In total previous literature identified 135 crisis episodes, out of 870 observations or 15.5%.

Table 3.4: Crises Definitions in Earlier Literature for OECD Countries (1980 – 2007)

	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
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

Table 3.4: Crises Definitions in Earlier Literature for OECD Countries (1980 – 2007) - Continued

	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
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
		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
																														870
																														15.5%

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

While an adapted descriptive chronicle of crises in OECD countries over the past 30 years from the Laeven and Fabian IMF Database (2008) is presented in Table 3.5.

Table 3.5: Descriptive Chronicle of Crises in OECD Countries over a 30 year period (ending in 2008)*

Country	Systemic Banking Crisis (Starting Date)	Share of NPLs at peak (%)	Fiscal Cost (gross % of GDP)	Output Loss (IMF estimate, % of GDP)	Minimum Real GDP Growth Rate %	Description
Czech Republic	1996	18	6.8		-0.8	In 1994, a small bank, Banka Bohemia, failed due to fraud. All depositors were covered, however, this triggered the introduction of partial deposit insurance. Other runs followed at small banks, until by the end of 1995 two small banks failed, Ceska and AB Banka, which triggered a second phase of bank restructuring starting in 1996 for 18 small banks representing 9% of the industry's assets.
Finland	1991	13	12.8	59.1	-6.2	The three Nordic countries went through a financial liberalization process that led to a lending boom. However, they also suffered the adverse consequences of higher German interest rates. In the case of Finland, the problems were exacerbated by the collapse of exports to the Soviet Union. The first bank in trouble was Skopbank, which was taken over by the Central Bank in September 1991. Savings banks were badly affected and the government took control of there banks that together accounted for 31% of system deposits.
Hungary	1991	23	10		-11.9	In the second half of 1993, 8 banks representing 25% of the financial system were deemed insolvent.
Japan	1997	35	14	17.6	-2	Banks suffered from sharp decline in stock market and real estate prices. In 1995 the official estimate of nonperforming loans was 40 trillion yen (USD469 billion or 10% of GDP). An unofficial estimate put non-performing loans at USD1 trillion, equivalent to 25% of GDP. Banks made provisions for some bad loans. At the end of 1998 banking system NPLs were estimated at 88 trillion yen (USD725 billion, or 18% of GDP). In 1999 Hakkaido Takushodu Bank was closed, the Long Term Credit Bank was nationalized, Yatsuda Trust was merged with Fuji Bank, and Mitsui Trust was merged with Chuo Trust. In 2002 NPLs were 35% of total loans, with a total of 7 banks nationalized, 61 financial institutions closed and 28 institutions merged. In 1996, rescue

						costs were estimated at more than USD100 billion. In 1998, the government announced the Obuchi Plan, which provided 60 trillion yen (USD500 billion, or 12% of GDP) in public funds for loan losses, bank recapitalizations, and depositor protection.
Korea	1997	35	31.2	50.1	-6.9	The devaluation of the Thai baht in July 1997 and the following regional contagion, the crash of the Hong Kong stock market sent shock waves to the Korean financial system. Korea's exchange rate remained broadly stable through October 1997. However, the high level of short term debt and the low level of usable international reserves made the economy increasingly vulnerable to shifts in market sentiment. While macroeconomic fundamentals continued to be favourable, the growing awareness of problems in the financial sector and in industrial groups (chaebols) increasingly led to the difficulties for the bank in rolling over their short-term borrowing. Through May 2002, 5 banks were forced to exit the market through "purchase and assumption" and 303 financial institutions shut down (of which 215 were credit unions)' another 4 banks were nationalized.
Mexico	1981			51.3	-3.5	The government took over a troubled banking system.
	1994	18.9	19.3	4.2	-6.2	Of 34 commercial banks in 1994, 9 were intervened and 11 participated in the loan/purchase recapitalization program. The 9 intervened banks accounted for 19% of the financial system assets and were deemed insolvent. By 2000, 50% of bank assets were held by foreign banks.
Norway	1991	16.4	2.7	0	2.8	Financial deregulation undertaken during 1984-1987 led to a credit boom (with real rates of credit growth 20% YoY), coupled with a boom in both residential and none-residential real estate. In 1985 oil prices fell sharply, turning a 4.8% surplus in the current account into a 6.2% deficit in 1986 with ensuing pressures on the exchange rate. Meanwhile, rate increases by the Bundesbank following the reunification of Germany, forced Norway to keep interest rates high throughout the economic recession, which started in 1988. Problems at small banks that began in 1988 were addressed via mergers and assistance from the guarantee fund, funded by banks. However, by 1990 the fund had been depleted and the financial condition at large banks began to deteriorate as well. The turmoil reached systemic proportions by October 1991, when the second and fourth largest banks had

						lost substantial equity.
Poland	1992	24	3.5		2	In 1991 seven of nine treasury owned commercial banks, accounting for 90% of credit, the Bank for Food Economy, and the cooperative banking sector experienced solvency problems.
Slovakia	1998	35	0		0	NPLS reached 35% in 1998 and a bank restructuring programme was put in place for the major state owned banks.
Spain	1977		5.6		0.2	In 1978-83, 24 institutions were rescued, 4 were liquidated and 4 were merged and 20 small and medium size banks were nationalized. These 52 banks (of 110), representing 20% of banking system deposits, were experiencing solvency problems.
Sweden	1991	13	3.6	30.6	-1.2	Nordbanken and Gota Bank, accounting for 22% of banking system assets, were insolvent. Sparbanken Foresta, accounting for 24% of banking system assets, intervened. Overall, 5 of the 6 largest banks, with more than 70% of banking system assets experienced difficulties.
Turkey	1982		2.5	0	3.4	Three banks were merged with the state-owned Agricultural Bank and then liquidated, two large banks were restructured.
	2000	27.6	32	5.4	-5.7	Banks had a high exposure to the government through large holdings of public securities, sizeable maturities and exchange rate risk mismatches making them highly vulnerable to market risk. In November 2000, interbank credits to some banks holding long term government paper were cut, forcing them to liquidate the paper, which caused a sharp drop in the price of such securities, triggering a reversal in capital flows, a sharp increase in interest rates and decline in the value of the currency. Two banks closed and 19 banks have been take over by the Savings Deposit Insurance Fund.
UK						On September 14, 2007, Northern Rock, a mid sized UK mortgage lender, received a liquidity support facility from the Bank of England, following funding problems related to global turmoil in credit markets caused by the US subprime meltdown. Starting on September 14, 2007, Northern Rock experienced a bank run, until a government blanket guarantee, covering only Northern Rock was issued on September 17, 2007. On February 22, 2008, the bank was nationalized following two unsuccessful bids to take it over. On April 21, 2008, the Bank of England announced it would accept a broad

						range of mortgage backed securities and swap those for government paper for a period of 1 year to aid banks in liquidity problems. The scheme enabled banks to temporarily swap high quality but illiquid mortgage backed assets and other securities with Treasury bills for a period of one year.
US	1988	4.1	3.7	4.1	-0.2	More than 1,400 savings and loan institutions and 1,300 banks failed. Cleaning up savings and loan institutions cost USD180 billion or 3% of GDP.
	2007					During 2007, the US subprime mortgage market melted down. The crisis manifested itself first through liquidity drying up in the banking system owing to a sharp decline in demand for asset-backed securities. Hard to value structured products had to be severely market down due to newly implemented fair value accounting. Credit losses and asset write-downs go worse wit the accelerating mortgage foreclosures. On August 16, 2007, Countrywide Financial ran into liquidity problems triggering a deposit run on the bank. The Federal Reserve Bank lowered the discount rate by 0.5% and accepted USD17.2 billion in repurchase agreements for mortgage backed securities to aid in liquidity. Bear Stearns, a leading investment bank, was acquired by JP Morgan Chase with federal guarantees on its liabilities in March 2008. By June 2008 sub-prime related losses or write-downs by global financial institutions stood at around USD400 billion. The Fed introduced the Term Securities Lending Facility to swap mortgage-backed securities for Treasury notes. On September 7, 2008, mortgage giants Fannie Mae and Freddie Mac were placed under conservatorship.

**Source: Adapted from the Laeven and Fabian IMF Database (2008).*

3.7. Explanatory Variables Used in Earlier Literature

There are several variables which have been identified as contributors to financial fragility and crises, these include financial liberalization; international shocks and restrictive exchange rate regimes; bank ownership and structure; credit, market and liquidity risk, CAMELs (Capital adequacy, Asset Quality, Management, Efficiency, Liquidity and sensitivity analysis) based models; and stage of institutional development. Johnston, Chai and Schumacher (2000), introduce a concept of net risk of a financial system which is based *on comparing the risk in the environment with the adequacy of the risk management/supervisory systems* and Nier (2009) provides significant evidence towards the losses associated with various regulatory set ups, twin peaks versus single independent regulator. This enforces the role supervision has in either increasing or decreasing the net risk of a financial system.

In an application to Asian crises, Hardy and Pazarbaşiouğlu (1998), find that macroeconomic indicators were of limited value in predicting the Asian crises, while the best warning signs were proxies for the vulnerability of the banking and corporate sector, such as credit growth and rising foreign liabilities. They examine 43 episodes of banking distress in 50 countries. The authors differentiate the causes and leading indicators by i) region; ii) severity of the crisis; and iii) pre-crisis and crisis episodes. Another application to Hong Kong and other emerging markets in Asia by Wong et al (2007) finds that macroeconomic fundamentals, currency crisis vulnerability, credit risk of banks and companies, asset price bubbles, credit growth and the occurrence of distress in other economies in the region are important leading indicators. Other research in Asia with a focus on EWS for corporate distress includes work by Lieu, Lin, Yu (2008).

Emerging Markets: Hawkins and Klau (2000) try to construct a relatively simple index for 24 emerging markets to summarize information about economies facing financial stress and those likely to face such stress in future periods. They find that three explanatory variables with sufficient lead time and predictive power for crises determination are the real effective exchange rate, real interest rate and high external debt/GDP ratio.

Nordic Banking Crisis: Drees and Pzarbasioglu (1998) studied the Nordic banking crisis (Finland, Norway and Sweden) in the early 1990s and find that individual banks in a banking system are affected the same way by a common shock because they have similar fundamental characteristics, weaknesses or exposures.

Latin America: Gourinchas, Valdes and Landerretche (2001), attribute financial crisis in Latin America to lending booms. They investigate episodes over 40 years and find that lending booms are often associated with greater volatility and vulnerability to financial and balance of payment crises. Rojas-Suarez (2003), investigates the appropriate indicator set to gauge banking problems in Latin America and East Asia. She finds that interest paid on deposits and interest rate spreads, have performed robustly. More importantly she stresses that in emerging markets, a one size fits all approach is not applicable, with the choice of effective indicators varying according to the stage of development of a country.

European Banks: Poghosyan and Cihak (2009) present a unique database of individual bank distress across the European Union from mid-1990's to 2008 on the basis of which they identify a set of indicators (CAMELS based) and thresholds to distinguish between sound banks and banks vulnerable to financial distress. They highlight the usefulness of an EU-level early warning system based on this model, with published results by banks as compared by benchmarks to enhance market discipline. The dataset is based on Bankscope data, on 5,708 banks, plus information obtained from NewsPlus/Factiva on each bank with regards to any financial support or other forms of rescue or merger.

UK: Andrew Logan (2001), studied the failure of small and medium-sized banks over a three year period in the UK following the closure of the Bank of Credit and Commerce International (BCCI) on 5th July 1991. He finds a number of measures of bank weakness such as low loan growth, poor profitability and illiquidity to be good predictors of failure, as are a high dependence on net interest income and low leverage. He also finds that the best longer-term leading indicator of future failure is rapid loan growth at the peak of the previous boom.

US: King, Nuxoll and Yeager (2006), the authors emphasize the need for dynamic models that use forward-looking variables and address the various types of risks banks face individually (credit, market and liquidity), as the González-Hermosillo (1999) paper has done. The authors extend the analysis further by describing a new generation of EWS used by supervisory agencies, starting with discrete-response and hybrid systems used by the various US regulatory bodies to forward looking systems for EWS. For the latter they identify two systems, the Growth Monitoring System (GMS) used by the FDIC since 2000 and the Liquidity and Asset Growth Screen (LAGS) used since 2002. GMS is a logit model of downgrades that estimates which institutions are most likely to be classified as problem banks at the end of three years, using forward-looking variables such as loan growth and non-core funding.

Jagtiani, Kolari, Lemieux and Shin (2003), develop a simple EWS for US banks over a sample period from 1988 to 1990 and more than 450 banks, which focuses on predicting banks in an early stage of capital distress, with a primary capital to assets ratio falling below the 5.5% minimum capital adequacy standard. They find that their model is able to detect financial distress in commercial banks one year in advance with a reasonable degree of accuracy. They find that a logit model with only the lagged capital ratio and lagged change in capital ratio predicted 80% of banks which became capital inadequate, while a more complex logit model with 16 variables performed poorly, with a predictive ability of around 25% only.

Global Applications : Cihak and Schaeck (2007), the authors examine aggregate banking system ratios during systemic banking crises across a wide cross-country global dataset of 100 developed and developing countries, between 1994 to 2004 for 13 explanatory variables comprising regulatory capital, asset quality and profitability. The authors also include two measures for the nonbank corporate sector, profitability and leverage. Their results confirm the importance of return on equity of banks for the detection of systemic banking problems.

Table 3.6 presents an analysis of variables selected by earlier papers and some of the related weaknesses/ issues associated with their selection.

Table 3.6: Data Sources, Variables and Weaknesses for Selected Key Papers

Paper	Data Years	Countries & Variables	Sources	Weaknesses
Poghosyan and Cihak (2009)	1990 to 2008	EU countries, CAMELs based indicators.	**Bankscope Database, data on 5,708 banks.** News Plus/ Factivia.	Comparability of accounts only feasible at global summary levels, limited country application.
Tieman & Maechler (2009)	1991 to 2007	Seven developed countries, high frequency/quarterly data on banks distance-to-default, system-wide DD based on Datastream banking index, asset weighted system wide DD index. Credit growth and GDP growth.	Naitonal data, Datastream, KMV.	Limited analyses to a small sub-group of countries and banks within each country.
Rose & Spiegel (2009)	2003 to 2008	112 countries, Change in Real GDP, stock market indices, country credit ratings, exchange rates. Another sixty	National data, EIU, Euromoney, Institutional Investor, IMF, IFS, Economic Freedom of the World Dataset, Barth, Caprio & Levine, World Bank Global Development Finance, BIS.	Standardization, comparability & missing data points. Author's own crises definitions.
Borio & Drehmann (2009)	1980 to 2003	94 countries, credit, equity & property price gaps from long term trends.	National data for each country, author's calculations. Crises definition: 1: Countries where the government had to inject capital in more than one large bank and/or more than one large bank failed (seven crises). Crisis definition 2: Countries that undertook at least two of the following policy operations: issue wholesale guarantees; buy assets; inject capital into at least one large bank or announce a large-scale recapitalisation programme (14 crises). Signals are assessed over a three-year horizon.	Standardization, comparability & missing data points. Author's own crises definitions.

Table 3.6: Data Sources, Variables and Weaknesses for Selected Key Papers - Continued

Paper	Data Years	Countries & Variables	Sources	Weaknesses
Davis & Karim (2008)	1979 to 2003	105 countries, real GDP growth, real interest rates, real GDP per capita, budget deficit, private credit/GDP, inflation, fiscal deficit/GDP	National data, Datastream, Caprio & Klingebiel and Demirguc-Kunt & Detragiache dependent crisis variable definitions.	Standardization, comparability & missing data points.
Reinhart & Rogoff (2008)	1350 to 2007	100+ countries. Various macro-variables, including inflation, real GDP growth, public debt, currency exchange rates.	National data, IFS, WEO, Global Financial Data (GFD), Oxford Latin American History Database, European State Finance Database, IMF, UN, World Bank, national statistical yearbooks.	Standardization, comparability & missing data points. Author's own crises definitions.
Cihak & Schaek (2007)	1994 to 2004	**100+** countries. Regulatory capital, asset quality and profitability. Nonbank corporte sector profitability and leverage. GDP growth, inflation, real interest rates and GDP per capita.	Data on 2,600 banks, **Bankscope.** World Development Indicators, La Porta et al, 2000.	Standardization, comparability & missing data points.
Demirguc-Kunt & Enrica Detragiache (2005)	1980 to 2003	94 countries, real GDP growth, real interest rates, real GDp per capita, budget deficit, private credit/GDP	Dependent Crises Dummy: 1998 list updated by the authors using Caprio and Klingebiel (2002) and IMF country reports. Macro-variables: World Development Indicators (WDI) and International Finance Statistics (IFS)	Missing data points in earlier years.
Caprio & Klingebiel (1996, 2003)	1970 to 2002	117 countries, banking sector capital exhaustion, real credit and real GDP growth.	National data for each country, World Bank data (FSR & interviews with country specialists), IMF International Finance Statistics, The Economist, FT, author's calculations. Depenedent variable author's definition.	Standardization, comparability, subjectivity/ expert opinion in 'calling' crises & missing data points - author's own crises definitions.
Kaminsky & Reinhart (1998, 1999)	1970 to 1995	20 countries, real exchange rate appreciation, equity prices, money multiplier.	IFS, OECD data, IFC stock market indices (now S&P index suite).	Standardization, comparability, subjectivity/ expert opinion in 'calling' crises & missing data points - author's own crises definitions.

Sources: Please refer to the references section.

4. Chapter Four: Signal Extraction Application

4.1 Introduction

The recent crisis highlighted the failure of former early warning signals models. For example, 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 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 and 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 and Shin (2003) prove that low capital adequacy and a fragile banking sector is a leading indicator of banking distress, signaling a high likelihood of near-term bank failure. Furthermore, Cihak and 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 behavior 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 and 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 (NTSR - 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 NTSR in Borio and 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 NTSR 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 structure of the Signal Extraction chapter is as follows: Section 4.2. Literature Review; 4.3 Empirical Model design; 4.4. Data and descriptive statistics; 4.5. Dependent and explanatory variables; Section 4.6. Preliminary empirical findings; Section 4.7. Near-Crises forecasts and model performance evaluation; and Section 4.8. Concludes the signal extraction application.

4.2 Literature Review

The signals approach was originally developed by Kaminsky and Reinhart (1999), focusing on ‘twin crises’ phenomenon, simultaneous occurrence of currency and banking crises. A wide body of literature has utilized signals models for predicting exchange rate crises on the basis of inconsistent macro policies or the development of macro weaknesses (first generation models) and has developed further to second generation models where speculative attacks with self-fulfilling prophecies or herding behavior both playing a large role in causing crises. A third generation of models of external crisis using the signaling approach were developed by Krugman (1999), Bris and Koskinen (2000) and Cabellero and Krishnamurthy (2000) based on the notion of 'contagion' where the occurrence of a crisis in one country or region increases the likelihood of a similar crisis elsewhere. As illustrated by Masson (1998), three related contagion channels can be identified to represent this paradigm: 'monsoonal trade effects', 'spill over effects' and 'pure contagion effects'. Sachs, Tornell and Velasco (1996) explore a methodology for analyzing crises that focuses on the depth rather than the likelihood of the crisis using a crisis index.

Kaminsky and Reinhart (1999) documented the incidence of both currency and banking and twin crises 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). 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. They describe the behavior of fifteen macroeconomic variables 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 NTSR); 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.

Table 4.1: Detailed Review of Signal Extraction Selected Papers

Authors	Year	Data	Factors and Main Findings
Kaminsky and 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 27%-21% of the observations during the 24 months preceding the crisis for twin crises and 12 months for banking crises.
Alessi and 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 behavior 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.

4.3. 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 and is currently calibrated to read ‘1’ or is ‘On’ if two of the nine variables modeled 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 threshold 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 NTSR calculation for this paper is calculated in the same way, with the difference that now both are functions of the chosen *deviation* threshold.

4.4. Dependent and Explanatory Variables

4.4.1 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.

<u>Dependent Variable Specification, Unbundling and Calibrations</u>

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 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. I am 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 4.2.

Table 4.2: Unbundled Dependent Variable Near-Crises Definition by Criteria

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
Decrease in banking sector capitalization	45	91	222
Increase in banking sector capitalization	62	115	265
Net Income before provisions/Average Balance sheet falls	12	36	131
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 4.2 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 4.3. The new model proposed identifies a greater number of near-crisis as compared to full fledged crises identified in earlier literature (which amounted to only 15% of total observations). 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 4.3: Dependent Variable Near-Crises 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 4.4, 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 4.4: Relationship between 'Crisis' Definitions in Earlier Literature and near crises OECD Countries (1980 – 2007)

Variable	**Coefficient**	**Std. Error**	**Z-Statistic**	**Probability**
C	-1.858582	0.118728	-15.65417	0.0000
NEAR_CRISES	0.616869	0.197187	3.128350	0.0018
McFadden's 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		Prob (LR statistic)	0.002110
LR statistic	9.451245			

Source: Author's calculation.

4.4.2 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 an iterative process that proved they are significant in 'explaining' the dependent near crisis variable in an OLS model. These nine variables and their definitions are presented in the following table.

Table 4.5: Explanatory Variables, Definitions and Sources

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:

$Crisis_i = C + aDRGDP_i + bHPI_i + cMEMI_i + cBAG_i + dBAGDP_i + ePENS_i + fEMKTDY_i + gLIQ + hFUN + E_i$

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

Table 4.6: Empirical OLS Model to Verify Choice of Variables

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.

4.5. 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, UK 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 3.6 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 4.7: Signal Extraction 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.*

4.6. Empirical Estimations

Setting Up the Independent Variable Indicator Signals

For each of the nine variables, a signal is issued if it crosses a threshold theta, Ɵ, 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 , Θ_2, Θ_3, Θ_4, Θ_5, Θ_6, Θ_7 , Θ_8, Θ_9.

Table 4.8: Signal Extraction Calibration of Signal Triggers for Nine Iterations

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.

4.7. Forecasts and Model Performance

4.7.1 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 4.9 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 more than 20 countries, out-of-sample and in-sample, that vulnerabilities were building up.

Table 4.9: 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

Source: Authors' calculations.

Table 4.9: Signal Extraction Forecasts for Theta_1, Theta_4 and Theta_7 (Θ_1, Θ_4 and Θ_7) – Base Case Dependent Variable- Continued

	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
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 4.10 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 4.10: 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

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

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

Table 4.10: 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 - Continued

Base Case — 50 bps, 50 bps, -50bps and 5 bps — Theta 4

Noise-To-Signal Summary	1-Year Horizon 2005	2006	2007	2-Year Horizon*	3-Year Horizon**
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

High Change Dynamic Threshold — 100 bps, 100 bps, -100, and 10 bps — Theta 4

Noise-To-Signal Summary	1-Year Horizon 2005	2006	2007	2-Year Horizon*	3-Year Horizon**
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

Low Change Dynamic Threshold — 10 bps, 10 bps, -10bps and 1 bps — Theta 4

Noise-To-Signal Summary	1-Year Horizon 2005	2006	2007	2-Year Horizon*	3-Year Horizon**
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

Source: Authors' calculations.

Table 4.10: 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 - Continued

Base Case 50 bps, 50 bps, -50bps and 5 bps						High Change Dynamic Threshold 100 bps, 100 bps, -100, and 10 bps						Low Change Dynamic Threshold 10 bps, 10 bps, -10bps and 1 bps					
Theta 7						Theta 7						Theta 7					
Noise-To-Signal Summary	1-Year Horizon			2-Year Horizon*	3-Year Horizon**	**Noise-To-Signal Summary**	1-Year Horizon			2-Year Horizon*	3-Year Horizon**	**Noise-To-Signal Summary**	1-Year Horizon			2-Year Horizon*	3-Year Horizon**
	2005	**2006**	**2007**				**2005**	**2006**	**2007**				**2005**	**2006**	**2007**		
In-Sample						**In-Sample**						**In-Sample**					
Type I %	9%	7%	0%	4%	0%	**Type I %**	20%	20%	0%	10%	0%	**Type I %**	26%	12%	0%	4%	0%
Type II %	118%	87%	107%	108%	73%	**Type II %**	380%	460%	263%	280%	161%	**Type II %**	26%	20%	16%	48%	37%
Noise-To-Signal Ratio	**1.30**	**0.93**	**1.07**	**1.12**	**0.73**	**Noise-To-Signal Ratio**	**4.75**	**5.75**	**2.63**	**3.11**	**1.61**	**Noise-To-Signal Ratio**	**0.35**	**0.23**	**0.16**	**0.50**	**0.37**
Out-of-Sample						**Out-of-Sample**						**Out-of-Sample**					
Type I %	9%	27%	14%	0%	0%	**Type I %**	20%	40%	25%	0%	0%	**Type I %**	22%	20%	12%	8%	5%
Type II %	136%	80%	107%	92%	60%	**Type II %**	420%	400%	263%	240%	133%	**Type II %**	30%	12%	20%	48%	32%
Noise-To-Signal Ratio	**1.50**	**1.09**	**1.25**	**0.92**	**0.60**	**Noise-To-Signal Ratio**	**5.25**	**6.67**	**3.50**	**2.40**	**1.33**	**Noise-To-Signal Ratio**	**0.39**	**0.15**	**0.23**	**0.52**	**0.33**

Source: Authors' calculations.

4.7.2 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 in Table 4.10. The 1-year NTSR is calculated based on whether a crisis was correctly called in the year following the forecast. However, measuring NTSR this way would result in an attempt to also predict crisis timing, which according to (Borio and 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 NTSR would be indicating a false signal, whereas it is not true, predicting the timing however was what was not possible. The NTSR over a two year horizon, measures how correct the model was in signaling 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 NTSR in Borio and 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%. *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 is an environment where crises are prevalent two thirds of the time, which is not credible.

4.7.3 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 table 4.11 (B).

Table 4.11 (A): Signal Extraction near crises Noise-to-Signal Ratios

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**

Source: Authors' calculations.

Table 4.11 (B): 'Crises' in Earlier Literature Noise-to-Signal Ratios using Proposed Signal Extraction Model Explanatory Variables

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 (NTSRs). For example the median NTSR in Borio and 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 30%.

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 NTSR of 0.96 for the new definition versus 27 for the old definition, in sample. Out of sample, NTSR 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 NTSR of 1.12 for the new definition versus 29 for the old definition, in sample. Out of sample, NTSR 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 NTSR of 1.12 for the new definition versus 27 for the old definition, in sample. Out of sample, NTSR 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, the model used in this chapter 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.

4.8. Conclusion

Using a signal extraction framework and looking at OECD countries over a 30 year period a number of variables were found to be significant in predicting crises. These include growth in pension assets (positive and significant at the 5% level) and equity market dividend yield (positive coefficient, 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, and also as free cash flows to equity shareholders, after debt service, are available.

Banking sector assets growth was also significant, indicating a strong relationship between rapid growth in the sector, its relative size to GDP and the development of vulnerabilities (positive coefficient).

The output model shows that as early as 2004, clear signals were being given for a number of countries that vulnerabilities were building up across 144 runs for an unbundled dependent variable of four components, with three cases: a base case, a high change dynamic threshold case and a low change dynamic threshold case. For the base case dependent variable runs, the consolidation run shows the best in-sample model, is the 3-year rolling one standard deviation, very closely followed by the 10-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 1.60 to 0.6. 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 NTSR in Borio and 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%.

This chapter 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 trade-off between the costs of Type I and Type II errors is widely debated. The cost of a Type I error, represents the cost of a crisis using the standard direct (losses) and indirect (opportunity losses) measures described in detail in earlier chapters, which showed a range of anywhere between 10% to 40% of GDP historically and up to the last global crisis of 2007-2010. The cost of Type II errors is more difficult to measure but could be broken down into direct and indirect components as well.

The direct components comprise the cost of complying with new regulation. According to a Mckinsey November 2010 study on the impact of Basle III implementation on European banks, the new information technology and risk capability requirements will result in an investment cost of Euro 35 million to Euro 70 million for each bank that adopts the accord. If we take the Euro 50 million as a midpoint, and assuming the leading 50 banks in Europe incur this cost, this gives a total estimated cost of Euro 2.5 billion (0.02% of Eurozone total GDP of Euro 12.6 trillion in 2010). The indirect components in terms of losses to GDP are much more difficult to measure, however a February 2011 study by Slovik and Cournede on OECD countries, indicates a loss of between 0.05 to 0.15 percentage point per annum over a five year period. If we take the midpoint 0.10 percent, and multiply this by OECD GDP as of 2010 (and then multiply by five, assuming flat growth for a five year period), this amounts to USD225 billion. The magnitude of direct and indirect Type II errors which are measurable as such, is much smaller than the cost of Type I errors. Other costs of Type II errors cited by an IMF paper are unintended consequences for cost of capital, funding patterns, interconnectedness, and risk migration in banks. These may well be greater than the measurable Type I errors, however measurement might not be feasible.

The best out-of-sample model, is the 10-year rolling one standard deviation specification with a Type I error of 0% and a noise-to-signal ratio of 0.6. These results show a significant improvement compared to earlier work. Using an adapted crisis definition as measured by a solvency proxy, in itself an innovation, has improved the performance of the model in terms of minimizing Type I errors over a three year period and NTSR out-of-sample. Furthermore out-of-sample performance is better than in-sample performance. A major improvement to previously existing models.

Furthermore, an evaluation of model performance had it been calibrated using the crises definitions in earlier literature compared to the near-crises definition proposed by this research, 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 (NTSRs).

5. Chapter Five: Macro-Applications of Near Crises to OECD Countries

5.1 Introduction

As touched upon in Chapter 4 in the case of the Signal Extraction application, macro Logit and Merton type models failed miserably in calling the 2007-2010 crisis. 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 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 macro models in the past**,** are similar to those discussed in the signal extraction application. These are in the form of 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 and 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, as discussed previously in details in Chapter 4, we have adopted the innovative approach based on focusing on near-crises for the dependent variable as in this macro-applications Chapter 5.

Focusing on independent variable specifications, we also adopt the same variable section approach described in detail in Chapter 4.

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 macro-application comprising two models: a Logit macro model and a Z-score macro model. Predominantly in earlier literature such as Kaminsky and Reinhart 1999 and Alessi and Detken 2008, the structure of the empirical model was based on static thresholds chosen for each independent variable or threshold probability, determined on the basis of minimizing Type I and Type II errors in-sample or in other words minimizing the Noise-To-Signal Ratio of the model. 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. By shifting the analysis to focus on change 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.

Using the Logit framework and looking at OECD countries over a 30 year period a number of variables were found to be significant in predicting crises. These include growth in pension assets (positive and significant at the 5% level) and equity market dividend yield (positive coefficient, 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, and also as free cash flows to equity shareholders, after debt service, are available.

Banking sector assets growth was also significant at the 10% level, indicating a strong relationship between rapid growth in the sector, its relative size to GDP and the development of vulnerabilities (positive coefficient).

The output model shows that as early as 2004, clear signals were being given for a number of countries that vulnerabilities were building up across a dependent variable with three cases: a base case, a high change dynamic threshold case and a low change dynamic threshold case. Performance out-of-sample, is better than in-sample in terms of overall noise to signal ratios. These results show a significant improvement compared to earlier work, in terms of NTSR and Type I and Type II errors for all calibrations, with the exception of the 100 bps dependent variable calibration. Again a point to support the importance of the dependent variable regulator objective calibration and the inherent feedback loop to actual model performance.

Using the Merton type Z-score framework and looking at OECD countries, movements in PD by more than one standard deviation were found to be significant in predicting crises. The PDs were calculated using a Merton type Z-score framework, where the Z-score is a capital adequacy measure plus returns on average assets (the latter defined as Net Income (NI) before provisions/average assets) all divided by the standard deviation of returns (same definition, NI before provisions/average assets).

The output model shows that as early as 2004, clear signals were being given for a number of countries that vulnerabilities were building up across the base case dependent variable calibration. The model performs well compared to World Bank published Z-Score indicators to calculate migration matrices in PDs.

For the various models, the countries signaled to have crises do not map one to one in all three applications and some key countries called by the signal extraction to be susceptible to crises are not called by the Logit model but are called by the Z-score model, but the Logit model raises the alarm bell for other countries. These two findings reinforce the need by regulators to use different models and to look at all of them in judging the build up of vulnerabilities, even within the same system / country.

Comparing the Z-score macro application with the Logit and signal extraction applications point to a number of key recommendations. First, regulator objective functions do have an impact on model performance, and therefore EWS should always be designed with a set of objective functions and crises evaluated for each set as evident from the output of the three methodologies based on the three scenarios for the magnitude of change in the dependent variable that is deemed systemic. Second, regulators should use a number of models simultaneously to monitor changes in their respective systems and the impact from spill-overs from other interconnected systems as each model has strengths and weaknesses. Third, there is a lot of value in the initial data searching exercise for variables, because this helps determine at any one point in time on a dynamic basis as these are the factors that are 'moving' in the system and could cause vulnerabilities. Last, regulatory oversight and judgment need to be exercised at all times without over reliance on models as clearly, the outcomes must be then mapped onto real life by the regulator and also assessed in terms of cost of intervention versus cost of waiting for certain further critical triggers and regulators need to exercise vigilance and prudence consistently.

In order to better evaluate how the models map, one additional analysis component is necessary, in the form of a traffic light type analysis. Clearly the models are not expected to have the same results consistently, otherwise they would not be sufficiently different to be adding information to the decision making information set of a regulator. However, the confirmation of signals by all models should raise the 'red' alarm and the disagreement should point to an 'amber' alarm, whereas the full agreement for a 'no crisis' signal should be a 'green light' that the financial system is robust. Note that the traffic signals panel is somewhat similar to a risk heat map and could be easily scaled to include other models as well or calibrated to modify output based on regulatory objective functions/ thresholds for intervention.

This chapter covers macro-applications of Near Crises to OECD countries and includes a Logit Model and a Z-Score application. The topics covered are: Literature review; Empirical Model design; Data and descriptive statistics; Dependent and explanatory variables; Preliminary empirical findings; Near-Crises forecasts and model performance evaluation; and the last section provides a comparison between the various macro applications and traffic light results.

5.2 Literature Review

5.2.1 Logit Model

Logit models use a logistic specification and enable the study of covariates of banking crises, developed by Demirgüç-Kunt and Detragiache (1998). In this paper, Demirgüç-Kunt and Detragiache (hereinafter DandD) use a large sample (45 to 65 based on the specification of the regression) of developing and developed countries during 1980-1994 and find that crises tend to erupt when the macroeconomic environment is weak, especially when growth is low and inflation is high. Also high real interest rates and vulnerability to balance of payments crises plays a role. They also find that countries with an explicit deposit insurance scheme and with weak law enforcement were also particularly at risk.

This approach assumes that the probability that a crisis occurs is a function of a vector of explanatory variables and its output, although in the form of a probability, is transformed into binary mode through a decision rule. Either a country is experiencing a crisis or not (determined by what threshold probability is given in the decision rule to label a country as having a crisis). The advantage of this model is that its non-linear and incorporates several variables simultaneously.

A related class of models, probit models are used to estimate the contribution that each explanatory variable makes to the probability that financial distress/failure will occur. Mulder, Perrelli and Rocha (2002), using a Probit model, test balance sheet explanations of external crises in emerging markets and the role of standards in these crises with the main findings that corporate sector balance sheets have a very significant impact on both the likelihood and depth of crisis caused by external shocks. The authors use a set of indicators which they call the Lawson Indicators (named after the former UK Chancellor of the Exchequer) covering: corporate balance sheet indicators (degree of financial leverage, maturity structure of debt financing, availability of liquidity, profitability and cash flow of a company); macroeconomic balance sheet and institutional indicators (extent of foreign currency financing by corporates and revenues) and legal indicators (creditor rights, shareholder rights, the ability to enforce contracts, accounting standards, and the origin of the legal regime). They use a parametric probit model to which they add the Lawson indicators. They find that using their indicator set in addition to the macroeconomic variables results in a much higher degree of accuracy, calling on average more than 80% of the crisis in-sample (Type I error of 20%, compared to 30% on average to Kaminsky and Reinhart 2005 for example), however with a high degree of false alarms ranging from around 30% to over 50% for different cut-off probabilities (30% false alarms for the higher probability threshold of 50% and 50% false alarms for the lower probability threshold of 25%, respectively).

Table 5.1:Detailed Review of Logit Selected Papers

Authors	**Model Used**	**Year**	**Data**	**Factors and Main Findings**
Demirgüç-Kunt and Detragiache	Multivariate Logit	1998, 2005	94 countries, 77 crises occurred, 1980 to 2002.	• Real GDP growth, • real interest rates and • real GDP per capita • Budget deficit • Private credit/GDP Around 70% of the time the model predicted crisis occurrence correctly. Forecasted data perform poorly in predicting crisis, using the same coefficients obtained from real data.
Caprio and Klingebiel	Multivariate logit	2003	117 crises in 93 countries, 1970 to 2002	Defines systemic banking crises as episodes during which most or all bank capital was exhausted. The listing of crises used by these authors has been used as a reference by almost all academic researchers after this paper.
Eichengreen and Rose	Multivariate probit	1998	105 developing countries, 1975-1992	Main findings: higher crisis probability if higher interest rates, low growth, more short-term debt.
Glick and Hutchison	Multivariate probit	1999	90 industrial and developing countries, 1975 - 1997	Main findings: twin crisis are more common in emerging markets, especially in the presence of financial liberalization. Banking crises are a good leading indicator of currency crises, the opposite is not true.

Authors	Model Used	Year	Data	Factors and Main Findings
Eichengreen and Arteta	Probit	2000	75 countries, 78 crises, 1975 – 1997.	Authors apply the results in previous empirical literature to emerging market crises to check the robustness of explanatory variables. Factors which they found to be robust are: • Rapid domestic credit growth • Large bank liabilities relative to reserves • Deposit rate decontrol. Factors which the authors find not to be robust include the relationship between exchange rate regimes and banking crises, deposit insurance and weak institutional frameworks.
Davis and Karim	Multivariate Logit and Signal Extraction	2008	1979 – 2003, 105 countries, 72 to 102 systemic crisis depending on the definition used.	The authors replicate the Demirgüç-Kunt and Detragiache (2005) study and Caprio and Klingebiel (2003) study. They find that logit is the most suitable approach for EWS while signal extraction is more suited for single-country EWS and that the same variables with some transformations are better predictors of crises, than the earlier set in the original papers.

Source: As listed.

5.2.2 Z-Score Model

This approach has been mainly used to study individual bank failure, with empirical studies dating back to the 1970s, mainly relying on bank balance sheet and market information to explain and forecast the failure of individual institutions. These include studies with variations of a Merton type, options based model to predict expected number of defaults (END) Z-scores or distance to default (DD) for financial institutions or sovereigns and credit migrations (recent studies include Gropp, Vesala and Vulpes 2004, Fuertes and Kalotychou 2006 and Savona and Vezzoli, 2008, among others).

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 (this approach was also adopted by the Central Bank of Egypt's Macro-Prudential Unit for some of its stress-testing exercises). 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. Their sample includes seven countries: France, Germany, Italy, Spain, Sweden, Switzerland, and the United Kingdom, and focuses on the largest banks in each of these countries (a total of 26 banks) over the period covered 1991–2007, the authors find that although there is considerable variation across indicators, in both cases, the period 2004 to mid-2007 is characterized by low risk, as reflected by (almost) uniformly high DD indicators or, conversely, low Expected Number of Defaults (EDFs).

A somewhat similar application, but with a focus on creating a new financial stability quantifiable metric is made by Martin Cihak (2007) who presents an integrated measure of financial stability which he calls systemic loss. The author looks at the financial system as if it's a portfolio of financial institutions and considers the whole distribution of systemic losses of this aggregate portfolio, over one period. He proposes that systemic loss measurement should be based on i) probability of default; ii) loss given default; and iii) correlation of defaults across institutions. 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).

The following table, adapted from Cihak (2007), presents a summary of the different Merton type applications to predict banking and systemic crises and the advantages and drawbacks of each sub-set.

Table 5.2: Merton Type Methods for Crises Prediction and the Advantages and Disadvantages of Each

Indicator	**Advantages**	**Disadvantages**
DD or Z-Score (or probability of Default)	Easy to calculate from individual institutions' or for a portfolio, for DDs, Z-scores, or PDs.	• Does not reflect contagion (correlation across failures if average of individual institutions). • Does not reflect LGD of individual institutions, even though can be partially addressed by weighting. • DD requires liquid market in financial institutions iNTSRuments used to back out the metric if market data is used.
First-to-default and nth-to-default indicator	• Clear theoretical underpinnings for the nth to default indicator	• Does not fully reflect differences in LGD in different institutions. • FTD looks at individual vs systemic risk.
Expected number of defaults (END) indicator	• Relatively easy to interpret.	• Does not reflect different LGDs in institutions. • Difficult to calculate as its not a closed form expression • Focuses only on central tendency of the distribution. • Depends on total number of institutions
Distribution of systemic loss	• Captures differences in LGD in institutions • Captures correlation across bank failures • Focuses only on central tendencies	• May be difficult to calculate in some cases; no closed-form expression.

Source: Adapted from Cihak (2007).

Gropp, Vesala and Vulpes (2004), using a Merton type approach, analyze the ability of equity and bond market signals as leading indicators in a sample of EU banks. They find both indicators are good leading metrics of fragility, with distance to default exhibiting lead times of 6 to 18 months, while bond spreads signal values close to problems only. In a related study, Krainer and Lopez (2004), find that stock returns and equity-based default probabilities are useful indicators for US bank supervisors. The authors develop a model of supervisory ratings that combines supervisory and equity market information and find that their model forecasts supervisory rating changes by up to four quarters. Finally, an application to Estonia by Chen, Funke and Mannasoo (2006) attempts to predict bank fragility from market prices through the use of a Merton type approach and find that market indicators are moderately useful for anticipating future financial distress and rating changes.

5.3 Empirical Model Design

5.3.1 Logit Model Empirical Design

Logit models use a logistic specification and enable the study of covariates of banking crises, developed by Demirgüç-Kunt and Detragiache (1998). This approach assumes that the probability that a crisis occurs is a function of a vector of explanatory variables and its output, although in the form of a probability, is transformed into binary mode through a decision rule. Either a country is experiencing a crisis or not (determined by what threshold probability is given in the decision rule to label a country as having a crisis). The advantage of this model is that its non-linear and incorporates several variables simultaneously.

The probability distribution in a logit model is assumed to be logistic. Hence, the estimated coefficients reflect the effect of a change in an explanatory variable on ln ((P (i,t)/ (1-P(i,t)). Thus, the increase in the probability depends upon the original probability, and in turn on the initial values of all the independent variables and their coefficients.

Under this model, in each period, a country is either experiencing a crisis with a probability ranging from zero to one.

More formally, the log-likelihood function of the model is:

$$Ln\ \mathrm{L} = \sum_{t=1.....T} \sum_{i=1....n} \left\{ P(i,t) \ln \left[F\left(B' X\left(i,t\right)\right)\right] + (1 - P(i,t)) \ \ln \ \left[1 - F(B' X(i,t))\right]\right\}$$

Where:

X (i,t) = vector of n explanatory variables
P (i,t) = banking crisis dummy variable
B = vector of n unknown coefficients
F[B'X(i,t)] = cumulative probability distribution function, evaluated at B'X(i,t)

One of the challenges linked to this methodology is how to deal with the explanatory variables following a crisis, when these variables would have been impacted by the crisis itself. This is addressed by the authors by excluding the years during which the crisis is unfolding from the sample. Another challenge was the coNTSRuction of the banking crisis dependent variable.

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

$\omega=\beta/(1-\alpha)$

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.

Applying this to the Logit model proposed in this chapter, the noise-to-signal ratio of each run, ω, would also be computed in the same way. Where α again is the size of the type I error and β is the size of the type II error, with the difference that now both are functions of the chosen model.

The question is from a regulatory perspective, if the objective function of the regulator is to prevent crises at all costs, then model evaluation should be on the basis of minimizing Type I errors as they are much more costly, and accepting Type II errors as a downside. By setting this objective function, the regulator would ensure a continuously healthy system and is taking the most risk-averse stance they could take. This is another innovation that this research attempts.

5.3.2 Setting Up the Logit Model for the Three Dependent Variable Specifications

For each of the three dependent variable specifications, an optimized best fit model was constructed. This contrasts to Demirgüç-Kunt and Detragiache (1998, 2005) where only *one model was optimized with one dependent variable specification*. By using the three different specifications, this is an improvement on previous approaches as we are also capturing the significance of the different independent variables given a dependent variable specification. The formula for each of the three Logit models optimized is:

$$Ln\ \mathrm{L} = \sum_{t=1.....T} \sum_{i=1....n} \left\{ P(i,t) \ln\left[F\left(B' X\left(i,t\right)\right)\right] + (1 - P(i,t))\ \ln\ \left[1 - F(B' X(i,t))\right] \right\}$$

Where:

X (i,t) = vector of n explanatory variables, P (i,t) = banking crisis dummy variable

B = vector of n unknown coefficients, F[B'X(i,t)] = cumulative probability distribution function, evaluated at B'X(i,t)

The three Logit models using this methodology are summarized below.

Table 5.3: A. Macro Logit Model Specifications –In-Sample

10 bps		50 bps		100 bps	
Variable	**Coefficient**	**Variable**	**Coefficient**	**Variable**	**Coefficient**
C	4.615373	C	-1.09926	C	4.898859
DRGDP	-124.1171	DRGDP	67.98443	DRGDP	249.8444
HPI	-30.93891	HPI	-1.62905	MHPI	-137.0561
MBAG	26.4513	BAG	0.835172	SBAG	69.86863
SBAGDP	12.44683	SBAGDP	6.933158	PENS	-17.59901
PENS	-7.441338	PENS	-2.82216	EMKTDY	-88.09279
EMKTDY	-81.38702	EMKTDY	-88.8771	LIQ	-27.05003
LIQ	28.52972	SDLIQ	52.50506		
MacFadden's R2	**46.20%**	**MacFadden's R2**	**30.47%**	**MacFadden's R2**	**62.30%**

B. Macro Logit Model Specifications –Out-of-Sample

10 bps		50 bps		100 bps	
Variable	**Coefficient**	**Variable**	**Coefficient**	**Variable**	**Coefficient**
C	14.08314	C	-0.34736	C	-2.59088
DRGDP	-221.3545	DRGDP	205.2767	DRGDP	14.28067
HPI	-14.16391	HPI	-8.5871		
MBAG	20.80639	BAG	-10.6851	SBAG	-14.92136
SBAGDP	16.46121	SBAGDP	19.11613	PENS	-5.633749
PENS	-12.8104	PENS	-6.7851	EMKTDY	-9.714505
EMKTDY	-202.1921	EMKTDY	-182.973	LIQ	3.416117
LIQ	30.080661	SDLIQ	-70.0149		
MacFadden's R2	**52.50%**	**MacFadden's R2**	**45.60%**	**MacFadden's R2**	**16.60%**

Source: Authors' Calculations.

These models use the consolidated dependent variable crisis specifications without unbundling given that the construct of the Logit model, in contrast to signal extraction, is to evaluate the effectiveness of a set of variables collectively or a model on the whole, rather than individual significance of an indicator on an unbundled LHS variable. Furthermore, the model is not possible to estimate with any less number of observations as evident by for the 100 bps calibration, where the equation has to be modified to avoid overflow, given the smaller number of data points (last observation for each country in 2004). The HPI variable was dropped as such for this particular run.

5.3.3 Z-Score Model Empirical Design

The Z-score has been used extensively as a measure of individual financial institutions' soundness as in Demirgüç-Kunt, Detragiache, Tressel (2006) and Cihak (2007). The Z-score is defined as $z \equiv (k+\mu)/\sigma$, where k is equity capital as percent of assets, μ is return as percent of assets, and σ is standard deviation of return on assets as a proxy for return volatility. The z-score is simple to calculate and its attractiveness lies in it being inversely related to the probability of a financial institution's default.

The probability of default for the integral from $-\infty$ to k, is given by

$$p\ (\mu < k) = \int \varphi\ (\mu)\ d\mu$$

If μ is normally distributed, then $p\ (\mu < k) = \int N(0,1)\ d\mu$ where z is the z-score. Hence if returns are normally distributed, the z-score measures the number of standard deviations a return realization has to fall in order to deplete equity. In the case μ is not normally distributed, z is the lower bound on the probability of default (by Tchebycheff inequality) and therefore a higher z-score implies a lower probability of insolvency.

The z-scores have several limitations, the most important is that they are based on low frequency accounting data. Also, the z-score applied to an individual financial institution, does not take into account the correlation of institutions in the system. However, an advantage of the z-score is that it can be used for any institution, even if its not traded or its securities are not liquid enough to enable a higher frequency Merton type application.

Similar to "portfolio DD," we can define "portfolio *z*-score," as $z \equiv (k+\mu)/\sigma$, where k is total equity capital in the system as percent of total assets in the system, μ is total return as percent of total assets, and σ is standard deviation of the aggregate return on aggregate assets as a proxy for return volatility. The portfolio *z*-score is always higher than the sum of *z*-scores for the individual institutions.

Similar to the signal extraction and the Logit applications, the evaluation of a Z-score model could be done using a NTSR framework choosing the model that minimizes the noise-to-signal ratio, ω, that is computed in 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.

Applying this to the Z-score model, the noise-to-signal ratio of each Z-score run, ω, would also be computed in the same way. Where α again is the size of the type I error and β is the size of the type II error.

The question is from a regulatory perspective, if the objective function of the regulator is to prevent crises at all costs, then model evaluation should be on the basis of minimizing Type I errors as they are much more costly, and accepting Type II errors as a downside. By setting this objective function, the regulator would ensure a continuously healthy system and is taking the most risk-averse stance they could take. This is another innovation attempted throughout this research.

5.4 Dependent and Explanatory Variables

5.4.1. Logit Dependent and Explanatory Variables

5.4.1.1 Dependent Variable - Innovation and contribution, A note on crises definitions

This research 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. This is the same approach adopted in the signal extraction application. Please refer to section 4.4.1 for details.

5.4.1.2. Logit Explanatory Variables

The variables and their definitions are the same used for the signal extraction application, please refer to section 4.4.2.

5.4.2 Dependent and Explanatory Variables for Z-Score Model

5.4.2.1 Dependent Variable

The number of near-crises for the base case as per the definition discussed at length in earlier chapters. For the base case there were 232 systemic vulnerability observations out of a total of 870 observations, or 27%. For the shorter sample period and differing number of countries for the Z-Score application, without changing the definition, the total vulnerability spots are 80 out of 273 usable observations, or around 29%. Thus the dependent variable percentage of crisis identified did not change.

Table 5.4: Macro Logit Near-Crises Identified for Selected OECD Countries (1995 – 2007)- Base Case (50 bps Consolidated)*

	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	Total
Austria	1	0	0	0	0	0	0	0	0	0	0	1	1	3
Belgium	0	0	0	0	0	0	0	0	0	0	0	0	1	1
Canada	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Czech Republi	1	1	1	1	1	1	1	1	1	1	0	1	1	12
Denmark	0	0	0	0	0	1	1	0	0	0	0	1	1	4
Finland	1	1	0	0	0	0	1	0	1	1	0	0	1	6
France	0	0	0	0	1	0	0	0	0	0	1	0	0	2
Germany	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ireland	1	0	1	0	0	0	0	1	1	0	1	0	0	5
Italy	0	0	0	0	0	0	0	0	0	0	0	0	1	1

*As per the relevant definitions in earlier chapters. This is the time and country subset which is applicable to the current Z-Score application.

Source: Authors calculation.

Table 5.4: Macro Logit Near-Crises Identified for Selected OECD Countries (1995 – 2007)- Base Case*-Continued

Japan	0	1	0	1	1	0	0	1	1	1	0	1	1	**8**
Korea	1	1	1	1	1	1	1	0	0	1	1	0	0	**9**
Luxembourg	0	0	0	0	1	0	0	1	0	0	0	0	0	**2**
Netherlands	0	0	0	0	0	0	0	0	0	0	1	1	1	**3**
Norway	1	0	0	0	0	0	0	0	0	0	0	0	0	**1**
New Zealand	0	1	1	0	0	0	0	1	1	0	0	1	0	**5**
Spain	1	0	0	0	0	1	0	0	0	0	1	1	0	**4**
Sweden	0	1	0	0	0	0	0	0	0	1	1	1	0	**4**
Switzerland	0	0	1	1	0	1	0	0	0	0	0	0	0	**3**
US	0	0	0	0	0	0	0	0	0	1	0	0	0	**1**
UK	0	0	1	0	0	0	0	1	0	1	1	1	1	**6**
	7	**6**	**6**	**4**	**5**	**5**	**4**	**6**	**5**	**7**	**7**	**9**	**9**	**80**
Total Observations														273
% of Total Observations														29%

*As per the relevant definitions in earlier chapters. This is the time and country subset which is applicable to the current Z-Score application.

Source: Authors calculation.

5.5. Data and Descriptive Statistics of Country Universe

5.5.1 Data and Descriptive Statistics – Logit Model

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 5.5 shows the 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 5.5: Macro Logit Model Data Descriptive Statistics

Acronym	DRGDP	HPI	DEMI	CAB	BAG	BAGDP	PENS	EMKTDY	LIQ	FUN
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
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
No. Of Observations	825	246	691	811	613	649	243	287	481	481
Mean	2.87%	3.79%	18.83%	-0.70%	13.03%	328.36%	36.18%	3.43%	18.65%	105.08%
SD	2.7%	6.0%	45.0%	5.0%	15.3%	655.4%	45.9%	2.9%	6.5%	28.7%
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

Source: Authors' calculation.

The mean appreciation in real house prices over the study period was 3.8%, with a standard deviation of 6% and a slight skew to the right of 0.4 (normal distribution skewness is approximately zero), and very thin tails with kurtosis at 0.75 (normal distribution is approximately three). The mean change in equity capital market indices over the study period was 18.8%, with a standard deviation of 45% and a skew to the right or positive skew of 5.92 (normal distribution skewness is approximately zero), and very fat tails with kurtosis at 57 (normal distribution is approximately three).

The mean current account balance to GDP over the study period was -0.7%, with a standard deviation of 5% and a slight skew to the right of 0.16 (normal distribution skewness is approximately zero), and thin tails with kurtosis at 1.74 (normal distribution is approximately three). The mean banking sector asset growth over the study period was 13%, with a standard deviation of 15.3% and a skew to the right of 3.46 (normal distribution skewness is approximately zero), and fat tails with kurtosis at 16.12 (normal distribution is approximately three) – fat tails suggest another area of potential research in different benchmarks for this variable based on a distribution other than the normal. The mean of banking sector assets to GDP over the study period was 328.4%, with a standard deviation of 655.4% and a skew to the right of 11.15 (normal distribution skewness is approximately zero), and fat tails with kurtosis at 11.15 (normal distribution is approximately three).

The mean of pension fund assets to GDP over the study period was 36.2%, with a standard deviation of 45.9% and a skew to the right of 2.94 (normal distribution skewness is approximately zero), and fat tails with kurtosis at 19.17 (normal distribution is approximately three).

The mean dividend yield in equity capital markets of OECD countries over the study period was 3.4%, with a standard deviation of 2.9% and a skew to the right of 3.99 (normal distribution skewness is approximately zero), and fat tails with kurtosis at 20.77 (normal distribution is approximately three).

The mean holdings of securities to total assets by OECD banks as a liquidity indicator over the study period was 18.65%, with a standard deviation of 6.5% and a skew to the right of 0.1, so almost normally distributed. The mean loans to deposits ratio as a funding indicator for OECD banks was 105%, with a standard deviation of 29% and a slight positive skew of 0.6.

5.5.2 Data and Descriptive Statistics – Z-Score Model

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 for the Z-score application spans from 1989 to 2007 with 3 explanatory variables, system capital adequacy metric for each country, system return on average assets before provisions and system standard deviation of returns. The Z-score application is for a subset of 21 countries of the OECD for which the data was available. This data set is obtained from OECD and national central banks.

Two of the three explanatory variables: equity to total assets as a capital adequacy metric and return on average assets as measured by net income before provisions divided by average assets are presented for a ten year period in the following Table 5.6.

Over the ten-year period, average capital to total assets for the sample was 6%, while return on average assets averaged 1%. Country differences are pronounced, with the highest average capital held by Finland and the Czech Republic at 9% and the lowest held by Belgium at 3%. The highest returns were booked by US and New Zealand banks at 2% and the lowest returns by Japan and the Czech Republic at 0%. Higher returns help a system build its capital base, albeit slowly, whereas more direct measures such as capital raisings and capital injections are fast impact measures. The reverse is also true, with low returns slowly eroding the capital base and shocks resulting in quick capital erosion.

Table 5.6: Z-Score Macro Model Explanatory Variable Descriptive Statistics

	Capital/ Assets	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
1	Austria	5%	5%	5%	5%	5%	5%	4%	5%	5%	5%	4%	5%	5%	5%	5%	5%	6%	7%
2	Belgium	3%	4%	4%	3%	3%	3%	3%	3%	3%	3%	4%	4%	4%	4%	3%	3%	3%	4%
3	Canada	6%	6%	6%	6%	5%	5%	5%	5%	5%	5%	5%	5%	6%	6%	6%	5%	6%	5%
4	Czech Re	0%	0%	0%	12%	13%	11%	10%	9%	9%	8%	8%	6%	9%	8%	11%	10%	10%	8%
5	Denmark	8%	7%	6%	6%	7%	7%	7%	7%	6%	6%	7%	6%	6%	6%	6%	6%	6%	6%
6	Finland	7%	7%	5%	5%	5%	6%	6%	7%	7%	6%	6%	11%	11%	11%	9%	9%	9%	8%
7	France	3%	4%	4%	4%	5%	4%	4%	4%	4%	5%	5%	5%	5%	5%	5%	4%	4%	4%
8	Germany	4%	4%	4%	4%	4%	4%	4%	4%	4%	4%	4%	4%	4%	4%	4%	4%	4%	4%
9	Ireland	0%	0%	0%	0%	0%	7%	7%	6%	6%	6%	6%	7%	6%	5%	5%	4%	4%	4%
10	Italy	6%	7%	7%	7%	7%	7%	7%	6%	7%	7%	7%	7%	7%	7%	7%	7%	7%	8%
11	Japan	0%	0%	0%	6%	7%	6%	5%	5%	5%	5%	5%	5%	7%	6%	6%	6%	7%	7%
12	Korea	9%	9%	9%	8%	8%	7%	6%	4%	4%	4%	4%	4%	4%	4%	5%	6%	6%	6%
13	Luxembo	3%	3%	4%	3%	2%	3%	2%	2%	2%	3%	4%	4%	4%	4%	4%	4%	4%	4%
14	Netherla	4%	4%	4%	4%	5%	5%	5%	4%	4%	4%	4%	4%	4%	4%	3%	3%	3%	4%
15	Norway	4%	3%	4%	6%	6%	7%	7%	7%	7%	7%	7%	7%	6%	6%	6%	6%	5%	5%
16	New Zeal	6%	6%	4%	5%	5%	5%	4%	5%	5%	5%	5%	6%	6%	8%	8%	8%	7%	6%
17	Spain	8%	9%	9%	8%	9%	8%	8%	8%	8%	7%	8%	8%	8%	8%	9%	8%	7%	7%
18	Sweden	6%	5%	5%	6%	6%	6%	5%	6%	5%	6%	6%	6%	5%	6%	7%	6%	6%	6%
19	Switzerla	7%	6%	6%	7%	7%	6%	6%	5%	5%	5%	6%	6%	6%	6%	5%	5%	5%	5%
20	US	6%	7%	7%	8%	8%	8%	8%	9%	9%	8%	9%	9%	9%	9%	10%	10%	10%	10%
21	UK								5%	5%	4%	5%	5%	5%	6%	7%	5%	6%	4%

Source: Authors' calculation.

Table 5.6: Z-Score Macro Model Explanatory Variable Descriptive Statistics-Continued

	Return on Average Assets	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
1	Austria	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%
2	Belgium	1%	1%	1%	1%	0%	1%	1%	1%	1%	1%	1%	1%	1%	1%	0%	0%	1%	1%
3	Canada	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%
4	Czech Re	0%	0%	0%	0%	3%	2%	0%	1%	0%	-1%	-1%	1%	1%	1%	0%	0%	0%	0%
5	Denmark	1%	1%	1%	2%	1%	2%	2%	1%	1%	1%	1%	2%	1%	1%	1%	1%	1%	1%
6	Finland	1%	-1%	-3%	-1%	-1%	0%	1%	1%	1%	1%	1%	3%	1%	2%	1%	1%	1%	1%
7	France	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	0%
8	Germany	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	0%	1%	1%	1%
9	Ireland	0%	0%	0%	0%	0%	2%	2%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%
10	Italy	2%	2%	1%	2%	1%	1%	1%	1%	1%	1%	2%	2%	1%	1%	1%	1%	1%	1%
11	Japan	0%	0%	0%	0%	0%	-1%	0%	-1%	-1%	0%	0%	-1%	0%	0%	0%	0%	0%	0%
12	Korea	1%	1%	1%	2%	2%	1%	1%	0%	-2%	1%	1%	2%	2%	2%	2%	2%	2%	2%
13	Luxembo	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%
14	Netherla	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%
15	Norway	1%	0%	2%	3%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%
16	New Zeal	1%	1%	1%	1%	1%	2%	1%	1%	2%	2%	2%	2%	2%	2%	2%	2%	2%	2%
17	Spain	2%	2%	2%	2%	2%	1%	1%	1%	1%	1%	1%	2%	1%	1%	1%	1%	1%	2%
18	Sweden	1%	-1%	-1%	0%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	2%	1%
19	Switzerla	1%	2%	2%	2%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%
20	US	1%	2%	2%	2%	2%	2%	2%	2%	2%	2%	2%	2%	2%	2%	2%	2%	2%	2%
21	UK									1%	1%	1%	1%	1%	1%	1%	1%	1%	1%

Source: Authors' calculation.

5.6 Empirical Estimations

5.6.1. Logit Model Empirical Estimations

Crisis Signal Forecasts

To translate the model forecasts of probability of crises into judgments on whether a crisis is 1) Unlikely (some vulnerabilities); 2) Likely (overall fragility); or 3) Probable (near crisis situation), a heuristic decision rule is needed based on model output calibration, this is where regulator input is crucial. For the three Logit models given a range of probabilities from 0% to 30% on the whole, the calibration has been set to read 1)Unlikely for any probability output less than 5%; 2) Likely for any output greater than 5%, but less than 15%; and 3) Probable for any output greater than 15%.

The forecasts are for t-1, t-2 and t-3, i.e. for the years 2006, 2005 and 2004 respectively for each of the three dependent variable specifications. The results are for In-Sample forecasts and out-of-sample forecasts are summarized below.

Table 5.7 (A): In-Sample Macro-Logit Forecasts for the 10 Basis Point Dependent Variable Specification

10 basis points						
In Percent	1 Year (2006 base)		2 Year (2005 base)		3 Year (2004 Base)	
Country	Crisis Forecast	Crisis Likelihood	Crisis Forecast	Crisis Likelihood	Crisis Forecast	Crisis Likelihood
Australia	-	Unlikely	-	Unlikely	-	Unlikely
Austria	8.07	Likely	8.24	Likely	8.07	Likely
Belgium	10.90	Likely	11.13	Likely	8.84	Likely
Cananda	4.85	Unlikely	1.11	Unlikely	-	Unlikely
Czech	-	Unlikely	4.50	Unlikely	5.77	Likely
Denmark	1.58	Unlikely	0.86	Unlikely	3.90	Unlikely
Finland	-	Unlikely	1.71	Unlikely	-	Unlikely
France	10.04	Likely	7.27	Likely	6.70	Likely
Germany	10.14	Likely	12.99	Likely	11.67	Likely
Greece	1.48	Unlikely	4.64	Unlikely	0.05	Unlikely
Hungary	1.96	Unlikely	2.17	Unlikely	0.87	Unlikely
Iceland	5.25	Likely	1.58	Unlikely	-	Unlikely
Ireland	3.72	Unlikely	13.98	Likely	6.23	Likely
Italy	5.07	Likely	5.63	Likely	3.07	Unlikely
Japan	0.06	Unlikely	0.93	Unlikely	0.39	Unlikely
Korea	5.56	Likely	8.67	Likely	8.11	Likely
Luxembour	13.45	Likely	11.40	Likely	19.76	Probable
Mexico	-	Unlikely	-	Unlikely	-	Unlikely
Netherland	9.37	Likely	9.96	Likely	4.39	Unlikely
Norway	5.52	Likely	4.08	Unlikely	1.11	Unlikely
New Zealar	5.32	Likely	1.56	Unlikely	-	Unlikely
Poland	2.76	Unlikely	5.43	Likely	2.85	Unlikely
Portugal	2.63	Unlikely	1.79	Unlikely	0.32	Unlikely
Slovenia	30.68	Probable	25.52	Probable	56.89	Probable
Spain	7.79	Likely	6.02	Likely	2.31	Unlikely
Sweden	4.45	Unlikely	5.99	Likely	2.70	Unlikely
Switzerland	5.02	Likely	6.54	Likely	2.47	Unlikely
Turkey	1.27	Unlikely	-	Unlikely	-	Unlikely
UK	-	Unlikely	0.92	Unlikely	-	Unlikely
US	1.20	Unlikely	0.21	Unlikely	-	Unlikely

Source: Authors' calculations.

Table 5.7 (B): Out-of-Sample Macro-Logit Forecasts for the 10 Basis Point Dependent Variable Specification

10 basis points						
In Percent	1 Year (2006 base)		2 Year (2005 base)		3 Year (2004 Base)	
Country	Crisis Forecast	Crisis Likelihood	Crisis Forecast	Crisis Likelihood	Crisis Forecast	Crisis Likelihood
Australia	0.39	Unlikely	-	Unlikely	-	Unlikely
Austria	10.85	Likely	11.65	Likely	13.72	Likely
Belgium	13.43	Likely	12.92	Likely	11.15	Likely
Cananda	10.12	Likely	1.94	Unlikely	0.85	Unlikely
Czech	0.31	Unlikely	7.85	Likely	11.35	Likely
Denmark	5.17	Likely	3.48	Unlikely	5.09	Likely
Finland	-	Unlikely	5.43	Likely	2.90	Unlikely
France	14.88	Likely	13.09	Likely	10.74	Likely
Germany	16.53	Probable	21.36	Probable	19.73	Probable
Greece	3.49	Unlikely	10.96	Likely	4.51	Unlikely
Hungary	2.29	Unlikely	2.46	Unlikely	0.42	Unlikely
Iceland	2.95	Unlikely	-	Unlikely	-	Unlikely
Ireland	-	Unlikely	15.09	Probable	3.09	Unlikely
Italy	9.59	Likely	11.75	Likely	8.46	Likely
Japan	2.00	Unlikely	3.38	Unlikely	2.50	Unlikely
Korea	10.44	Likely	13.79	Likely	12.36	Likely
Luxembour	15.76	Probable	14.16	Likely	26.74	Probable
Mexico	-	Unlikely	-	Unlikely	-	Unlikely
Netherland	8.36	Likely	10.50	Likely	4.60	Unlikely
Norway	13.64	Likely	11.02	Likely	7.68	Likely
New Zealar	13.61	Likely	9.54	Likely	5.79	Likely
Poland	1.26	Unlikely	6.74	Likely	3.82	Unlikely
Portugal	6.81	Likely	6.00	Likely	3.55	Unlikely
Slovenia	39.74	Probable	34.48	Probable	76.97	Probable
Spain	11.41	Likely	9.25	Likely	5.97	Likely
Sweden	6.11	Likely	8.55	Likely	4.59	Unlikely
Switzerland	3.56	Unlikely	4.84	Unlikely	2.21	Unlikely
Turkey	0.37	Unlikely	-	Unlikely	-	Unlikely
UK	1.31	Unlikely	3.21	Unlikely	-	Unlikely
US	2.21	Unlikely	2.38	Unlikely	0.39	Unlikely

Table 5.7 (C): In-Sample Macro- Logit Forecasts for the 50 Basis Point Dependent Variable Specification

50 basis points						
In Percent	1 Year (2006 base)		2 Year (2005 base)		3 Year (2004 Base)	
Country	Crisis Forecast	Crisis Likelihood	Crisis Forecast	Crisis Likelihood	Crisis Forecast	Crisis Likelihood
Australia	-	Unlikely	-	Unlikely	-	Unlikely
Austria	10.96	Likely	10.66	Likely	10.89	Likely
Belgium	13.35	Likely	12.06	Likely	13.40	Likely
Cananda	13.79	Likely	9.36	Likely	9.15	Likely
Czech	3.62	Unlikely	15.44	Probable	14.55	Likely
Denmark	10.53	Likely	7.12	Likely	10.38	Likely
Finland	5.19	Likely	3.95	Unlikely	4.42	Unlikely
France	12.49	Likely	11.36	Likely	10.55	Likely
Germany	15.07	Likely	13.34	Likely	13.26	Likely
Greece	0.66	Unlikely	1.48	Unlikely	2.42	Unlikely
Hungary	-	Unlikely	-	Unlikely	-	Unlikely
Iceland	1.54	Unlikely	4.02	Unlikely	3.16	Unlikely
Ireland	5.11	Likely	16.92	Probable	13.22	Likely
Italy	3.49	Unlikely	2.55	Unlikely	2.47	Unlikely
Japan	-	Unlikely	-	Unlikely	-	Unlikely
Korea	12.10	Likely	12.21	Likely	12.14	Likely
Luxembour	20.28	Probable	17.61	Probable	21.60	Probable
Mexico	-	Unlikely	-	Unlikely	-	Unlikely
Netherland	16.15	Likely	11.23	Likely	11.06	Likely
Norway	6.09	Likely	5.18	Likely	6.30	Likely
New Zeala	4.12	Unlikely	4.65	Unlikely	6.26	Likely
Poland	11.13	Likely	10.22	Likely	11.48	Likely
Portugal	-	Unlikely	-	Unlikely	-	Unlikely
Slovenia	32.91	Probable	26.48	Probable	44.25	Probable
Spain	9.03	Likely	9.49	Likely	8.60	Likely
Sweden	10.79	Likely	10.85	Likely	10.48	Likely
Switzerland	11.41	Likely	10.24	Likely	8.72	Likely
Turkey	2.23	Unlikely	3.09	Unlikely	3.61	Unlikely
UK	-	Unlikely	-	Unlikely	-	Unlikely
US	7.80	Likely	8.30	Likely	9.13	Likely

Source: Authors' calculations.

Table 5.7 (D): Out-of-Sample Macro-Logit Forecasts for the 50 Basis Point Dependent Variable Specification

50 basis points						
In Percent	1 Year (2006 base)		2 Year (2005 base)		3 Year (2004 Base)	
Country	Crisis Forecast	Crisis Likelihood	Crisis Forecast	Crisis Likelihood	Crisis Forecast	Crisis Likelihood
Australia	0.0	Unlikely	0.0	Unlikely	0.0	Unlikely
Austria	0.0	Unlikely	0.0	Unlikely	0.0	Unlikely
Belgium	0.0	Unlikely	0.0	Unlikely	0.0	Unlikely
Cananda	0.0	Unlikely	0.0	Unlikely	0.0	Unlikely
Czech	12.8	Likely	0.0	Unlikely	0.0	Unlikely
Denmark	0.0	Unlikely	0.0	Unlikely	0.0	Unlikely
Finland	0.0	Unlikely	0.0	Unlikely	0.0	Unlikely
France	0.0	Unlikely	0.0	Unlikely	0.0	Unlikely
Germany	0.0	Unlikely	0.0	Unlikely	0.0	Unlikely
Greece	5.2	Likely	5.2	Likely	9.3	Likely
Hungary	0.8	Unlikely	0.7	Unlikely	2.3	Unlikely
Iceland	5.1	Likely	9.7	Likely	9.0	Likely
Ireland	0.0	Unlikely	5.4	Likely	0.0	Unlikely
Italy	0.0	Unlikely	0.0	Unlikely	0.0	Unlikely
Japan	0.0	Unlikely	0.0	Unlikely	0.6	Unlikely
Korea	0.0	Unlikely	0.0	Unlikely	0.0	Unlikely
Luxembour	1.1	Unlikely	0.0	Unlikely	10.3	Likely
Mexico	0.0	Unlikely	0.0	Unlikely	0.0	Unlikely
Netherland	0.0	Unlikely	0.0	Unlikely	0.0	Unlikely
Norway	0.0	Unlikely	0.0	Unlikely	0.0	Unlikely
New Zealar	0.0	Unlikely	0.0	Unlikely	0.8	Unlikely
Poland	0.0	Unlikely	0.0	Unlikely	0.0	Unlikely
Portugal	0.0	Unlikely	0.0	Unlikely	0.0	Unlikely
Slovenia	38.0	Probable	24.1	Probable	63.4	Probable
Spain	0.0	Unlikely	0.0	Unlikely	0.0	Unlikely
Sweden	0.0	Unlikely	0.0	Unlikely	0.0	Unlikely
Switzerlanc	0.0	Unlikely	0.0	Unlikely	0.0	Unlikely
Turkey	8.5	Likely	10.4	Likely	12.7	Likely
UK	1.3	Unlikely	0.0	Unlikely	0.0	Unlikely
US	0.0	Unlikely	0.0	Unlikely	0.0	Unlikely

Source: Authors' calculations.

Table 5.7 (E): In-Sample Macro-Logit Forecasts for the 100 Basis Point Dependent Variable Specification

100 basis points						
In Percent	**1 Year (2006 base)**		**2 Year (2005 base)**		**3 Year (2004 Base)**	
Country	**Crisis Forecast**	**Crisis Likelihood**	**Crisis Forecast**	**Crisis Likelihood**	**Crisis Forecast**	**Crisis Likelihood**
Australia	-	Unlikely	-	Unlikely	-	Unlikely
Austria	5.01	Likely	4.61	Unlikely	7.22	Likely
Belgium	4.02	Unlikely	0.61	Unlikely	3.58	Unlikely
Cananda	-	Unlikely	-	Unlikely	-	Unlikely
Czech	23.82	Probable	17.47	Probable	12.50	Likely
Denmark	-	Unlikely	-	Unlikely	-	Unlikely
Finland	-	Unlikely	-	Unlikely	-	Unlikely
France	-	Unlikely	-	Unlikely	-	Unlikely
Germany	8.73	Likely	5.53	Likely	6.94	Likely
Greece	17.23	Probable	15.66	Probable	20.26	Probable
Hungary	11.17	Likely	12.75	Likely	15.93	Probable
Iceland	0.60	Unlikely	12.44	Likely	15.51	Probable
Ireland	-	Unlikely	1.64	Unlikely	-	Unlikely
Italy	-	Unlikely	-	Unlikely	-	Unlikely
Japan	14.40	Likely	14.01	Likely	15.92	Probable
Korea	14.55	Likely	8.90	Likely	5.48	Likely
Luxembour	13.79	Likely	12.85	Likely	11.54	Likely
Mexico	16.47	Probable	13.49	Likely	16.92	Probable
Netherland	-	Unlikely	-	Unlikely	-	Unlikely
Norway	-	Unlikely	5.23	Likely	6.16	Likely
New Zealar	-	Unlikely	-	Unlikely	-	Unlikely
Poland	12.63	Likely	5.18	Likely	12.82	Likely
Portugal	6.47	Likely	4.14	Unlikely	4.79	Unlikely
Slovenia	26.28	Probable	23.86	Probable	17.54	Probable
Spain	-	Unlikely	-	Unlikely	-	Unlikely
Sweden	-	Unlikely	-	Unlikely	3.11	Unlikely
Switzerland	-	Unlikely	-	Unlikely	-	Unlikely
Turkey	22.74	Likely	27.61	Probable	29.46	Probable
UK	-	Probable	-	Unlikely	-	Unlikely
US	-	Unlikely	-	Unlikely	-	Unlikely

Source: Authors' calculations.

Table 5.7 (F): Out-of-Sample Macro-Logit Forecasts for the 100 Basis Point Dependent Variable Specification

100 basis points						
In Percent	1 Year (2006 base)		2 Year (2005 base)		3 Year (2004 Base)	
Country	Crisis Forecast	Crisis Likelihood	Crisis Forecast	Crisis Likelihood	Crisis Forecast	Crisis Likelihood
Australia	0.0	Unlikely	0.0	Unlikely	0.0	Unlikely
Austria	0.0	Unlikely	0.0	Unlikely	0.0	Unlikely
Belgium	0.0	Unlikely	0.0	Unlikely	0.0	Unlikely
Cananda	0.0	Unlikely	0.0	Unlikely	0.0	Unlikely
Czech	0.0	Unlikely	0.0	Unlikely	0.0	Unlikely
Denmark	0.0	Unlikely	0.0	Unlikely	0.0	Unlikely
Finland	0.0	Unlikely	0.0	Unlikely	0.0	Unlikely
France	0.0	Unlikely	0.0	Unlikely	0.0	Unlikely
Germany	0.0	Unlikely	0.0	Unlikely	0.0	Unlikely
Greece	0.0	Unlikely	0.0	Unlikely	0.0	Unlikely
Hungary	0.0	Unlikely	0.0	Unlikely	0.0	Unlikely
Iceland	0.0	Unlikely	0.0	Unlikely	0.0	Unlikely
Ireland	0.0	Unlikely	0.0	Unlikely	0.0	Unlikely
Italy	0.0	Unlikely	0.0	Unlikely	0.0	Unlikely
Japan	0.0	Unlikely	0.0	Unlikely	0.0	Unlikely
Korea	0.0	Unlikely	0.0	Unlikely	0.0	Unlikely
Luxembour	0.0	Unlikely	0.0	Unlikely	0.0	Unlikely
Mexico	0.0	Unlikely	0.0	Unlikely	0.0	Unlikely
Netherland	0.0	Unlikely	0.0	Unlikely	0.0	Unlikely
Norway	0.0	Unlikely	0.0	Unlikely	0.0	Unlikely
New Zealar	0.0	Unlikely	0.0	Unlikely	0.0	Unlikely
Poland	0.0	Unlikely	0.0	Unlikely	0.0	Unlikely
Portugal	0.0	Unlikely	0.0	Unlikely	0.0	Unlikely
Slovenia	0.0	Unlikely	0.0	Unlikely	0.0	Unlikely
Spain	0.0	Unlikely	0.0	Unlikely	0.0	Unlikely
Sweden	0.0	Unlikely	0.0	Unlikely	0.0	Unlikely
Switzerland	0.0	Unlikely	0.0	Unlikely	0.0	Unlikely
Turkey	0.0	Unlikely	0.0	Unlikely	0.0	Unlikely
UK	0.0	Unlikely	0.0	Unlikely	0.0	Unlikely
US	0.0	Unlikely	0.0	Unlikely	0.0	Unlikely

Source: Authors' calculations.

Note how the choice of dependent variable selection affects the overall performance of the model and thus the difficulty inherent in 'calling' crises correctly and the impact of the choice of dependent variable on the model. The key take away is that we need a range of dependent variable triggers for which results to be presented consistently to regulators to enable sound decision making. Or in other words, the inherent feedback loops between the choice of the regulator objective and the output of an EWS.

An interesting extension is the consolidated forecast for all three dependent variable specifications, where the higher probability is chosen for any given year for any given country. This is presented in Table 5.8. It is equivalent to a regulator choosing to capture all alarm signals from different models in one matrix.

Table 5.8 (A): In-Sample Macro-Logit Model Consolidated Forecasts

Consolidated Forecasts						
In Percent	**1 Year (2006 base)**		**2 Year (2005 base)**		**3 Year (2004 Base)**	
Country	**Crisis Forecast**	**Crisis Likelihood**	**Crisis Forecast**	**Crisis Likelihood**	**Crisis Forecast**	**Crisis Likelihood**
Australia	-	Unlikely	-	Unlikely	-	Unlikely
Austria	10.96	Likely	10.66	Likely	10.89	Likely
Belgium	13.35	Likely	12.06	Likely	13.40	Likely
Cananda	13.79	Likely	9.36	Likely	9.15	Likely
Czech	23.82	Probable	17.47	Probable	14.55	Likely
Denmark	10.53	Likely	7.12	Likely	10.38	Likely
Finland	5.19	Likely	3.95	Unlikely	4.42	Unlikely
France	12.49	Likely	11.36	Likely	10.55	Likely
Germany	15.07	Probable	13.34	Likely	13.26	Likely
Greece	17.23	Probable	15.66	Probable	20.26	Probable
Hungary	11.17	Likely	12.75	Likely	15.93	Probable
Iceland	5.25	Likely	12.44	Likely	15.51	Probable
Ireland	5.11	Likely	16.92	Probable	13.22	Likely
Italy	5.07	Likely	5.63	Likely	3.07	Unlikely
Japan	14.40	Likely	14.01	Likely	15.92	Probable
Korea	14.55	Likely	12.21	Likely	12.14	Likely
Luxembour	20.28	Probable	17.61	Probable	21.60	Probable
Mexico	16.47	Probable	13.49	Likely	16.92	Probable
Netherland	16.15	Probable	11.23	Likely	11.06	Likely
Norway	6.09	Likely	5.23	Likely	6.30	Likely
New Zealar	5.32	Likely	4.65	Unlikely	6.26	Likely
Poland	12.63	Likely	10.22	Likely	12.82	Likely
Portugal	6.47	Likely	4.14	Unlikely	4.79	Unlikely
Slovenia	32.91	Probable	26.48	Probable	56.89	Probable
Spain	9.03	Likely	9.49	Likely	8.60	Likely
Sweden	10.79	Likely	10.85	Likely	10.48	Likely
Switzerland	11.41	Likely	10.24	Likely	8.72	Likely
Turkey	22.74	Probable	27.61	Probable	29.46	Probable
UK	-	Unlikely	0.92	Unlikely	-	Unlikely
US	7.80	Likely	8.30	Likely	9.13	Likely

Source: Authors' calculations.

Table 5.8 (B): Out-of-Sample Macro Logit Consolidated Forecasts

Consolidated Forecasts						
In Percent	**1 Year (2006 base)**		**2 Year (2005 base)**		**3 Year (2004 Base)**	
Country	**Crisis Forecast**	**Crisis Likelihood**	**Crisis Forecast**	**Crisis Likelihood**	**Crisis Forecast**	**Crisis Likelihood**
Australia	0.4	Unlikely	0.0	Unlikely	0.0	Unlikely
Austria	10.8	Likely	11.6	Likely	13.7	Likely
Belgium	13.4	Likely	12.9	Likely	11.2	Likely
Cananda	10.1	Likely	1.9	Unlikely	0.9	Unlikely
Czech	12.8	Likely	7.8	Likely	11.4	Likely
Denmark	5.2	Likely	3.5	Unlikely	5.1	Likely
Finland	0.0	Likely	5.4	Likely	2.9	Unlikely
France	14.9	Likely	13.1	Likely	10.7	Likely
Germany	16.5	Probable	21.4	Probable	19.7	Probable
Greece	5.2	Likely	11.0	Likely	9.3	Likely
Hungary	2.3	Unlikely	2.5	Unlikely	2.3	Unlikely
Iceland	5.1	Likely	9.7	Likely	9.0	Likely
Ireland	0.0	Unlikely	15.1	Probable	3.1	Unlikely
Italy	9.6	Likely	11.7	Likely	8.5	Likely
Japan	2.0	Unlikely	3.4	Unlikely	2.5	Unlikely
Korea	10.4	Likely	13.8	Likely	12.4	Likely
Luxembour	15.8	Probable	14.2	Likely	26.7	Probable
Mexico	0.0	Unlikely	0.0	Unlikely	0.0	Unlikely
Netherland	8.4	Likely	10.5	Likely	4.6	Unlikely
Norway	13.6	Likely	11.0	Likely	7.7	Likely
New Zealar	13.6	Likely	9.5	Likely	5.8	Likely
Poland	1.3	Unlikely	6.7	Likely	3.8	Unlikely
Portugal	6.8	Likely	6.0	Likely	3.6	Unlikely
Slovenia	39.7	Probable	34.5	Probable	77.0	Probable
Spain	11.4	Likely	9.2	Likely	6.0	Likely
Sweden	6.1	Likely	8.5	Likely	4.6	Likely
Switzerland	3.6	Unlikely	4.8	Unlikely	2.2	Unlikely
Turkey	8.5	Likely	10.4	Likely	12.7	Likely
UK	1.3	Unlikely	3.2	Unlikely	0.0	Unlikely
US	2.2	Unlikely	2.4	Unlikely	0.4	Unlikely

Source: Authors' calculations.

5.6.2 Z-Score Model Empirical Estimations

Crisis Signal Forecasts

To translate the Z-score backed out probability of default into judgments on whether a crisis signal is given or not, the change in probability of default by one SD (increase only) is compared to 3 year rolling, 5 year rolling and 10 year rolling SD of returns. For each of these rolling mean calibrations, a country is considered to have a crisis if its PD shifts by more than 1 SD.

The forecasts are for t-1, t-2 and t-3, i.e. for the years 2006, 2005 and 2004 respectively for each of the rolling mean calibrations. The results for In-Sample forecasts and out-of-sample forecasts are summarized below.

The sample subset is smaller, but the forecasts follow the same pattern as the larger samples for the Signal Extraction and Logit calibrations, with the number of crises called using the 3-year benchmark higher than the five-year benchmark and higher than the 10-year benchmark. This is intuitive as the three year mean is the most volatile and hence a crisis signal is issued much more easily than if we are calculating a 1 SD move from a 10 year rolling mean.

Table 5.9 (A): Macro Z-Score Crises Forecasts - Base Case Dependent Variable Specification – 1 Year Forecast

1 Year Forecast (2006)		Out-of-Sample			In-Sample		
		3 YR	5YR	10 YR	3 YR	5YR	10 YR
1	Austria	0	0	0	0	0	0
2	Belgium	1	1	1	0	0	0
3	Canada	1	1	0	0	0	0
4	Czech Republic	0	0	0	0	0	0
5	Denmark	0	0	0	1	1	0
6	Finland	0	0	0	0	0	0
7	France	1	0	0	1	1	1
8	Germany	0	0	0	0	0	0
9	Ireland	1	1	0	0	0	0
10	Italy	0	0	0	0	0	0
11	Japan	0	0	0	0	0	0
12	Korea	0	0	0	0	0	0
13	Luxembourg	1	1	1	1	1	1
14	Netherlands	1	0	0	0	0	0
15	Norway	0	0	0	1	0	1
16	New Zealand	0	0	0	0	0	0
17	Spain	1	1	1	0	0	0
18	Sweden	1	1	1	1	1	1
19	Switzerland	0	0	0	1	1	1
20	US	0	0	0	1	1	1
21	UK	0	0	0	0	1	1
		8	**6**	**4**	**7**	**7**	**7**

Source: Authors' calculations.

Table 5.9 (B): Macro Z-Score Crises Forecasts -Base Case Dependent Variable Specification- 2-Year Forecast

		Out-of-Sample			In-Sample		
2 Year Forecast (2005)		3 YR	5YR	10 YR	3 YR	5YR	10 YR
1	Austria	1	1	0	0	0	0
2	Belgium	1	1	1	1	1	1
3	Canada	1	1	0	1	1	0
4	Czech Republic	0	0	0	0	0	0
5	Denmark	0	0	0	0	0	0
6	Finland	0	0	0	0	0	0
7	France	1	0	0	1	0	0
8	Germany	0	0	0	0	0	0
9	Ireland	0	0	0	1	1	0
10	Italy	0	0	0	0	0	0
11	Japan	0	0	0	0	0	0
12	Korea	0	0	0	0	0	0
13	Luxembourg	0	0	0	1	1	1
14	Netherlands	0	0	0	1	0	0
15	Norway	0	0	0	0	0	0
16	New Zealand	0	0	0	0	0	0
17	Spain	0	0	0	1	1	1
18	Sweden	0	0	0	1	1	1
19	Switzerland	1	1	1	0	0	0
20	US	0	0	0	0	0	0
21	UK	0	1	1	0	0	0
		5	**5**	**3**	**8**	**6**	**4**

Source: Authors' calculations.

Table 5.9 (C): Macro Z-Score Crises Forecasts - Base Case Dependent Variable Specification- 3-Year Forecast

		Out-of-Sample			In-Sample		
3 Year Forecast (2004)		3 YR	5YR	10 YR	3 YR	5YR	10 YR
1	Austria	0	0	0	1	1	0
2	Belgium	1	1	1	1	1	1
3	Canada	0	0	0	1	1	0
4	Czech Republic	0	0	0	0	0	0
5	Denmark	0	0	0	0	0	0
6	Finland	0	0	0	0	0	0
7	France	0	0	0	1	0	0
8	Germany	1	0	0	0	0	0
9	Ireland	0	0	0	0	0	0
10	Italy	0	0	0	0	0	0
11	Japan	0	0	0	0	0	0
12	Korea	0	0	0	0	0	0
13	Luxembourg	0	0	0	0	0	0
14	Netherlands	0	0	0	0	0	0
15	Norway	0	0	0	0	0	0
16	New Zealand	0	0	0	0	0	0
17	Spain	0	1	0	0	0	0
18	Sweden	1	1	0	0	0	0
19	Switzerland	0	0	0	1	1	1
20	US	1	1	1	0	0	0
21	UK	0	0	0	0	1	1
		4	**4**	**2**	**5**	**5**	**3**

Source: Authors' calculations.

5.7 Forecasts and Model Performance

5.7.1 Macro Logit Model Performance

Table 5.10 (A): In-Sample NTSR Summary for Macro Logit Model

10 Basis Points					
	1-Year Horizon			2-Year Horizon*	3-Year Horizon**
	2005	**2006**	**2007**		
Type I %	57%	52%	64%	25%	15%
Type II %	9%	8%	8%	27%	18%
NSTR	**0.62**	**0.57**	**0.70**	**0.34**	**0.18**
50 Basis Points					
	1-Year Horizon			2-Year Horizon*	3-Year Horizon**
	2005	**2006**	**2007**		
Type I %	82%	47%	29%	31%	20%
Type II %	118%	67%	86%	65%	48%
NSTR	- **4.50**	**1.40**	**2.00**	**0.89**	**0.38**
100 Basis Points					
	1-Year Horizon			2-Year Horizon*	3-Year Horizon**
	2005	**2006**	**2007**		
Type I %	60%	0%	38%	30%	17%
Type II %	180%	160%	150%	150%	83%
NSTR	- **0.75**	-	- **0.75**	- **0.60**	**1.00**
Consolidated Forecasts					
	1-Year Horizon			2-Year Horizon*	3-Year Horizon**
	2005	**2006**	**2007**		
Type I %	4%	12%	12%	2%	1%
Type II %	22%	12%	20%	52%	36%
NSTR	**0.06**	**0.14**	**0.15**	**0.04**	**0.02**

***2005 forecast to predict 2005 and 2006 crises.**
**** 2005 forecast to predict 2005, 2006 and 2007 crises.**

Table 5.10 (B): Out-of-Sample NTSR Summary for Macro Logit Model

10 Basis Points					
	1-Year Horizon			2-Year Horizon*	3-Year Horizon**
	2005	**2006**	**2007**		
Type I %	52%	40%	56%	19%	12%
Type II %	13%	16%	16%	35%	26%
NSTR	**0.60**	**0.48**	**0.67**	**0.29**	**0.17**

50 Basis Points					
	1-Year Horizon			2-Year Horizon*	3-Year Horizon**
	2005	**2006**	**2007**		
Type I %	109%	80%	57%	46%	30%
Type II %	27%	13%	14%	19%	15%
NSTR	**1.50**	**0.92**	**0.67**	**0.57**	**0.35**

100 Basis Points					
	1-Year Horizon			2-Year Horizon*	3-Year Horizon**
	2005	**2006**	**2007**		
Type I %	160%	100%	63%	80%	44%
Type II %	0%	0%	0%	0%	0%
NSTR	**1.60**	**1.00**	**0.63**	**0.80**	**0.44**

Consolidated Forecasts					
	1-Year Horizon			2-Year Horizon*	3-Year Horizon**
	2005	**2006**	**2007**		
Type I %	35%	32%	44%	15%	10%
Type II %	13%	16%	16%	44%	30%
NSTR	**0.40**	**0.38**	**0.52**	**0.26**	**0.14**

***2005 forecast to predict 2005 and 2006 crises.**

**** 2005 forecast to predict 2005, 2006 and 2007 crises.**

5.7.2 Z-Score Model Performance

5.7.2.1 Noise-To-Signal-Ratios

Table 5.11 summarizes the model evaluation in terms of noise-to-signal ratios.

Table 5.11 (A): Out-of-Sample Macro Z-Score Noise-To-Signal Ratio (NTSR)

3 Years Rolling Mean					
	1-Year Horizon			2-Year Horizon*	3-Year Horizon**
	2005	**2006**	**2007**		
Type I %	100%	89%	67%	38%	24%
Type II %	86%	44%	33%	50%	40%
NSTR	**N/M**	**1.60**	**1.00**	**0.75**	**0.40**

5 Year Rolling Mean					
	1-Year Horizon			2-Year Horizon*	3-Year Horizon**
	2005	**2006**	**2007**		
Type I %	114%	78%	56%	38%	24%
Type II %	71%	33%	22%	44%	32%
NSTR	**4.00**	**1.17**	**0.71**	**0.67**	**0.35**

10 Year Rolling Mean					
	1-Year Horizon			2-Year Horizon*	3-Year Horizon**
	2005	**2006**	**2007**		
Type I %	114%	89%	78%	44%	28%
Type II %	43%	22%	22%	31%	24%
NSTR	**2.00**	**1.14**	**1.00**	**0.64**	**0.37**

Source: Authors' calculations.

The results show better out of sample performance in the 10-year rolling mean calibration, over the three year forecast horizon, in terms of NTSR, these are consistent with Borio and Drehman (2009) in general who find the 10-year calibration out-performing out-of-sample. Out-of-Sample Type I errors are low in the 2 and 3 year forecast horizon and so are Type II errors, however, they are higher (worse) than the Signal Extraction and Logit model calibrations. Signal extraction is the best performing methodology in terms of Type I errors, while the Logit methodology is the best in terms of NTSRs.

Table 5.11 (B): In-Sample Macro Z-Score Noise-To-Signal Ratio (NTSR)

3 Years Rolling Mean					
	1-Year Horizon			2-Year Horizon*	3-Year Horizon**
	2005	**2006**	**2007**		
Type I %	114%	67%	67%	38%	20%
Type II %	86%	56%	44%	56%	40%
NSTR	**N/M**	**1.50**	**1.20**	**0.86**	**0.33**
5 Year Rolling Mean					
	1-Year Horizon			2-Year Horizon*	3-Year Horizon**
	2005	**2006**	**2007**		
Type I %	100%	78%	67%	38%	20%
Type II %	71%	44%	44%	50%	40%
NSTR	**3.50**	**1.40**	**1.20**	**0.75**	**0.33**
10 Year Rolling Mean					
	1-Year Horizon			2-Year Horizon*	3-Year Horizon**
Type I %	114%	78%	67%	44%	28%
Type II %	86%	22%	22%	44%	36%
NSTR	**N/M**	**1.00**	**0.86**	**0.78**	**0.44**

Source: Authors' calculations.

5.7.2.2 Z-Score Model Comparison to World Bank

In order to check the model output for robustness, the results are compared to the Z-Scores published by the World Bank for the countries in the sample. The comparison is presented in Tables 5.12 (A) and 5.12 (B). The key highlights are as follows:

For the 20 countries in the sub-sample, from 1992 to 2007, there were 3 countries for which the WB had no data but which were compiled for this research - these are Finland, Korea, New Zealand.

In general for all the countries for which data was available (17) the WB PDs are higher than the ones calculated under the methodology used in this application and the difference can be explained by the calculation methodology whereby WB uses standard deviation of NI as the denominator, whereas for this research the denominator is the SD of Operating profit before provisions (which is lower than NI volatility due to smoothing tools at the disposition of management).

IF SDs are much higher for WB calculation of the Z-Score, then in turn WB Z-scores are lower than this research (this is indeed the case for all countries in the sample) and their inverse, the PD calculated by the World Bank is much higher (also true).

This research focuses on the migration matrix rather than absolute thresholds, because this is the crisis indicator utilized. Comparing the migration matrices using the same methodology, a shift by more than 1 SD over a 5 year rolling mean, shows that for 14 countries the migrations using both the WB data and data in this paper are the same in count, but with a small difference in timing (+/- 1 year). Also the indicator used in this application signals a crisis or a migration to a higher probability of default, one period before the migrations calculated using World Bank data (i.e. outperforming World Bank results). The migrations are dissimilar for six countries, for which one country there is no WB data and for the research the data was compiled (namely Korea).

Table 5.12 (A) Macro Z-Score Model Output in Comparison to World Bank

Comparison Own Vs WB (PD, 5 YR Mean)	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
Austria (Own)	0.4%	0.3%	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%
Austria (WB)	0.00%	0.49%	0.34%	0.77%	0.93%	0.97%	1.03%	1.17%	1.14%	1.09%	1.92%	2.07%	2.16%	2.28%	2.26%	1.50%
Belgium (Own)	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%	0.0%	0.1%
Belgium (WB)	0.27%	0.25%	0.24%	0.36%	0.46%	0.72%	0.79%	1.10%	0.99%	1.05%	1.06%	1.23%	1.09%	1.53%	1.50%	1.58%
Canada (Own)	1.2%	1.2%	0.9%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Canada (WB)	0.00%	3.73%	2.48%	2.00%	1.66%	1.54%	0.94%	0.86%	0.77%	4.73%	5.01%	5.18%	5.71%	6.41%	2.54%	2.43%
Czech Republic (Own)					0.2%	0.2%	0.4%	0.5%	0.5%	0.5%	1.1%	1.0%	1.1%	1.2%	1.3%	0.7%
Czech Republic (WB)	0.00%	0.08%	0.15%	0.21%	122.49%	102.48%	102.55%	105.02%	105.19%	7.66%	3.26%	3.48%	1.30%	1.37%	1.38%	1.47%
Denmark (Own)	2.7%	0.3%	0.5%	0.7%	0.6%	0.5%	0.6%	0.6%	0.3%	0.2%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%
Denmark (WB)	0.00%	1.12%	1.15%	1.08%	1.01%	1.07%	1.11%	1.07%	1.12%	1.21%	1.15%	1.07%	1.01%	0.93%	0.85%	0.84%
Finland (Own)	0.7%	16.9%	16.3%	15.8%	15.5%	15.5%	2.8%	1.7%	1.0%	0.7%	0.2%	0.3%	0.3%	0.3%	0.3%	0.3%
Finland (WB)	0.00%	0.00%	0.00%	0.06%	0.06%	0.06%	0.07%	0.20%	0.27%	0.27%	0.27%	0.45%	0.00%	0.00%	0.05%	0.05%
France (Own)	0.7%	0.7%	0.5%	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%
France (WB)	4.52%	5.71%	5.48%	4.34%	5.01%	5.38%	4.15%	4.25%	4.40%	5.37%	4.86%	5.41%	5.06%	4.84%	3.35%	3.04%
Germany (Own)	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.0%
Germany (WB)	0.57%	0.51%	0.54%	0.54%	0.55%	0.57%	0.71%	0.85%	1.04%	1.84%	1.84%	1.91%	1.92%	1.80%	1.14%	1.09%
Ireland (Own)						0.0%	0.8%	0.8%	0.7%	0.6%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Ireland (WB)	0.00%	0.00%	0.00%	0.31%	0.31%	0.17%	0.12%	0.12%	0.05%	0.04%	0.05%	0.06%	0.06%	0.10%	0.25%	0.40%
Italy (Own)	0.0%	0.0%	0.0%	0.0%	0.1%	0.1%	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Italy (WB)	0.03%	0.03%	0.38%	0.34%	0.34%	0.41%	0.49%	0.39%	0.85%	2.20%	2.16%	2.59%	3.58%	3.29%	1.73%	1.96%

Table 5.12 (A) Macro Z-Score Model Output in Comparison to World Bank - Continued

Comparison Own Vs WB (PD, 5 YR Mean)	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
Japan (Own)					0.2%	0.2%	0.2%	0.2%	0.1%	0.1%	0.0%	0.1%	0.2%	0.2%	0.1%	0.0%
Japan (WB)	0.04%	0.05%	0.30%	1.20%	1.47%	2.47%	4.11%	4.45%	3.87%	3.91%	3.55%	2.08%	1.67%	1.67%	1.25%	0.79%
Korea (Own)	0.0%	0.3%	0.3%	0.3%	0.2%	0.3%	1.1%	21.4%	20.8%	19.9%	19.8%	20.2%	5.0%	4.9%	0.5%	0.1%
Korea (WB)	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Luxembourg (Own)	0.0%	0.0%	0.0%	0.0%	0.1%	0.1%	0.1%	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Luxembourg (WB)	0.79%	0.80%	0.79%	0.84%	0.75%	0.93%	1.20%	1.31%	1.44%	1.76%	1.83%	1.59%	1.53%	1.37%	1.11%	1.04%
Netherlands (Own)	0.1%	0.1%	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Netherlands (WB)	0.00%	0.18%	0.16%	0.18%	0.23%	0.26%	0.37%	0.46%	0.61%	0.72%	0.96%	1.38%	4.02%	5.52%	7.26%	8.51%
Norway (Own)	1.8%	1.7%	1.6%	1.6%	1.6%	0.7%	0.7%	0.3%	0.3%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Norway (WB)	49.59%	49.59%	26.56%	26.56%	18.82%	2.95%	2.59%	2.28%	2.11%	1.52%	1.48%	1.20%	1.20%	1.07%	1.38%	1.01%
New Zealand (Own)	0.1%	0.6%	0.6%	0.6%	0.5%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
New Zealand (WB)	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	1.55%	2.83%
Spain (Own)	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%	0.0%	0.0%
Spain (WB)	1.10%	1.23%	1.08%	0.84%	0.65%	0.63%	0.45%	1.03%	0.99%	0.96%	2.83%	3.35%	2.64%	2.58%	3.81%	1.48%
Sweden (Own)	1.7%	2.6%	2.6%	2.3%	2.1%	2.2%	0.9%	0.9%	0.5%	0.1%	0.1%	0.1%	0.0%	0.0%	0.0%	0.1%
Sweden (WB)	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.60%	0.70%	0.65%	0.82%	0.88%	1.03%	1.27%
Switzerland (Own)	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%	0.0%	0.0%
Switzerland (WB)	0.65%	0.66%	0.73%	0.82%	0.74%	0.95%	1.45%	1.69%	2.03%	2.38%	2.42%	2.02%	1.78%	1.54%	1.25%	1.19%
US (Own)	0.0%	0.1%	0.1%	0.1%	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
US (WB)	0.00%	0.87%	1.37%	1.32%	1.22%	1.08%	1.14%	1.42%	1.66%	1.93%	2.31%	2.73%	2.64%	2.78%	2.96%	3.77%
UK (Own)	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	1.4%	1.6%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%
UK (WB)	0.00%	0.42%	0.68%	0.52%	0.62%	0.67%	0.97%	0.98%	0.96%	1.15%	1.30%	1.31%	1.47%	1.69%	1.93%	2.00%

Table 5.12 (B) Macro Z-Score Model Output in Comparison to World Bank (Migration Matrix)

Comparison Own Vs WB (Change in PD by More than 1 SD)	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
Austria (Own)	0	0	0	1	0	0	0	0	0	0	1	0	0	1	0	0
Austria (WB)	1	0	1	0	0	0	0	0	0	1	1	0	0	0	0	0
Belgium (Own)	0	0	1	0	0	0	0	0	1	0	1	0	1	1	1	0
Belgium (WB)	0	0	1	1	1	0	1	0	0	0	1	0	1	0	0	0
Canada (Own)	0	0	0	0	0	0	1	0	0	0	0	0	0	1	1	0
Canada (WB)	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
Czech Republic (Own)	0	0	0	0	1	0	0	1	0	1	0	0	0	0	0	0
Czech Republic (WB)	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0
Denmark (Own)	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1
Denmark (WB)	1	1	0	0	1	0	0	1	1	0	0	0	0	0	0	0
Finland (Own)	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Finland (WB)	0	0	1	0	0	1	1	1	0	0	1	0	0	0	0	0
France (Own)	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1
France (WB)	1	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0
Germany (Own)	0	0	0	1	1	0	1	1	1	0	0	0	0	0	0	0
Germany (WB)	0	1	0	0	1	1	1	1	1	0	0	0	0	0	0	0
Ireland (Own)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
Ireland (WB)	0	0	1	0	0	0	0	0	0	0	0	0	1	1	1	0
Italy (Own)	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0
Italy (WB)	1	1	0	0	0	0	0	1	1	0	0	1	0	0	0	0

Source: Authors' calculations.

Table 5.12 (B) Macro Z-Score Model Output in Comparison to World Bank (Migration Matrix) - Continued

Comparison Own Vs WB (Change in PD by More than 1 SD)	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
Japan (Own)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Japan (WB)	1	1	1	0	1	1	0	0	0	0	0	0	0	0	0	0
Korea (Own)	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0
Korea (WB)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Luxembourg (Own)	0	0	1	1	0	0	1	0	0	0	0	0	0	0	1	1
Luxembourg (WB)	1	0	1	0	1	1	1	0	1	0	0	0	0	0	0	0
Netherlands (Own)	0	0	0	0	0	0	1	0	0	1	1	0	0	0	0	0
Netherlands (WB)	1	0	1	1	1	1	1	1	1	1	1	1	1	1	0	0
Norway (Own)	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
Norway (WB)	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
New Zealand (Own)	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
New Zealand (WB)	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0
Spain (Own)	0	0	0	1	0	0	0	0	0	1	0	0	1	0	1	0
Spain (WB)	1	0	0	0	0	0	1	0	0	1	1	0	0	1	0	0
Sweden (Own)	1	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1
Sweden (WB)	0	0	0	0	0	0	0	0	1	1	0	1	1	1	1	0
Switzerland (Own)	1	0	1	1	0	0	0	0	0	1	0	0	0	1	0	1
Switzerland (WB)	1	1	1	0	1	1	1	1	0	0	0	0	0	0	0	0
US (Own)	1	0	0	0	0	0	0	0	0	0	1	0	1	0	0	1
US (WB)	1	1	0	0	0	0	1	1	1	1	1	0	0	0	1	0
UK (Own)	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1
UK (WB)	1	1	0	1	1	1	1	0	0	1	0	1	1	1	0	0

Source: Authors' calculations.

5.8 Conclusion

5.8.1 Logit Model Conclusion

Using a Logit framework and looking at OECD countries over a 30 year period a number of variables were found to be significant in predicting crises. These include growth in pension assets (positive and significant at the 5% level) and equity market dividend yield (positive coefficient, 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, and also as free cash flows to equity shareholders, after debt service, are available.

Banking sector assets growth was closely significant to the 10% level, indicating a strong relationship between rapid growth in the sector, its relative size to GDP and the development of vulnerabilities (positive coefficient).

The output model shows that as early as 2004, clear signals were being given for a number of countries that vulnerabilities were building up across a dependent variable with three cases: a base case, a high change dynamic threshold case and a low change dynamic threshold case. Performance out-of-sample, is better than in-sample in terms of overall noise to signal ratios. These results show a significant improvement compared to earlier work, in terms of NTSR and Type I and Type II errors for all calibrations, with the exception of the 100 bps dependent variable calibration. Again a point to support the importance of the dependent variable regulator objective calibration and the inherent feedback loop to actual model performance.

5.8.2. Z-Score Model Conclusion

Using a Merton type Z-score framework and looking at OECD countries, movements in PD by more than one standard deviation were found to be significant in predicting crises. The PDs were calculated using a Merton type Z-score framework, where the Z-score is a capital adequacy measure plus returns on average assets (the latter defined as NI before provisions/average assets) all divided by the standard deviation of returns (same definition, NI before provisions/average assets).

The output model shows that as early as 2004, clear signals were being given for a number of countries that vulnerabilities were building up across the base case dependent variable calibration.

The model performs well compared to World Bank published Z-Score indicators to calculate migration matrices in PDs.

For the various models, the countries signaled to have crises do not map one to one in all three applications and some key countries called by the signal extraction to be susceptible to crises are not called by the Logit model but are called by the Z-score model, but the Logit model raises the alarm bell for other countries. These two findings reinforce the need by regulators to use different models and to look at all of them in judging the build up of vulnerabilities, even within the same system / country.

5.9 Model Comparisons and Traffic Lights Summary

In order to better evaluate how the various models map, one additional analysis component is necessary, in the form of a traffic light type analysis. Clearly one or more models are not expected to have the same results consistently, otherwise they would not be sufficiently different to be adding information to the decision making information set of a regulator. However, the confirmation of signals by both models should raise the red alarm and the disagreement should point to an amber alarm, whereas the full agreement for a no crisis signal should be a green light that the financial system is robust.

This section is structured as follows: Macro Logit Model compared to Signal Extraction Model; Traffic Light Summary (Macro Logit Model and Signal Extraction); Macro-Applications (Z-Score and Logit) and Signal Extraction Comparison; Traffic Light Summary (Macro-applications and Signal Extraction); and Conclusion.

5.9.1. Logit Comparison to Signal Extraction Findings

For the Logit model, out-of-Sample performance shows consistently better results in terms of NTSR, Type I and Type II errors, with the exception of the 100 bps run which shows higher Type I error out of sample. Again a point to support the importance of the dependent variable regulator objective calibration as it has an impact on model performance in calling the defined near crisis by the regulator. The Logit results improve to the NTSR calculation of the signal extraction application, however, Type I errors are worse for the Logit calibration. Also the countries signaled to have crises do not fully map in both applications. These two findings reinforce the need by regulators to use different models and to look at all of them in judging the build up of vulnerabilities.

Table 5.13 below presents the forecasts for both models, for the base case 50 basis points bundled calibration.

Table 5.13 - Macro Forecast Comparison Between Signal Extraction and Logit Models
50 basis points bundled calibration

	1 Year (2006 base)			2 Year (2005 base)			3 Year (2004 Base)		
Country	Crisis Forecast (Prob %)	Crisis Likelihood	Signal Extraction Output (Theta4:1 SD, 5 Yr Rolling Mean, Out of Sample)	Crisis Forecast (Prob %)	Crisis Likelihood	Signal Extraction Output (Theta4:1 SD, 5 Yr Rolling Mean, Out of Sample)	Crisis Forecast (Prob %)	Crisis Likelihood	Signal Extraction Output (Theta4:1 SD, 5 Yr Rolling Mean, Out of Sample)
Australia	0.0	Unlikely	1	0.0	Unlikely	1	0.0	Unlikely	1
Austria	0.0	Unlikely	1	0.0	Unlikely	1	0.0	Unlikely	1
Belgium	0.0	Unlikely	1	0.0	Unlikely	1	0.0	Unlikely	1
Cananda	0.0	Unlikely	1	0.0	Unlikely	1	0.0	Unlikely	0
Czech	12.8	Likely	1	0.0	Unlikely	1	0.0	Unlikely	1
Denmark	0.0	Unlikely	1	0.0	Unlikely	1	0.0	Unlikely	1
Finland	0.0	Unlikely	1	0.0	Unlikely	1	0.0	Unlikely	1
France	0.0	Unlikely	1	0.0	Unlikely	1	0.0	Unlikely	0
Germany	0.0	Unlikely	1	0.0	Unlikely	1	0.0	Unlikely	1
Greece	5.2	Likely	0	5.2	Likely	1	9.3	Likely	1
Hungary	0.8	Unlikely	1	0.7	Unlikely	1	2.3	Unlikely	1
Iceland	5.1	Likely	1	9.7	Likely	1	9.0	Likely	1
Ireland	0.0	Unlikely	1	5.4	Likely	1	0.0	Unlikely	1
Italy	0.0	Unlikely	1	0.0	Unlikely	1	0.0	Unlikely	1
Japan	0.0	Unlikely	1	0.0	Unlikely	1	0.6	Unlikely	1
Korea	0.0	Unlikely	1	0.0	Unlikely	1	0.0	Unlikely	1
Luxembourg	1.1	Unlikely	1	0.0	Unlikely	1	10.3	Likely	0
Mexico	0.0	Unlikely	1	0.0	Unlikely	0	0.0	Unlikely	1
Netherlands	0.0	Unlikely	1	0.0	Unlikely	1	0.0	Unlikely	1
Norway	0.0	Unlikely	1	0.0	Unlikely	1	0.0	Unlikely	1
New Zealand	0.0	Unlikely	1	0.0	Unlikely	0	0.8	Unlikely	1
Poland	0.0	Unlikely	1	0.0	Unlikely	1	0.0	Unlikely	1
Portugal	0.0	Unlikely	1	0.0	Unlikely	0	0.0	Unlikely	0
Slovenia	38.0	Probable	1	24.1	Probable	1	63.4	Probable	0
Spain	0.0	Unlikely	0	0.0	Unlikely	1	0.0	Unlikely	1
Sweden	0.0	Unlikely	1	0.0	Unlikely	1	0.0	Unlikely	1
Switzerland	0.0	Unlikely	1	0.0	Unlikely	1	0.0	Unlikely	1
Turkey	8.5	Likely	0	10.4	Likely	0	12.7	Likely	0
UK	1.3	Unlikely	1	0.0	Unlikely	1	0.0	Unlikely	1
US	0.0	Unlikely	1	0.0	Unlikely	1	0.0	Unlikely	1

Source: Authors' calculations.

5.9.2. Traffic Light Summary (Logit and Signal Extraction)

Table 5.14 presents the traffic lights signal to regulators using the decision rule explained in section 5.9. Note that the traffic signals panel is somewhat similar to a risk heat map and could be easily scaled to include other models as well or calibrated to modify output based on regulatory objective functions/ thresholds for intervention.

Table 5.14: Traffic Lights for Logit and Signal Extraction Macro Models -50 BPs Bundled Calibration

Country	1 Year	2 Year	3 Year
Australia	A	A	A
Austria	A	A	A
Belgium	A	A	A
Cananda	A	A	G
Czech	A	A	A
Denmark	A	A	A
Finland	A	A	A
France	A	A	G
Germany	A	A	A
Greece	A	R	R
Hungary	A	A	A
Iceland	R	R	R
Ireland	A	R	A
Italy	A	A	A
Japan	A	A	A
Korea	A	A	A
Luxembourg	A	A	A
Mexico	A	G	A
Netherlands	A	A	A
Norway	A	A	A
New Zealand	A	G	A
Poland	A	A	A
Portugal	A	G	A
Slovenia	R	R	A
Spain	G	A	A
Sweden	A	A	A
Switzerland	A	A	A
Turkey	A	A	A
UK	A	A	A
US	A	A	A

Key
R = Red, A=Amber, G = Green.

Source: Authors' calculations.

These results also improve to the NTSR calculation of the signal extraction application, however, Type I errors are worse for the Logit calibration as compared to the Signal extraction application. Also as mentioned, the countries signaled to have 'crises' do not map one to one in both applications and some key countries called by the signal extraction to be susceptible to crises are not called by the Logit model, but the Logit model raises the alarm bell for other countries. These two findings reinforce the need by regulators to use different models and to look at all of them in judging the build up of vulnerabilities, even within the same system / country.

Different models will invariably have different output in some aspects, one way to summarize the results is by looking at EWS models as a traffic light system, where a system is considered to be in the Red if more than two models used as decision making tools indicate a crisis, whereas in Amber mode, the system is in flux and needs to be monitored closely, while for Green mode, the system is robust with all models showing no signals. This traffic light approach is comparable to the risk heat maps adopted by global institutions analyzing financial stability and is scalable to incorporate as many models as required by regulators.

Looking at the traffic light signals issued by the synthesis of the macro Logit and Signal extraction model outputs, most of the countries for the three years have amber signals, which is expected as most systems would be in flux with various variables moving picked up by both models. The model design is based on capturing movement and volatility in the system, whereby bigger movements translate into larger signals. Canada has a Green signal in 2007, meaning that the financial system and other explanatory variables were stable and the system as a whole was resilient in terms of stocks and flows. The same for France in 2007, although the ratio of bank/assets to GDP was much higher at 337% of GDP, compared to 177% of GDP in Canada. Other countries that have green signals include Mexico in 2006, New Zealand in 2006, and Spain in 2005. This again reflects a period of relative tranquility in the system, as the models are based on movement. The implication of this is that the traffic lights need to be monitored not only at a point in time, but also within the perspective of a rolling window.

Finally, the countries that have red signals associated are correctly called by the synthesis of these two macro-models: Greece, Iceland, Ireland and Slovenia. One of the significant explanatory variables, banking assets to GDP in all three countries stood at 172% in Greece, Iceland almost 1300% and Ireland 707%, and Slovakia almost 30 times GDP. Furthermore, banking sector asset growth, another significant explanatory variable, in all three countries saw a 20% increase in the years prior to a signal being issued.

It is interesting to investigate further the inter-play between state and financial sectors. Juxtaposing Iceland and Greece, the former had good state management, but an extremely overleveraged banking sector at 1300% of GDP. While the latter had a healthy banking sector, at 172% of GDP, but poor state management of macro structural issues which currently threaten its exit altogether from the

European Union. The interconnection between state sector health, banking and sovereign crises is another area of research where EWS models would be of great value.

The two macro models however, did not pick up on some of the countries which should have had red signals in hindsight, including the US and the UK. This improves substantially with the macro Z-score model overlay discussed later and also the micro-model overlay for the final traffic lights synthesis.

5.9.3. Macro-Applications (Z-Score, Logit) and Signal Extraction Comparison

Comparing the Z-score macro application with the Logit macro application and signal extraction applications point to a number of key recommendations. First, regulator objective functions do have an impact on model performance, and therefore EWS should always be designed with a set of objective functions and crises evaluated for each set as evident from the output of the three methodologies based on the three scenarios for the magnitude of change in the dependent variable that is deemed systemic. Second, regulators should use a number of models simultaneously to monitor changes in their respective systems and the impact from spillovers from other interconnected systems as each model has strengths and weaknesses. Third, there is a lot of value in the initial data searching exercise for variables, because this helps determine at any one point in time on a dynamic basis as these are the factors that are moving in the system and could cause vulnerabilities. Last, regulatory oversight and judgment need to be exercised at all times without over reliance on models as clearly, the outcomes must be then mapped onto real life by the regulator and also assessed in terms of cost of intervention versus cost of waiting for certain further critical triggers and regulators need to exercise vigilance and prudence consistently. Table 5.15 below, presents the forecasts for all three models, for the base case 50 basis points bundled calibration dependent variable.

Table 5.15 - Out-of-Sample Forecast Comparison Between Macro Z-Score, Signal Extraction and Logit Models (50 basis points bundled dependent variable calibration)

	1 Year (2006 base)				2 Year (2005 base)				3 Year (2004 Base)			
Country	Crisis Forecast (Prob %)	Crisis Likelihood	Signal Extraction Output (Theta4:1 SD, 5 Yr Rolling Mean, Out of Sample)	Z-Score Forecast (5 Yr Rolling Mean)	Crisis Forecast (Prob %)	Crisis Likelihood	Signal Extraction Output (Theta4:1 SD, 5 Yr Rolling Mean, Out of Sample)	Z-Score Forecast (5 Yr Rolling Mean)	Crisis Forecast (Prob %)	Crisis Likelihood	Signal Extraction Output (Theta4:1 SD, 5 Yr Rolling Mean, Out of Sample)	Z-Score Forecast (5 Yr Rolling Mean)
Australia	0.0	Unlikely	1	0	0.0	Unlikely	1	0	0.0	Unlikely	1	0
Austria	0.0	Unlikely	1	0	0.0	Unlikely	1	1	0.0	Unlikely	1	0
Belgium	0.0	Unlikely	1	1	0.0	Unlikely	1	1	0.0	Unlikely	1	1
Cananda	0.0	Unlikely	1	1	0.0	Unlikely	1	1	0.0	Unlikely	0	0
Czech	12.8	Likely	1	0	0.0	Unlikely	1	0	0.0	Unlikely	1	0
Denmark	0.0	Unlikely	1	0	0.0	Unlikely	1	0	0.0	Unlikely	1	0
Finland	0.0	Unlikely	1	0	0.0	Unlikely	1	0	0.0	Unlikely	1	0
France	0.0	Unlikely	1	0	0.0	Unlikely	1	0	0.0	Unlikely	0	0
Germany	0.0	Unlikely	1	0	0.0	Unlikely	1	0	0.0	Unlikely	1	0
Greece	5.2	Likely	0	0	5.2	Likely	1	0	9.3	Likely	1	0
Hungary	0.8	Unlikely	1	0	0.7	Unlikely	1	0	2.3	Unlikely	1	0
Iceland	5.1	Likely	1	0	9.7	Likely	1	0	9.0	Likely	1	0
Ireland	0.0	Unlikely	1	1	5.4	Likely	1	0	0.0	Unlikely	1	0
Italy	0.0	Unlikely	1	0	0.0	Unlikely	1	0	0.0	Unlikely	1	0

**For Z-score model, countries not in current sample, get a calibration of 0*

Source: Authors' calculations.

Table 5.15 - Out-of-Sample Forecast Comparison Between Macro Z-Score, Signal Extraction and Logit Models (50 basis points bundled dependent variable calibration) - Continued

Country	1 Year (2006 base)				2 Year (2005 base)				3 Year (2004 Base)			
	Crisis Forecast (Prob %)	Crisis Likelihood	Signal Extraction Output (Theta4:1 SD, 5 Yr Rolling Mean, Out of Sample)	Z-Score Forecast (5 Yr Rolling Mean)	Crisis Forecast (Prob %)	Crisis Likelihood	Signal Extraction Output (Theta4:1 SD, 5 Yr Rolling Mean, Out of Sample)	Z-Score Forecast (5 Yr Rolling Mean)	Crisis Forecast (Prob %)	Crisis Likelihood	Signal Extraction Output (Theta4:1 SD, 5 Yr Rolling Mean, Out of Sample)	Z-Score Forecast (5 Yr Rolling Mean)
Japan	0.0	Unlikely	1	0	0.0	Unlikely	1	0	0.6	Unlikely	1	0
Korea	0.0	Unlikely	1	0	0.0	Unlikely	1	0	0.0	Unlikely	1	0
Luxembourg	1.1	Unlikely	1	1	0.0	Unlikely	1	0	10.3	Likely	0	0
Mexico	0.0	Unlikely	1	0	0.0	Unlikely	0	0	0.0	Unlikely	1	0
Netherlands	0.0	Unlikely	1	0	0.0	Unlikely	1	0	0.0	Unlikely	1	0
Norway	0.0	Unlikely	1	0	0.0	Unlikely	1	0	0.0	Unlikely	1	0
New Zealand	0.0	Unlikely	1	0	0.0	Unlikely	0	0	0.8	Unlikely	1	0
Poland	0.0	Unlikely	1	0	0.0	Unlikely	1	0	0.0	Unlikely	1	0
Portugal	0.0	Unlikely	1	0	0.0	Unlikely	0	0	0.0	Unlikely	0	0
Slovenia	38.0	Probable	1	0	24.1	Probable	1	0	63.4	Probable	0	0
Spain	0.0	Unlikely	0	1	0.0	Unlikely	1	0	0.0	Unlikely	1	1
Sweden	0.0	Unlikely	1	1	0.0	Unlikely	1	0	0.0	Unlikely	1	1
Switzerland	0.0	Unlikely	1	0	0.0	Unlikely	1	1	0.0	Unlikely	1	0
Turkey	8.5	Likely	0	0	10.4	Likely	0	0	12.7	Likely	0	0
UK	1.3	Unlikely	1	0	0.0	Unlikely	1	0	0.0	Unlikely	1	0
US	0.0	Unlikely	1	0	0.0	Unlikely	1	0	0.0	Unlikely	1	1
			27	6			26	4			24	4

**For Z-score model, countries not in current sample, get a calibration of 0*

Source: Authors' calculations.

5.9.4. Traffic Light Summary (Z-Score, Logit and Signal Extraction)

In order to better evaluate how the various models map, we add the traffic light analysis component. Clearly the three models are not expected to have the same results consistently, otherwise they would not be sufficiently different to be adding information to the decision making information set of a regulator. However, the confirmation of signals by the three models should raise the red alarm and the disagreement should point to an amber alarm, whereas the full agreement for a no crisis signal should be a green light that the financial system is robust. Table 5.16 presents the traffic lights signal to regulators using the decision rule explained above for all three models. Note that the traffic signals panel is somewhat similar to a risk heat map and could be easily scaled to include other models as well or calibrated to modify output based on regulatory objective functions/ thresholds for intervention.

Table 5.16: Traffic Light Summary for Macro Z-Score, Logit and Signal Extraction Models
50 Basis Points Dependent Variable Bundled Calibration

Country	1 Year	2 Year	3 Year
Australia	A	A	A
Austria	A	R	A
Belgium	R	R	R
Cananda	R	R	G
Czech	A	A	A
Denmark	A	A	A
Finland	A	A	A
France	A	A	G
Germany	A	A	A
Greece	A	R	R
Hungary	A	A	A
Iceland	R	R	R
Ireland	R	R	A
Italy	A	A	A
Japan	A	A	A
Korea	A	A	A
Luxembourg	R	A	A
Mexico	A	G	A
Netherlands	A	A	A
Norway	A	A	A
New Zealand	A	G	A
Poland	A	A	A
Portugal	A	G	A
Slovenia	R	R	A
Spain	A	A	R
Sweden	R	A	R
Switzerland	A	R	A
Turkey	A	A	A
UK	A	A	A
US	A	A	R

Different models will invariably have different output in some aspects, one way to summarize the results is by looking at EWS models as a traffic light system, where a system is considered to be in the 'Red' if more than two models used as decision making tools indicate a crisis, whereas in Amber mode, the system is in flux and needs to be monitored closely, while for Green mode, the system is robust with all models showing no signals. This traffic light approach is comparable to the risk heat maps adopted by global institutions analyzing financial stability and is scalable to incorporate as many models as required by regulators.

Source: Authors' calculations.

Looking at the traffic light signals issued by the synthesis of the macro Logit, Signal extraction and Z-score model outputs, most of the countries for the three years have amber signals, which is expected as most systems would be in flux with various variables moving picked up by the three models, although we have an increase in red signals to 21, versus 8 in the Logit and Signal extraction synthesis. The model design is based on capturing movement and volatility in the system, whereby bigger movements translate into larger signals. Canada still has a 'Green' signal in 2007 after adding the third model, confirming that the financial system and other explanatory variables were stable and the system as a whole was resilient in terms of stocks and flows. The same for France in 2007, although the ratio of bank/assets to GDP was much higher at 337% of GDP, compared to 177% of GDP in Canada. Other countries that have ‘green’ signals include Mexico in 2006, New Zealand in 2006, and Spain in 2005 and Portugal in 2006. This again reflects a period of relative ‘tranquility’ in the system, as the three models are based on movement. The implication of this is that the traffic lights need to be monitored not only at a point in time, but also within the perspective of a rolling window.

Finally, the countries that have ‘red’ signals associated are correctly called by the synthesis of these three macro-models, and improve on just the use of two models: Austria (2006), Belgium (2005, 2006, 2007), Canada (2005, 2006), Greece (2006,2007), Iceland (2005, 2006, 2007), Ireland (2005, 2006), Luxembourg (2005) and Slovenia (2005, 2006), Sweden (2005), Switzerland (2006) and the US (2007). Two of the significant explanatory variables, banking assets to GDP and banking sector asset growth, significant explanatory variables, in all these countries were either very high as a percentage of GDP (ranging from a low of 2 x to a high of 30 x GDP), while banking sector asset growth in the year prior to a signal being issued was close to 20%.

The three macro models however, did improve by picking up on some of the countries, including the US which should have had ‘red’ signals in hindsight in the two model synthesis. The UK is still in amber mode for this synthesis as it had the smallest equity index movements, another significant explanatory variable. This improves substantially with the micro-model overlay for the final traffic lights synthesis which incorporates the health of the top five banks in this picture.

5.9.5. Conclusion

The comparison of all three models point to a number of key recommendations. Firstly, regulator objective functions do have an impact on model performance, and therefore EWS should always be designed with a set of objective functions and crises evaluated for each set as evident from the output of the three methodologies based on the three scenarios for the magnitude of change in the dependent variable that is deemed systemic. Secondly, regulators should use a number of models simultaneously to monitor changes in their respective systems and the impact from spill-overs from other interconnected systems as each model has strengths and weaknesses. Thirdly, there is a lot of value in the initial data searching exercise for variables, because this helps determine at any one point in time on a dynamic basis as these are the factors that are ‘moving’ in the system and could cause vulnerabilities. Lastly, regulatory oversight and judgment need to be exercised at all times without over reliance on models as clearly, the outcomes must be then mapped onto real life by the regulator and also assessed in terms of cost of intervention versus cost of waiting for certain further critical triggers and regulators need to exercise vigilance and prudence consistently.

6. Chapter Six: Micro-Application to Individual Banks and Rating Implications

6.1 Introduction

The recent crisis highlighted the failure of former early warning signals models, both on the macro and micro levels. Neither systemic crises were predicted nor individual bank failures by previously existing models, including Z-score type applications used by rating agencies. For example Moody's KMV subset in application to banks, did not call the subsequent failure of key systemic institutions that collapsed. On the macro level, using a sample of 105 countries, covering the years 1979 to 2003, Davis and Karim (2008) cited earlier demonstrate this. 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 in this micro-application.

Commonly used dependent variable specifications in the past are ex-post measures of the cost of banking distress in the form of direct bailout funds, an elevated level of NPLs, nationalization and/or other form of government intervention or workout or restructuring solution. In the case of the failure of more than one institution, or the prevalence of any of the above measures across an entire banking system in a country or several countries, then the failures are deemed a systemic crisis. The history of costs of systemic crises as cited earlier includes Caprio and Klingebiel (1996) who find bailout costs averaged 10% of GDP in previous crises, 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 discussed earlier in chapters 4 and 5 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 fragility in an individual institution as a necessary and sufficient condition to predict failure. By focusing on near failure, 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 failure costs of an institution, mitigate contagion effects and avert systemic crises.

This is an important extension in two ways: firstly the addition of micro analysis to the previous chapters adds depth, with systems which have more institutions under stress, being scaled on the traffic light matrix as worse than systems that do not. The second extension is with regards to credit ratings or rankings within a system, whereby the micro application would allow regulators to do so. This way the EWS would be credible and usable by policy makers on both the macro and micro levels, and thus effective. Also the specification of the dependent variable to signal near-failure, means that a lot of data which was not previously utilized in a bank failure and EWS analysis will now be taken into account.

Focusing on independent variable specifications, similar to the macro models, 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, among others. Second generation was based on self-fulfilling prophecies and herding behavior 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 chapter 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 banking distress fall into *four* categories and use the same approaches as in the previous applications discussed in Chapters 3 and 4. These include: i) signals models; ii) logit/probit models; iii) Merton type models; and a less used class of models, iv) Binary recursive trees. In this chapter we use a signal extraction methodology. Predominantly in earlier literature such as Kaminsky and Reinhart 1999 and Alessi and 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 (NTSR - 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 show similar performance in-sample and out-of-sample, unlike the previous applications which showed better out-of-sample performance and better lead time. This is explained by the length of the data series for the micro application. However, Type I errors for the 2-Year and 3-Year horizons are 14% in-sample and 17% out-of-sample, which out-performs earlier literature. This compares to higher Out-of-Sample Type I errors for the 2 and 3 year forecast horizon in the Z-Score macro application, so there is an improvement here. The Signal extraction methodology remains the best performing methodology in terms of Type I errors, while the Logit macro methodology is the best in terms of NTSRs.

The output model shows that as early as 2004, clear signals were being given for a number of banks that vulnerabilities were building up. Performance out-of-sample, is better than in-sample in terms of overall noise to signal ratios. These results show a significant improvement compared to earlier work, in terms of NTSR and Type I and Type II errors for all calibrations. Signal extraction performed best in terms of Type I errors, the macro Logit model in terms of NTSR and the macro Z-score model in terms of Type II errors.

The overlay of the micro model improves the traffic lights matrix substantially, with countries like Portugal, Italy, Ireland and the UK in 2007, which were in Amber mode before, moving to Red. These two findings reinforce the need by regulators to use different models and to look at all of them in judging the build up of vulnerabilities, even within the same system / country.

Different models will invariably have different output in some aspects, one way to summarize the results is by looking at EWS models as a traffic light system, where a system is considered to be in the Red if more than two models used as decision making tools indicate a crisis, whereas in Amber mode, the system is in flux and needs to be monitored closely, while for Green mode, the system is robust with all models showing no signals. This traffic light approach is comparable to the risk heat maps adopted by global institutions analyzing financial stability and is scalable to incorporate as many models as required by regulators. Also micro model improves the EWS system considerably.

Using a Merton type Z-score framework and looking at OECD countries, movements in Probability of Default (PD) by more than one standard deviation in member banks in the sample which were aggregated were found to be significant in predicting crises. The PDs were calculated using a Merton type Z-score framework, where the Z-score is a capital adequacy measure plus returns on average assets all divided by the standard deviation of returns. Our innovation in the calculation of the Z-score on the micro level, is the same as what we have applied on the macro level. We use net income before provisions and taxes to average assets to gauge the true operating returns of a bank (system in the case of the macro model) and we also use the volatility of this same series for the denominator.

The output model shows that as early as 2004, clear signals were being given for a number of countries that vulnerabilities were building up across their banking sectors. The countries signaled to have 'crises' in the previous applications do not map one to one in all of them and some key countries called by the signal extraction to be susceptible to crises are not called by the Logit model but are called by the Z-score model. The overlay of the micro model improves the traffic lights matrix substantially, with countries like Portugal, Italy, Ireland and the UK in 2007, which were in Amber mode before, moving to Red. These two findings reinforce the need by regulators to use different models and to look at all of them in judging the build up of vulnerabilities, even within the same system / country.

The last section of this chapter overlays the micro model findings to the previous suite of models, Z-Score, Logit and signal extraction and points to a measured improvement resulting from combining the micro and macro analysis. Regulator objective functions do have an impact on model performance, and therefore EWS should always be designed with a set of objective functions and crises evaluated for each set as evident from the output of the three methodologies based on the three scenarios for the magnitude of change in the dependent variable that is deemed systemic. Similarly the micro model is a valuable overlay to complete the picture. Also, regulators should use a number of models simultaneously to monitor changes in their respective systems and the impact from spill-overs from other interconnected systems as each model has strengths and weaknesses. In addition, there is a lot of value in the initial data searching exercise for variables, because this helps determine at any one point in time on a dynamic basis as these are the factors that are 'moving' in the system and could cause vulnerabilities. Also as evident from the micro model, building robust databases on the micro level and the macro level are elementary to setting up an effective EWS. Lastly, regulatory oversight and judgment need to be exercised at all times without over reliance on models as clearly, the outcomes must be then mapped onto real life by the regulator and also assessed in terms of cost of intervention versus cost of waiting for certain further critical triggers and regulators need to exercise vigilance and prudence consistently.

This rest of the chapter is structured as follows: Literature Review on Micro-Applications with a special focus on Merton Applications and Z-Score Subset and bank rating applications; Data and Descriptive Statistics of Bank Universe; Dependent Variable Set-Up for Z-Score Model; Explanatory Variable Set-Up for Z-Score Model; Preliminary Empirical Estimations; Forecasts and Model Performance; Bank Rating application and conclusions and traffic light summary.

6.2. Literature Review – Micro-Applications

This approach has been mainly used to study individual bank failure, with empirical studies dating back to the 1970s, mainly relying on bank balance sheet and market information to explain and forecast the failure of individual institutions. These include studies with variations of a Merton type, options based model to predict expected number of defaults (END) Z-scores or distance to default (DD) for financial institutions or sovereigns and credit migrations (recent studies include Gropp, Vesala and Vulpes 2004, Fuertes and Kalotychou 2006 and Savona and Vezzoli, 2008, among others).

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 (this approach was also adopted by the Central Bank of Egypt's Macro-Prudential Unit for some of its stress-testing exercises). 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. Their sample includes seven countries: France, Germany, Italy, Spain, Sweden, Switzerland, and the United Kingdom, and focuses on the largest banks in each of these countries (a total of 26 banks) over the period covered 1991–2007, the authors find that although there is considerable variation across indicators, in both cases, the period 2004 to mid-2007 is characterized by low risk, as reflected by (almost) uniformly high DD indicators or, conversely, low EDFs.

A somewhat similar application, but with a focus on creating a new financial stability quantifiable metric is made by Martin Cihak (2007) who presents an integrated measure of financial stability which he calls *'systemic loss'*. The author looks at the financial system as if it's a 'portfolio' of financial institutions' and considers the whole 'distribution' of systemic losses of this aggregate portfolio, over one period. He proposes that systemic loss measurement should be based on i) probability of default; ii) loss given default; and iii) correlation of defaults across institutions. 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). The following table, adapted from Cihak (2007), presents a summary of the different Merton type applications to predict banking and systemic crises and the advantages and drawbacks of each sub-set.

Table 6.1: Detailed Review of Micro Merton Type Methods for Crises Prediction and the Advantages and Disadvantages of Each

Indicator	**Advantages**	**Disadvantages**
DD or Z-Score (or probability of Default)	Easy to calculate from individual institutions' or for a portfolio, for DDs, Z-scores, or PDs.	• Does not reflect contagion (correlation across failures if average of individual institutions). • Does not reflect LGD of individual institutions, even though can be partially addressed by weighting. • DD requires liquid market in financial institutions iNTSRuments used to back out the metric if market data is used.
First-to-default and nth-to-default indicator	• Clear theoretical underpinnings for the nth to default indicator	• Does not fully reflect differences in LGD in different institutions. • FTD looks at individual vs systemic risk.
Expected number of defaults (END) indicator	• Relatively easy to interpret.	• Does not reflect different LGDs in institutions. • Difficult to calculate as its not a closed form expression • Focuses only on central tendency of the distribution. • Depends on total number of institutions
Distribution of systemic loss	• Captures differences in LGD in institutions • Captures correlation across bank failures • Focuses only on central tendencies	• May be difficult to calculate in some cases; no closed-form expression.

Source: Adapted from Cihak (2007).

Gropp, Vesala and Vulpes (2004), using a Merton type approach, analyze the ability of equity and bond market signals as leading indicators in a sample of EU banks. They find both indicators are good leading metrics of fragility, with distance to default exhibiting lead times of 6 to 18 months, while bond spreads signal values close to problems only. In a related study, Krainer and Lopez (2004), find that stock returns and equity-based default probabilities are useful indicators for US bank supervisors. The authors develop a model of supervisory ratings that combines supervisory and equity market information and find that their model forecasts supervisory rating changes by up to four quarters. Finally, an application to Estonia by Chen, Funke and Mannasoo (2006) attempts to predict bank fragility from market prices through the use of a Merton type approach and find that market indicators are moderately useful for anticipating future financial distress and rating changes.

6.3. Data and Descriptive Statistics of Bank Universe

In this chapter we look at micro individual bank data, looking at a sample of 139 banks, with assets of around USD50 trillion and capturing 55% of total banking assets in eleven OECD countries: the US, the UK, Germany, France, Italy, Japan, Canada, Spain, Ireland and Greece. Collectively, these banks captured a minimum of 54% to 97% of their respective country banking market shares. OECD data on individual banks is available for 15 years, back to 1997 for on-balance sheet activities from Bankscope and Bloomberg. The data period for the Z-score application as such spans from 1997 to 2007 (this contrasts with the macro Z-score application, where we have data going back to 1989) with 3 explanatory variables, capital adequacy metric for each bank, return on average assets before provisions for each bank and standard deviation of returns for each bank.

Table 6.2 shows the number of banks studied in each country, total sample assets, total sector assets, country GDP and sector assets as a percentage of GDP. Note how banking sector assets to GDP in Ireland stood at 760% in 2007 and in the UK at 441%, the highest in this sub-sample of 11 countries. Also the highest concentration is in Portugal, with the top 5 banks capturing 86% of total sector assets, and the least is in the US where the market is more fragmented, at 23% (however, post the crisis, with bank failures and mergers, concentration ratios are conjectured to have increased significantly. For example, Fannie Mae's balance sheet has grown from USD882 billion in 2007 to a whopping USD3.2 trillion, and Bank of America from USD1.7 trillion to USD2.3 trillion, respectively).

Banking sectors in Europe are highly concentrated as seen in the rest of the nine countries, which is one of the factors adding to the riskiness of the sector and to the implications of cross border interbank lending in the case of default in any part of Europe. Further more there are implications with regards to the funding that European banks are currently providing to US banks, another contagion channel in addition to plain vanilla asset exposures.

Table 6.2: Micro Model Country Summary for 11 OECD Countries (Assets and Market Share Summary)

No	Country	No. of Banks	T. Assets of Sample (USD Bil.)*	T. Sector Assets (USD Bil.)*	Market Share of Sample/T. Sector Assets	Market Share of Top 5 Banks/T. Sector Assets (2007)	GDP (USD Bil).*	Sector Assets % of GDP
1.	US**	20	17, 436	32,000	54%	23%	13,808	230%
2.	UK	9	12,081	12,728	94%	40%	2,803	441%
3.	Germany	17	9,394	9,714	97%	58%	3,321	283%
4.	France	7	7,738	9,337	83%	77%	2,594	298%
5.	Italy	20	3,859	4,876	79%	61%	2,118	230%
6.	Japan	17	5,965	7,752	77%	60%	4,384	177%
7.	Canada	14	2,575	2,737	94%	82%	1,436	191%
8.	Spain	14	3,747	4,170	90%	69%	1,440	290%
9.	Ireland	6	1,498	1,980	75%	61%	261	760%
10.	Greece	8	498	575	87%	73%	313	260%
11.	Portugal	7	532	579	92%	86%	224	260%
	Total	**139**	**47,887**	**86,448**	**55%**	**67%**	**32,702**	**264%**

**2007, OECD data.*

*** Note the US reports banking data excluding NBFI's, the most important and systemically significant in our view are Fannie and Freddie Mac. Therefore we have included these in our calculation. Their exclusion results in sector assets to GDP of only 100%, which is the figure quoted in almost all literature on the US banking system.*

Source: OECD, Bankscope, Bloomberg, authors' calculation.

The following Table 6.3 provides key indicators for the top five banks in every country. The metrics for Fannie Mae and Freddie Mac are also included given their systemic importance in the US. A common theme is especially weak or negative return on average assets calculated on the basis of operating profits versus not income, for failed institutions.

Table 6.3: Micro Model Country Key Indicators for Top Five Banks in 11 OECD Countries

No.	Bank	Country	Market Share (2007)	Bank Assets/GDP (2007)	Eq/TA	Assets/Equity	ROAA (operating profit)	ROAA (NI)
1	Fannie Mae	US	3%	6%	-0.1%	-1280.1	0.45%	-0.69%
2	Bank of America	US	6%	12%	10.1%	9.9	1.08%	-0.10%
3	Freddie Mac	US	3%	6%	0.0%	-5640.3	-0.13%	-0.90%
4	JP Morgan	US	4%	10%	7.6%	13.2	1.56%	0.73%
5	Citigroup	US	7%	16%	8.7%	11.5	1.97%	0.58%
6	HSBC	UK	37%	168%	4.0%	24.9	0.85%	0.34%
7	Barclays PLC	UK	20%	88%	4.2%	23.9	0.66%	0.25%
8	RBS	UK	18%	80%	2.8%	35.9	0.47%	-0.06%
9	Lloyds	UK	6%	25%	4.7%	21.1	0.95%	-0.03%
10	NatWest	UK	5%	22%	4.5%	22.4	0.76%	-0.62%
11	Deutsche Bank	Germany	29%	85%	2.6%	37.8	0.19%	0.23%
12	Commerzbank	Germany	9%	27%	3.8%	26.3	0.46%	0.18%
13	Landesbank Baden	Germany	7%	20%	2.7%	37.6	-0.07%	-0.08%
14	UniCredit Bank	Germany	6%	19%	6.4%	15.7	0.63%	0.45%
15	Hypo Real Estate Holding	Germany	6%	18%	2.4%	42.3	-0.11%	-0.25%
16	BNP Paribas	France	27%	96%	5.7%	17.5	0.86%	0.64%
17	Credit Agricole	France	24%	87%	6.5%	15.4	0.35%	0.17%
18	Societe Generale	France	17%	61%	4.5%	22.2	0.89%	0.54%
19	Dexia Credit Local	France	5%	20%	0.1%	1279.7	-0.09%	-0.19%
20	CIC	France	4%	14%	4.1%	24.5	0.69%	0.46%
21	UniCredit SPA	Italy	31%	71%	9.7%	10.3	0.96%	0.23%
22	Intesa Sanpaolo	Italy	17%	40%	11.1%	9.0	0.99%	0.50%
23	Gruppo Monte dei Paschi	Italy	5%	11%	9.5%	10.5	1.39%	0.57%
24	Banco Popolare	Italy	4%	9%	8.8%	11.3	1.13%	0.24%
25	UBI Banca	Italy	4%	8%	12.2%	8.2	0.91%	0.26%
26	Mitsubishi Financial	Japan	19%	34%	5.5%	18.3	0.09%	0.25%
27	Mizuho	Japan	16%	28%	3.8%	26.1	0.41%	0.23%
28	Sumitomo	Japan	11%	19%	5.9%	17.1	0.86%	0.33%
29	Norinchukin Bank	Japan	7%	13%	5.8%	17.2	0.66%	0.05%
30	Resona Holdings (Daiwa)	Japan	7%	13%	3.8%	26.4	0.63%	0.42%

**Data as of 2010, unless otherwise stated.*

Source: Bankscope, Bloomberg, authors' calculation.

Table 6.3: Micro Model Country Key Indicators for Top Five Banks in 11 OECD Countries (Continued)

No.	Bank	Country	Market Share (2007)	Bank Assets/GDP (2007)	Eq/TA	Assets/Equity	ROAA (operating profit)	ROAA (NI)
31	Royal Bank of Canada	Canada	23%	44%	5.4%	18.4	1.31%	0.79%
32	Toronto Dominion Bank	Canada	16%	31%	7.1%	14.1	1.37%	0.83%
33	Bank of Nova Scotia	Canada	16%	30%	5.4%	18.7	1.47%	0.87%
34	Bank of Montreal	Canada	14%	27%	5.6%	17.7	1.19%	0.74%
35	CIBC	Canada	13%	25%	4.5%	22.1	1.51%	0.74%
36	Banco Santander	Spain	32%	113%	8.9%	11.3	1.88%	1.03%
37	BBVA	Spain	18%	51%	6.8%	14.7	2.05%	1.18%
38	LA Caixa	Spain	9%	27%	7.7%	13.0	1.62%	0.52%
39	Caja Madrid	Spain	6%	19%	3.1%	32.7	0.05%	0.13%
40	Banco Popular Espanol	Spain	4%	12%	6.3%	15.8	1.33%	0.64%
41	Bank of Ireland	Ireland	13%	86%	4.4%	22.8	-0.47%	-0.53%
42	Allied Irish Bank	Ireland	13%	74%	3.0%	33.4	-3.76%	-7.56%
43	Depfa Bank	Ireland	16%	74%	2.5%	40.3	-0.36%	-0.36%
44	Irish Life & Permanent	Ireland	6%	39%	2.1%	46.8	-0.73%	-0.20%
45	Anglo Irish Bank	Ireland	7%	37%	4.9%	20.4	-30.95%	-21.52%
46	National Bank of Greece	Greece	23%	52%	12.1%	8.3	1.78%	0.54%
47	EFG Eurobank	Greece	18%	37%	9.3%	10.7	1.75%	0.16%
48	Alpha Bank	Greece	14%	29%	11.6%	8.6	1.61%	0.32%
49	Piraeus Bank	Greece	12%	25%	7.6%	13.2	1.08%	0.02%
50	Agricultual Bank of Greec	Greece	6%	13%	3.2%	31.2	0.66%	-1.23%
51	Caixa Geral De Depositos	Portugal	26%	75%	6.2%	16.0	0.34%	0.23%
52	Millenium BCP	Portugal	22%	60%	7.2%	13.8	0.94%	0.36%
53	Banco Espirito Santo	Portugal	17%	50%	11.9%	8.4	1.21%	0.84%
54	Santander Totta	Portugal	11%	29%	6.3%	16.0	1.40%	0.87%
55	Banco BPI	Portugal	10%	27%	4.3%	23.2	0.91%	0.61%

**Data as of 2010, unless otherwise stated.*

Source: Bankscope, Bloomberg, authors' calculation.

From the table, the average equity / total assets of the top 55 banks stood at 6% in 2010, significantly below the Basel III guidelines of Tier 1 capital of 8.5% plus 2% as a conservation buffer for a total capital ratio of 10.5%. Assets/equity averaged 17x and both operating profit returns and net income returns are zero on average.

6.4. Dependent Variable Set-Up for the Micro Model

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

Dependent Variable Specification

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

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

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

7. 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);

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

this bank 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.

The number of near-crises by bank and year are 1,030 observations out of 1,946 or 53% as per the following Table 6.4. From the perspective of a regulator, this paper puts forward the argument that regulators should always be concerned with predicting the 'near failures' and working on the conditions within their purview to prevent them from developing into failures.

Table 6.4: Micro Model Bank Distress Definitions

No.	**Criteria**	**Fragility Spots**
1	Decrease in bank capitalization by 50 bps	478
2	Increase in bank capitalization by 50 bps	434
3	Net income before provisions/ average balance sheet falls by more than 50 bps	228
4	Net income before provisions / average balance sheet is less than - 5 bps	114
Total before eliminations		1,254
Eliminations for double counting		1,030
Total Observations		1,946
Percentage Fragility Spots		53%

Source: Authors' calculation.

Notes

*The use of component two as part of the dependent variable specification was tested separately in the macro applications 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.

6.5. Explanatory Variable Set-Up for the Micro Model

Two of the components of the Z-score explanatory variable for the top five banks in every country: equity to total assets as a capital adequacy metric and return on average assets as measured by net income before provisions divided by average assets are presented for a ten year period in the following Table 6.5. PDs are backed out and the migration matrix calibrated whereby a shift in PDs is the explanatory variable that signals a near crisis.

Over the ten-year period, average equity to total assets for the sample was 6%, while return on average assets averaged 0%. Bank differences are pronounced, with the highest average capital held by Italian banks in general, UBI Banca (16.7% and Intesa San Paolo in Italy 16.3%) and the lowest held by ten banks, across all countries, which hold less than 3.5% (Dexia Credit Locale, France, Depfa Ireland, Hypo Real Estate Holdings Germany, Agricultural Bank of Greece, Freddie Mac and Fannie Mae, Landesbank, Deutsche and Commerzbank in Germany and Barclays in the UK). The highest returns were booked by US, Greek and Spanish banks, 2% and above, which could be a reflection of credit risk on the books of these banks (BBVA Spain, National Bank of Greece, Citigroup in the US, Bank of America, EFG Eurobank Greece, and Banco Popular in Spain). Two Irish banks have the lowest returns, Anglo Irish and Depfa. Higher returns help a system build its capital base, albeit slowly, whereas more direct measures such as capital raisings and capital injections are fast impact measures. The reverse is also true, with low returns slowly eroding the capital base and shocks resulting in quick capital erosion.

Table 6.5.(A) : Micro Model Bank Explanatory Variable Descriptive Statistics – Equity/Assets

Year	Country	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Fannie Mae	US	3.1%	2.3%	3.5%	3.2%	3.8%	4.7%	4.9%	5.0%	-1.7%	-1.8%	-0.1%
Bank of America	US	7.4%	7.8%	7.6%	6.7%	9.0%	7.9%	9.3%	8.6%	9.7%	10.4%	10.1%
Freddie Mac	US	3.2%	3.5%	4.5%	4.2%	4.1%	3.5%	3.4%	3.4%	-3.6%	0.5%	0.0%
JP Morgan	US	5.9%	6.2%	5.7%	6.0%	8.5%	8.7%	8.4%	8.2%	7.4%	7.9%	7.6%
Citigroup	US	7.3%	7.7%	7.9%	7.8%	7.4%	7.5%	6.4%	5.2%	7.4%	8.3%	8.7%
HSBC	UK	5.3%	5.2%	4.8%	4.6%	4.0%	3.8%	3.2%	2.9%	2.7%	3.5%	4.0%
Barclays PLC	UK	4.7%	4.1%	3.8%	3.8%	3.1%	2.6%	2.7%	2.6%	2.3%	4.2%	4.2%
RBS	UK	11.5%	10.1%	9.1%	8.4%	6.5%	5.0%	4.5%	2.1%	1.7%	2.4%	2.8%
Lloyds	UK	4.8%	4.6%	3.4%	4.1%	4.1%	3.4%	3.3%	3.5%	2.2%	4.3%	4.7%
NatWest	UK	3.8%	4.8%	5.4%	5.2%	4.3%	3.9%	3.8%	3.9%	4.2%	4.4%	4.5%
Deutsche Bank	Germany	3.2%	3.3%	4.0%	3.5%	3.1%	3.0%	2.1%	1.9%	1.4%	2.5%	2.6%
Commerzbank	Germany	3.0%	2.6%	2.4%	2.7%	2.6%	3.1%	2.5%	2.6%	3.2%	3.1%	3.8%
Landesbank Bade	Germany			3.6%	3.6%	3.4%	2.8%	2.5%	2.4%	1.4%	2.6%	2.7%
UniCredit Bank	Germany	3.1%	3.9%	2.3%	2.7%	3.0%	3.1%	3.9%	5.7%	5.0%	6.5%	6.4%
Hypo Real Estate	Germany					1.9%	2.0%	2.1%	1.5%	-0.4%	1.3%	2.4%
BNP Paribas	France	6.9%	5.9%	7.1%	6.6%	5.3%	4.3%	5.0%	5.2%	4.0%	5.6%	5.7%
Credit Agricole	France	11.5%	12.6%	12.5%	8.2%	8.0%	5.8%	6.5%	7.3%	5.8%	6.9%	6.5%
Societe Generale	France	8.5%	7.9%	8.3%	7.9%	7.3%	5.3%	4.6%	2.9%	3.6%	4.6%	4.5%
Dexia Credit Local	France							2.6%	1.8%	-0.5%	0.4%	0.1%
CIC	France							3.7%	3.6%	2.9%	3.8%	4.1%
UniCredit SPA	Italy	20.2%	20.1%	20.1%	18.6%	17.1%	5.9%	6.8%	9.0%	7.8%	9.8%	9.7%
Intesa Sanpaolo	Italy	15.4%	16.7%	20.0%	22.4%	21.7%	22.4%	13.0%	13.5%	11.0%	12.4%	11.1%
Gruppo Monte de	Italy	5.7%	5.7%	5.5%	6.4%	6.1%	6.0%	6.9%	8.1%	9.8%	11.2%	9.5%
Banco Popolare	Italy								8.6%	8.4%	8.9%	8.8%
UBI Banca	Italy			20.0%	20.4%	20.1%	19.9%	13.5%	15.6%	14.0%	14.5%	12.2%
Mitsubishi Financ	Japan			3.5%	3.9%	4.2%	5.5%	5.9%	5.3%	4.5%	5.8%	5.5%
Mizuho	Japan				3.0%	3.5%	3.6%	4.3%	4.6%	3.8%	2.8%	3.8%
Sumitomo	Japan				4.1%	3.9%	5.4%	5.5%	4.9%	4.0%	5.9%	
Norinchukin Bank	Japan	3.3%	3.7%	3.3%	2.9%	4.1%	4.7%	5.6%	6.5%	5.3%	4.0%	5.8%
Resona Holdings (	Japan			1.5%	2.9%	3.9%	4.7%	5.0%	6.5%	5.6%	5.7%	3.8%
Royal Bank of Can	Canada	4.7%	5.3%	5.2%	5.2%	4.2%	4.4%	4.2%	4.1%	4.3%	5.7%	5.4%
Toronto Dominior	Canada	4.9%	4.8%	4.7%	4.8%	4.1%	4.8%	5.6%	5.2%	5.9%	7.2%	7.1%
Bank of Nova Scot	Canada	5.3%	5.4%	5.5%	5.2%	5.6%	5.2%	4.7%	4.7%	4.4%	5.1%	5.4%
Bank of Montreal	Canada	5.3%	4.6%	4.9%	4.9%	5.0%	4.7%	4.7%	4.5%	4.6%	5.5%	5.6%
CIBC	Canada	4.3%	4.2%	4.6%	4.4%	4.4%	4.1%	4.1%	4.0%	4.0%	4.3%	4.5%
Banco Santander	Spain	13.9%	14.1%	16.6%	16.0%	9.0%	6.1%	7.1%	8.7%	7.9%	9.5%	8.9%
BBVA	Spain	1.8%	2.4%	3.6%	4.1%	4.2%	4.4%	5.4%	5.6%	4.9%	5.7%	6.8%
LA Caixa	Spain	9.4%	10.0%	9.3%	8.5%	6.8%	7.4%	6.9%	8.4%	7.3%	7.9%	7.7%
Caja Madrid	Spain	8.1%	8.2%	8.1%	7.8%	7.0%	6.7%	5.9%	5.5%	5.5%	5.1%	3.1%
Banco Popular Es	Spain	10.7%	9.0%	8.2%	7.1%	6.4%	6.9%	6.5%	6.2%	6.4%	6.5%	6.3%
Bank of Ireland	Ireland	6.1%	5.4%	4.8%	4.5%	4.0%	3.7%	3.2%	3.6%	3.3%	3.6%	4.4%
Allied Irish Bank	Ireland	6.1%	5.5%	5.1%	6.3%	7.1%	6.3%	6.3%	5.5%	5.7%	6.5%	3.0%
Depfa Bank	Ireland							1.2%	1.4%	0.0%	0.7%	2.5%
Irish Life & Perma	Ireland	6.2%	5.5%	5.3%	4.8%	4.2%	3.4%	3.1%	3.3%	3.2%	2.5%	2.1%
Anglo Irish Bank	Ireland	17.2%	12.4%	10.4%	8.8%	11.3%	5.7%	3.7%	7.1%	4.1%	4.9%	4.9%
National Bank of (	Greece	8.4%	7.7%	8.1%	8.5%	9.0%	8.5%	15.2%	13.9%	11.3%	12.5%	12.1%
EFG Eurobank	Greece	15.4%	13.8%	10.9%	10.1%	9.3%	9.0%	8.9%	11.5%	7.8%	10.8%	9.3%
Alpha Bank	Greece	9.3%	9.5%	10.5%	10.3%	9.7%	8.4%	9.6%	11.6%	8.4%	12.4%	11.6%
Piraeus Bank	Greece	15.2%	14.3%	12.3%	13.0%	12.0%	9.0%	7.7%	10.5%	7.7%	9.6%	7.6%
Agricultual Bank c	Greece	-3.7%	-3.2%	-3.4%	-3.3%	-2.4%	6.9%	8.6%	9.2%	4.5%	6.0%	3.2%
Caixa Geral De De	Portugal							5.2%	5.4%	4.9%	5.9%	6.2%
Millenium BCP	Portugal						6.0%	6.4%	5.6%	6.6%	7.6%	7.2%
Banco Espirito Sa	Portugal	6.7%	6.6%	6.6%	6.9%	7.8%	7.1%	10.7%	11.7%	8.6%	12.1%	11.9%
Santander Totta	Portugal							6.9%	6.4%	6.6%	6.6%	6.3%
Banco BPI	Portugal	4.0%	4.1%	4.4%	4.5%	4.9%	4.9%	4.9%	4.7%	4.6%	4.9%	4.3%

Source: Authors' calculation.

Table 6.5.(B): Micro Model Bank Explanatory Variable Descriptive Statistics- RoAA

Year	Country	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Fannie Mae	US	0.95%	1.06%	0.59%	1.15%	0.62%	0.88%	0.58%	-0.07%	-1.77%	-1.19%	0.45%
Bank of America	US	2.16%	2.28%	2.60%	2.71%	2.62%	2.34%	2.63%	1.82%	1.52%	2.34%	1.08%
Freddie Mac	US	0.85%	0.83%	2.14%	0.90%	0.48%	0.34%	0.32%	-0.39%	-3.42%	-0.48%	-0.13%
JP Morgan	US	1.61%	1.16%	0.80%	1.33%	0.52%	0.91%	1.54%	1.64%	2.06%	2.04%	1.56%
Citigroup	US	3.10%	2.96%	3.16%	2.86%	2.18%	3.46%	2.15%	0.93%	-0.92%	1.47%	1.97%
HSBC	UK	1.19%	0.98%	0.87%	0.84%	1.25%	1.17%	1.05%	0.96%	0.83%	1.06%	0.85%
Barclays PLC	UK	1.39%	1.25%	1.19%	1.29%	1.36%	0.93%	1.06%	0.84%	0.42%	0.48%	0.66%
RBS	UK	1.88%	1.43%	1.54%	1.82%	1.76%	1.40%	1.42%	0.86%	-0.22%	0.00%	0.47%
Lloyds	UK	2.25%	1.67%	1.30%	1.72%	1.68%	1.56%	1.80%	1.57%	-1.50%	-0.31%	0.95%
NatWest	UK	1.25%	1.70%	1.89%	2.24%	2.16%	1.73%	1.64%	1.30%	0.66%	1.63%	0.76%
Deutsche Bank	Germany	0.82%	0.27%	0.49%	0.43%	0.53%	0.67%	0.69%	0.53%	-0.25%	0.44%	0.19%
Commerzbank	Germany	0.95%	0.12%	0.32%	-0.30%	0.40%	0.56%	0.71%	0.53%	0.22%	-0.39%	0.46%
Landesbank Bade	Germany				0.46%	0.41%	0.29%	0.35%	0.12%	-0.42%	-0.16%	-0.07%
UniCredit Bank	Germany	0.52%	0.51%	0.32%	0.01%	0.36%	0.10%	0.62%	0.95%	0.02%	0.57%	0.63%
Hypo Real Estate	Germany					0.38%	0.36%	0.50%	0.11%	-1.82%	-0.03%	-0.11%
BNP Paribas	France	1.04%	1.04%	0.82%	0.89%	0.92%	0.82%	0.86%	0.82%	0.42%	0.83%	0.86%
Credit Agricole	France	0.81%	0.66%	0.43%	0.47%	0.59%	0.75%	0.82%	0.73%	0.33%	0.42%	0.35%
Societe Generale	France	1.33%	0.93%	0.64%	0.97%	0.92%	0.96%	0.96%	0.26%	0.78%	1.08%	0.89%
Dexia Credit Local	France							0.56%	0.38%	-2.09%	0.11%	-0.09%
CIC	France							1.15%	0.97%	0.17%	0.68%	0.69%
UniCredit SPA	Italy	2.30%	2.17%	2.18%	2.07%	1.70%	0.98%	1.33%	1.07%	0.76%	1.13%	0.96%
Intesa Sanpaolo	Italy	1.35%	1.39%	0.87%	1.31%	1.49%	2.08%	1.86%	1.06%	0.43%	1.18%	0.99%
Gruppo Monte de	Italy	1.81%	1.53%	1.37%	1.16%	1.03%	1.06%	1.08%	1.24%	0.31%	0.75%	1.39%
Banco Popolare	Italy								1.81%	0.85%	1.09%	1.13%
UBI Banca	Italy				1.46%	1.44%	2.30%	2.18%	1.31%	0.82%	1.24%	0.91%
Mitsubishi Financ	Japan			-0.88%	1.28%	0.19%	1.40%	1.01%	0.78%	0.15%	0.69%	0.09%
Mizuho	Japan					1.07%	0.93%	0.83%	0.83%	0.61%	-0.21%	0.41%
Sumitomo	Japan				0.99%	0.71%	1.20%	0.80%	1.20%	0.45%	0.86%	
Norinchukin Bank	Japan	0.59%	0.31%	0.30%	0.24%	0.58%	0.38%	0.88%	1.13%	1.24%	-0.77%	0.66%
Resona Holdings (	Japan			-1.02%	-2.74%	1.26%	1.08%	1.48%	1.02%	1.21%	0.72%	0.63%
Royal Bank of Can	Canada	1.55%	1.51%	1.45%	1.47%	1.01%	1.14%	1.34%	1.48%	1.02%	1.38%	1.31%
Toronto Dominior	Canada	0.77%	0.78%	0.88%	0.66%	1.00%	0.94%	1.68%	1.56%	1.05%	1.18%	1.37%
Bank of Nova Scot	Canada	1.55%	1.68%	1.61%	1.65%	1.59%	1.49%	1.41%	1.50%	0.89%	1.38%	1.47%
Bank of Montreal	Canada	1.36%	1.24%	1.12%	1.29%	1.32%	1.27%	1.20%	0.86%	0.75%	0.97%	1.19%
CIBC	Canada	1.51%	1.04%	0.69%	1.36%	1.36%	0.59%	1.35%	1.49%	-0.88%	1.01%	1.51%
Banco Santander	Spain	1.73%	2.02%	1.67%	2.10%	1.20%	1.50%	1.46%	1.62%	1.76%	1.97%	1.88%
BBVA	Spain	2.02%	1.84%	1.48%	1.96%	1.31%	1.68%	1.87%	2.30%	2.04%	1.88%	2.05%
LA Caixa	Spain	2.26%	2.17%	0.25%	1.64%	0.90%	1.44%	3.26%	1.67%	1.34%	1.74%	1.62%
Caja Madrid	Spain	1.77%	1.46%	1.39%	1.52%	1.64%	1.74%	1.58%	2.77%	1.47%	0.71%	0.05%
Banco Popular Es	Spain	2.83%	2.73%	3.36%	3.30%	2.39%	2.52%	2.41%	2.25%	2.24%	2.08%	1.33%
Bank of Ireland	Ireland	1.63%	1.26%	1.41%	1.10%	1.21%	1.14%	1.27%	1.39%	1.17%	0.59%	-0.47%
Allied Irish Bank	Ireland	1.62%	0.08%	1.34%	1.18%	1.80%	1.74%	2.36%	1.71%	1.68%	1.46%	-3.76%
Depfa Bank	Ireland							0.21%	0.03%	-0.06%	-0.19%	-0.36%
Irish Life & Perma	Ireland	1.08%	0.17%	1.37%	1.08%	1.30%	0.88%	0.72%	0.65%	-0.27%	-0.91%	-0.73%
Anglo Irish Bank	Ireland	1.94%	1.97%	1.86%	1.80%	1.75%	1.72%	1.51%	1.67%	1.57%	3.42%	-30.95%
National Bank of (	Greece	2.44%	2.01%	0.99%	1.36%	1.31%	1.92%	2.15%	2.70%	2.53%	2.37%	1.78%
EFG Eurobank	Greece	2.99%	2.42%	1.61%	1.95%	2.42%	2.62%	2.40%	2.39%	2.25%	1.90%	1.75%
Alpha Bank	Greece	1.86%	1.85%	1.52%	1.48%	1.18%	2.33%	2.26%	2.32%	1.96%	1.74%	1.61%
Piraeus Bank	Greece	2.72%	1.37%	1.67%	1.63%	1.50%	1.86%	2.34%	2.36%	1.57%	1.44%	1.08%
Agricultual Bank c	Greece	1.53%	0.52%	0.28%	1.15%	0.87%	1.57%	1.70%	1.80%	0.88%	1.11%	0.66%
Caixa Geral De De	Portugal							1.41%	1.61%	0.71%	0.51%	0.34%
Millenium BCP	Portugal						1.73%	1.87%	1.30%	0.78%	0.79%	0.94%
Banco Espirito Sa	Portugal	1.94%	1.28%	1.33%	1.76%	0.99%	1.20%	1.40%	1.58%	0.95%	1.68%	1.21%
Santander Totta	Portugal							1.80%	2.12%	1.45%	1.67%	1.40%
Banco BPI	Portugal	1.77%	1.32%	1.03%	1.04%	1.33%	1.41%	1.57%	1.64%	0.63%	1.06%	0.91%

Source: Authors' calculation.

6.6. Empirical Estimations

Empirical Model

The Z-score has been used extensively as a measure of individual financial institutions' soundness as in Demirgüç-Kunt, Detragiache, Tressel (2006) and Cihak (2007). The Z-score is defined as $z \equiv (k+\mu)/\sigma$, where k is equity capital as percent of assets, μ is return as percent of assets, and σ is standard deviation of return on assets as a proxy for return volatility. The z-score is simple to calculate and its attractiveness lies in it being inversely related to the probability of a financial institution's default.

The probability of default for the integral from $-\infty$ to k, is given by

$$p\ (\mu < k) = \int \varphi\ (\mu)\ d\mu$$

If μ is normally distributed, then $p\ (\mu < k) = \int N(0,1)\ d\mu$ where z is the z-score. Hence if returns are normally distributed, the z-score measures the number of standard deviations a return realization has to fall in order to deplete equity. In the case μ is not normally distributed, z is the lower bound on the probability of default (by Tchebycheff inequality) and therefore a higher z-score implies a lower probability of insolvency.

The z-scores have several limitations as discussed in Table 6.1, the most important is that they are based on low frequency accounting data. Also, the z-score applied to an individual financial institution, does not take into account the correlation of institutions in the system. However, an advantage of the z-score is that it can be used for any institution, even if its not traded or its securities are not liquid enough to enable a higher frequency Merton type application.

Similar to "portfolio DD," we can define "portfolio *z*-score," as $z \equiv (k+\mu)/\sigma$, where k is total equity capital in the system as percent of total assets in the system, μ is total return as percent of total assets, and σ is standard deviation of the aggregate return on aggregate assets as a proxy for return volatility. The portfolio *z*-score is always higher than the sum of *z*-scores for the individual institutions.

Similar to the signal extraction and the Logit applications, the evaluation of a Z-score model could be done using a NTSR framework choosing the model that minimizes the noise-to-signal ratio, ω, that is computed in 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.

Applying this to the Z-score model, the noise-to-signal ratio of each Z-score run, ω, would also be computed in the same way. Where α again is the size of the type I error and β is the size of the type II error.

The question is from a regulatory perspective, if the objective function of the regulator is to prevent crises at all costs, then model evaluation should be on the basis of minimizing Type I errors as they are much more costly, and accepting Type II errors as a downside. By setting this objective function, the regulator would ensure a continuously healthy system and is taking the most risk-averse stance they could take. This is another innovation attempted throughout all three applications.

6.7. Forecasts and Model Performance

6.7.1 Crisis Signal Forecasts

To translate the Z-score backed out probability of default into judgments on whether a crisis signal is given or not, the change in probability of default by one SD (increase only) is compared to 3 year rolling PDs, a bank is considered to have a crisis if its PD shifts by more than 1 SD.

As the data period for the individual banks is only 15 years, compared to 30 years for the macro application, the number of observations is significantly reduced. Furthermore, as the failure signals are calculated on the basis of standard deviations from a 3 year rolling mean, which in turn is calculated on the basis of a three year rolling standard deviation of returns, we lose a total of six years of data in this exercise, leaving only 9 years of usable observations for the banks which have the full 15 years available. This also means we have had to include the crisis years in the calculation, 2008, 2009 and 2010 to ensure a minimum number of data points.

The forecasts are for t-1, t-2 and t-3, i.e. for the years 2008, 2009 and 2010 respectively. The results for In-Sample forecasts and out-of-sample forecasts for the 139 banks are summarized below.

The sample subset in terms of number of banks is larger, but the years less. The forecasts in-sample show 64 banks with vulnerabilities in 2008, 32 banks in 2009 and 29 banks in 2010, while out-of-sample the corresponding forecasts are 29, 64 and 32 respectively. The forecasts correctly call the fragility in Fannie Mae, Freddie Mac, Royal Bank of Scotland, Lloyds, Bradford and Bingley, Hypo Real Estate Holding in Germany, HELABA (which recently failed the EBA stress testing exercise), Credit Agricole in France, Intesa San Paolo in Italy, Gruppo Monte dei Pasche, UBI Banca and several others. For institutions that failed prior to 2008, for example Lehman Brothers, the model shows zeroes as the institutions no longer exist.

Table 6.6: Micro Z-Score Bank Fragility Forecasts for 139 Banks

Forecasts			**In-Sample**			**Out-of-Sample**		
	Bank		**2008**	**2009**	**2010**	**2008**	**2009**	**2010**
1	Fannie Mae	US	1	0	1	1	1	0
2	Bank of America	US	1	0	1	1	1	0
3	Freddie Mac	US	1	1	0	0	1	1
4	JP Morgan Chase and Co	US	0	0	0	0	0	0
5	Citigroup Inc	US	1	0	0	1	1	0
6	Wells Fargo and Company	US	1	0	0	0	1	0
7	Goldman Sachs Group	US	1	0	1	0	1	0
8	Federal Home Loan Bank	US	1	1	0	0	1	1
9	Morgan Stanley	US	0	0	0	1	0	0
10	Wachovia Corp	US	0	0	0	1	0	0
11	GE Capital	US	1	0	0	0	1	0
12	Merrill Lynch and Co	US	1	0	0	1	1	0
13	Prudential Financial	US	1	0	0	0	1	0
14	First Union National Bank	US	1	0	0	1	1	0
15	Lehman Brothers Holdings inc	US	0	0	0	0	0	0
16	Bear Stearns	US	0	0	0	1	0	0
17	Credit Suisse USA Inc	US	0	0	0	0	0	0
18	Washington Mutual Inc	US	0	0	0	1	0	0
19	Barclays Capital Inc	US	0	0	0	1	0	0
20	US Bancorp	US	1	0	0	1	1	0
21	Barclays PLC	UK	1	0	0	0	1	0
22	Royal Bank of Scotland Plc	UK	1	0	0	1	1	0
23	Lloyds TSB Bank	UK	1	0	0	0	1	0
24	HSBC Holdings	UK	0	0	0	0	0	0
25	HBOS Plc	UK	1	0	0	0	1	0
26	National Westminster PLC	UK	1	0	1	0	1	0
27	Standard Chartered Plc	UK	1	0	0	0	1	0

28	Bradford and Bingley	UK	1	1	0	1	1	1
29	Northern Rock	UK	1	0	0	1	1	0
30	Deutsche Bank	Germany	0	0	0	0	0	0
31	Commerzbank AG	Germany	0	1	0	0	0	1
32	Dresdner Bank AG	Germany	1	0	0	0	1	0
33	Landesbank Baden-Wuerttemberg	Germany	1	0	0	1	1	0
34	UniCredit Bank AG	Germany	1	0	0	0	1	0
35	Hypo Real Estate Holding	Germany	1	1	0	1	1	1
36	Bayerische Landesbank	Germany	1	0	1	0	1	0
37	Eurohypo AG	Germany	1	0	0	0	1	0
38	WestLB	Germany	0	0	0	0	0	0
39	HELABA GER	Germany	1	1	0	0	1	1
40	HSH Nordbank	Germany	1	0	0	1	1	0
41	LBB Holding	Germany	0	0	0	0	0	0
42	WGZ	Germany	1	0	1	0	1	0
43	Hypo Real Estate Intl	Germany	0	0	0	1	0	0
44	Volkswagen Fin Services	Germany	0	0	1	0	0	0
45	Sachsen Bank	Germany	0	0	0	0	0	0
46	BNP Paribas	France	1	0	1	0	1	0
47	Credit Agricole Group	France	1	0	0	0	1	0
48	Societe Generale	France	0	0	0	1	0	0
49	Dexia Credit Local	France	0	0	1	0	0	0
50	Credit Industriel et Commercial - CIC	France	0	1	0	0	0	1
51	HSBC France	France	0	0	0	0	0	0
52	Unicredit SPA	Italy	0	0	0	0	0	0
53	Intesa San Paolo	Italy	1	0	0	1	1	0
54	Gruppo Monte dei Paschi	Italy	1	0	1	0	1	0
55	Banco Popolare	Italy	0	0	0	0	0	0
56	UBI Banca	Italy	1	0	0	1	1	0
57	Banca Nationale del Lavoro	Italy	0	1	0	1	0	1
58	Mediobanca	Italy	0	1	0	0	0	1
59	Banca Popolare dell'Emilia	Italy	1	0	0	0	1	0

	Romagna							
60	Banca Popolare di Milano	Italy	1	0	0	0	1	0
61	BIIS SPA	Italy	0	0	0	0	0	0
62	Casa di Risparmio di Parma	Italy	0	0	0	0	0	0
63	CREDIOP-DEXIA	Italy	0	0	0	0	0	0
64	Banca Carige	Italy	0	0	0	0	0	0
65	Banca Populare di Vicenza	Italy	0	0	0	0	0	0
66	Banca Firenza	Italy	1	0	1	0	1	0
67	CREDEM	Italy	0	0	0	0	0	0
68	Credito Valtellinese	Italy	0	1	0	0	0	1
69	Banco Popolare di Sondrio	Italy	1	1	1	0	1	1
70	Deutsche Bank Italy	Italy	1	0	0	1	1	0
71	Mitsubishi	Japan	0	0	0	0	0	0
72	Mizuho	Japan	1	1	0	0	1	1
73	Sumitomo	Japan	1	0	0	0	1	0
74	Norinchukin Bank	Japan	0	1	0	0	0	1
75	Resona Holdings (Daiwa)	Japan	0	0	1	0	0	0
76	Nomura	Japan	1	1	0	0	1	1
77	Development Bank of Japan	Japan	0	0	0	0	0	0
78	Ueda Yagi Tanshi	Japan	0	1	0	0	0	1
79	Tokyo Tanshi	Japan	0	0	0	0	0	0
80	Bank of Yokohama	Japan	0	0	0	0	0	0
81	Shinsei Bank Limited	Japan	1	1	1	1	1	1
82	Chiba Bank Ltd	Japan	0	1	0	0	0	1
83	Hokuhoku Fin Group	Japan	0	1	0	0	0	1
84	Japan Bank for Intl Coop	Japan	0	0	1	0	0	0
85	Shizuoka Bank	Japan	0	1	0	0	0	1
86	Bank of Fukuoka Ltd	Japan	1	0	0	0	1	0
87	Royal Bank of Canada	Canada	0	1	0	0	0	1
88	Toronto Dominion Bank	Canada	0	0	0	0	0	0
89	Bank of Nova	Canada	1	0	0	0	1	0

	Scotia							
90	Bank of Montreal	Canada	1	0	0	1	1	0
91	Canadian Imperial Bank of Commerce (CIBC)	Canada	1	0	0	1	1	0
92	Desjardings Group	Canada	1	0	0	0	1	0
93	HSBC Canada	Canada	0	1	1	0	0	1
94	Export Development Canada	Canada	1	0	0	0	1	0
95	National Bank Financial Canada	Canada	1	0	0	0	1	0
96	Laurentian Bank of Canada	Canada	0	0	0	0	0	0
97	Manulife Bank of Canada	Canada	1	0	1	0	1	0
98	Banque de Developpement du Canada	Canada	1	1	0	0	1	1
99	Canadian Western Bank	Canada	1	0	1	0	1	0
100	Banco Santander SA	Spain	0	0	0	0	0	0
101	Banco Bilbao Vizcaya Argentaria	Spain	0	0	0	0	0	0
102	LA CAIXA - Caja de Ahorros Barcelona	Spain	1	0	0	0	1	0
103	CAJA Madrid	Spain	1	1	1	1	1	1
104	Banco Popular Espanole	Spain	0	0	1	0	0	0
105	Banco Espanol de Credito BANESTO	Spain	0	0	0	0	0	0
106	Caja de Ahorros de Valencia	Spain	1	0	0	1	1	0
107	Banco de Sabadell	Spain	1	1	0	0	1	1
108	Caja de Ahorros del Mediterraneo	Spain	0	1	0	0	0	1
109	Novacaixa Galicia	Spain	0	1	1	0	0	1
110	Caixa d'Estlavis de Catalunya	Spain	0	1	0	0	0	1
111	Santander Consumer Finance	Spain	0	0	0	0	0	0

112	Instituto de Credito Official	Spain	0	0	0	0	0	0
113	Bankinter SA	Spain	0	0	0	0	0	0
114	Bank of Ireland	Ireland	1	1	1	0	1	1
115	Allied Irish Bank	Ireland	0	0	1	0	0	0
116	Depfa Bank	Ireland	0	0	0	0	0	0
117	Irish Life and Permanent	Ireland	1	1	0	0	1	1
118	Anglo Irish Bank	Ireland	1	1	1	0	1	1
119	Ulster Bank Ireland	Ireland	0	0	0	0	0	0
120	National Bank of Greece	Greece	0	0	0	0	0	0
121	EFG Eurobank	Greece	0	0	1	0	0	0
122	Alpha Bank	Greece	0	0	0	0	0	0
123	Piraeus Bank	Greece	1	0	1	0	1	0
124	Agricultural Bank of Greece	Greece	0	0	1	0	0	0
125	Emporiki Bank of Greece	Greece	1	0	0	0	1	0
126	Marfin Egnatia	Greece	0	0	0	0	0	0
127	Caixa Geral de Depositos	Portugal	0	0	0	0	0	0
128	Millinium BCP	Portugal	0	0	0	0	0	0
129	Banco Espirito Santo	Portugal	0	0	1	0	0	0
130	Santander Totta SGPS	Portugal	0	0	0	0	0	0
131	Banco BPI SA	Portugal	1	0	0	0	1	0
132	BANIF SGPS	Portugal	1	1	1	1	1	1
133	Banco Popular Portugal	Portugal	0	0	0	0	0	0
134	BBVA Portugal	Portugal	0	0	0	0	0	0
135	Banco Itau	Portugal	0	0	0	0	0	0
136	Deutsche Bank Portugal	Portugal	0	0	0	0	0	0
137	Banco Finantia	Portugal	0	0	0	0	0	0
138	Banco BAI Europe	Portugal	0	0	0	0	0	0
139	Tecnicredito SGPS	Portugal	0	1	0	0	0	1
			64	**32**	**29**	**29**	**64**	**32**

Source: Authors' calculations.

6.7.2 Model Performance and Noise-To-Signal Ratios

The results show similar performance in-sample and out-of-sample, unlike the previous three macro applications which showed better out-of-sample performance and better lead time. This is explained by the length of the data series for the micro application. However, Type I errors for the 2-Year and 3-Year horizons are 14% in-sample and 17% out-of-sample, which out-performs earlier literature. This compares to higher Out-of-Sample Type I errors the 2 and 3 year forecast horizon in the Z-Score macro application in paper 3 are slightly higher than the micro application, so there is an improvement here. The Signal extraction macro methodology remains the best performing methodology in terms of Type I errors, while the Logit macro methodology is the best in terms of NTSRs.

Table 6.7 summarizes the model evaluation in terms of noise-to-signal ratios and shows In-Sample NTSR's of 0.5 for the micro model over a three year horizon vs 0.33 for the macro model. Out-of-sample the micro model NSTR stands at 0.6 versus 0.42 for the macro model, over a three year horizon, respectively. The poorer NSTR performance for the micro model is explained by the shorter number of years data for this application. The micro overlay improves the traffic lights matrix substantially, however.

Table 6.7: Z-Score Noise-To-Signal Ratio (NTSR) Micro Model and Macro Model Comparison

Micro Model In -Sample			**Macro Model In -Sample**		
	2-Year*	**3-Year****		**2-Year***	**3-Year****
Type I %	28%	14%	**Type I %**	36%	18%
Type II %	56%	44%	**Type II %**	64%	45%
NTSR	**0.8**	**0.5**	**NTSR**	**1.0**	**0.33**
Out-of-Sample			**Out-of-Sample**		
	2-Year*	**3-Year****		**2-Year***	**3-Year****
Type I %	36%	17%	**Type I %**	36%	23%
Type II %	59%	47%	**Type II %**	57%	45%
NTSR	**0.9**	**0.6**	**NTSR**	**0.83**	**0.42**

Source: Authors' calculations.

The output model shows that as early as 2004, clear signals were being given for a number of banks that vulnerabilities were building up across the base case dependent variable calibration. These results show a significant improvement compared to earlier work, in terms of NTSR and Type I and

Type II errors for all calibrations. Signal extraction performed best in terms of Type I errors, the Logit model in terms of NTSR and the Z-score model in terms of Type II erros.

The overlay of the micro model improves the traffic lights matrix substantially, with countries like Portugal, Italy, Ireland and the UK in 2007, which were in 'Amber' mode before, moving to 'Red'. These two findings reinforce the need by regulators to use different models and to look at all of them in judging the build up of vulnerabilities, even within the same system / country.

Different models will invariably have different output in some aspects, one way to summarize the results is by looking at EWS models as a traffic light system, where a system is considered to be in the 'Red' if more than two models used as decision making tools indicate a crisis, whereas in Amber mode, the system is in flux and needs to be monitored closely, while for Green mode, the system is robust with all models showing no signals. This traffic light approach is comparable to the risk heat maps adopted by global institutions analysing financial stability and is scalable to incorporate as many models as required by regulators. Also micro model improves the EWS system considerably.

For a recap of model performance for the previous applications, please refer to the relevant chapters.

6.8. Bank Rating Application

With the dataset for the 139 banks for this paper in the eleven OECD countries, we construct a simple rating system, based on the number of 1 signals issued by bank to the total number of 1 and 0 signals by each bank. A high percentage indicates high levels of stress, and vice versa. A number of banks for which data is missing are currently showing 0%, but this is because of the lack of signals, rather than their true rating, so these should be looked at in this light.

We then rank the findings into quartiles for 2007 Vs 2010 and see which banks migrate between the two groups. The findings are interesting in terms of the ranking of the individual institutions as well in the stability of the migrations, which could indicate that this model outperforms other traditional rating methodologies. This could be an area of further research. Table 6.8 presents the quartiles for 2007 Vs 2010, while Table 6.9 presents the bank ratings.

The quartile members do not change between both periods, as the fragility which resulted in failure was there before 2007. Replicating the exercise for older time periods at three year intervals would be an interesting extension.

Table 6.8: No of Banks in Risk Rating Quartiles (2007 Vs 2010)

Quartile	**2007**	**Quartile**	**2010**
First	73	First	73
Second	50	Second	50
Third	10	Third	10
Fourth	6	Fourth	6

Source: Authors' calculations.

There are a total of 16 banks in the third and fourth quartiles, they are in order of better to worse rating: Natwest (UK), CIBC (Canada), BANIF (Portugal), Caja Madrid (Spain), Citigroup (US), HSH Nordbank (Germany), Banco Popolare di Sondrio (Italy), Bradford and Bingley (UK), Mizuho (Japan), Hypo Real Estate Holding (Germany), Caja de Ahorros de Valencia (Spain), Novacaixa Galicia (Spain), Caixa d'Estlavis de Catalunya (Spain), Tecnicredito SGPS (Portugal).

Table 6.9 – Bank Ratings in 2010

		Country	1' Signals % of Total Signals by bank
1	Credit Suisse USA Inc	US	0%
2	WestLB	Germany	0%
3	Credit Industriel et Commercial - CIC	France	0%
4	HSBC France	France	0%
5	Banco Popolare	Italy	0%
6	BIIS SPA	Italy	0%
7	Casa di Risparmio di Parma	Italy	0%
8	CREDIOP-DEXIA	Italy	0%
9	Banca Populare di Vicenza	Italy	0%
10	CREDEM	Italy	0%
11	Mitsubishi	Japan	0%
12	Development Bank of Japan	Japan	0%
13	Bank of Yokohama	Japan	0%
14	Banco Bilbao Vizcaya Argentaria	Spain	0%
15	Santander Consumer Finance	Spain	0%
16	Instituto de Credito Official	Spain	0%
17	Depfa Bank	Ireland	0%
18	Ulster Bank Ireland	Ireland	0%
19	Alpha Bank	Greece	0%
20	Caixa Geral de Depositos	Portugal	0%
21	Millinium BCP	Portugal	0%
22	Santander Totta SGPS	Portugal	0%
23	Banco Popular Portugal	Portugal	0%
24	BBVA Portugal	Portugal	0%
25	Banco Itau	Portugal	0%
26	Deutsche Bank Portugal	Portugal	0%
27	Banco Finantia	Portugal	0%
28	Unicredit SPA	Italy	10%
29	LBB Holding	Germany	11%
30	Toronto Dominion Bank	Canada	11%
31	Banco Espanol de Credito BANESTO	Spain	11%
32	National Bank of Greece	Greece	11%
33	EFG Eurobank	Greece	11%
34	Agricultural Bank of Greece	Greece	11%
35	Emporiki Bank of Greece	Greece	11%
36	JP Morgan Chase and Co	US	13%
37	Desjardings Group	Canada	13%
38	Wells Fargo and Company	US	14%
39	Washington Mutual Inc	US	14%
40	Chiba Bank Ltd	Japan	14%
41	Shizuoka Bank	Japan	14%

42	LA CAIXA - Caja de Ahorros Barcelona	Spain	14%
43	Morgan Stanley	US	17%
44	GE Capital	US	17%
45	HBOS Plc	UK	17%
46	Japan Bank for Intl Coop	Japan	17%
47	Wachovia Corp	US	20%
48	Deutsche Bank	Germany	20%
49	Volkswagen Fin Services	Germany	20%
50	BNP Paribas	France	20%
51	Banca Nationale del Lavoro	Italy	20%
52	Deutsche Bank Italy	Italy	20%
53	Resona Holdings (Daiwa)	Japan	20%
54	Barclays PLC	UK	22%
55	Lloyds TSB Bank	UK	22%
56	HSBC Holdings	UK	22%
57	Standard Chartered Plc	UK	22%
58	Societe Generale	France	22%
59	Royal Bank of Canada	Canada	22%
60	Bank of Nova Scotia	Canada	22%
61	Bank of Montreal	Canada	22%
62	Laurentian Bank of Canada	Canada	22%
63	Banque de Developpement du Canada	Canada	22%
64	Allied Irish Bank	Ireland	22%
65	Banco Espirito Santo	Portugal	22%
66	Banco BPI SA	Portugal	22%
67	Merrill Lynch and Co	US	25%
68	Prudential Financial	US	25%
69	First Union National Bank	US	25%
70	Commerzbank AG	Germany	25%
71	UniCredit Bank AG	Germany	25%
72	Irish Life and Permanent	Ireland	25%
73	Banco BAI Europe	Portugal	25%
74	Banca Carige	Italy	27%
75	Freddie Mac	US	29%
76	Goldman Sachs Group	US	29%
77	Lehman Brothers Holdings inc	US	29%
78	US Bancorp	US	29%
79	Norinchukin Bank	Japan	29%
80	Banca Popolare dell'Emilia Romagna	Italy	30%
81	Barclays Capital Inc	US	33%
82	Dresdner Bank AG	Germany	33%
83	Eurohypo AG	Germany	33%
84	Credit Agricole Group	France	33%
85	Banca Firenza	Italy	33%
86	Credito Valtellinese	Italy	33%
87	Sumitomo	Japan	33%

88	Ueda Yagi Tanshi	Japan	33%
89	HSBC Canada	Canada	33%
90	Manulife Bank of Canada	Canada	33%
91	Canadian Western Bank	Canada	33%
92	Banco Santander SA	Spain	33%
93	Banco de Sabadell	Spain	33%
94	Bank of Ireland	Ireland	33%
95	Piraeus Bank	Greece	33%
96	Intesa San Paolo	Italy	36%
97	Export Development Canada	Canada	38%
98	Bankinter SA	Spain	38%
99	Federal Home Loan Bank	US	40%
100	Bear Stearns	US	40%
101	Landesbank Baden-Wuerttemberg	Germany	40%
102	Sachsen Bank	Germany	40%
103	Gruppo Monte dei Paschi	Italy	40%
104	Mediobanca	Italy	40%
105	Nomura	Japan	40%
106	Bank of America	US	43%
107	HELABA GER	Germany	43%
108	Bank of Fukuoka Ltd	Japan	43%
109	Marfin Egnatia	Greece	43%
110	Royal Bank of Scotland Plc	UK	44%
111	Northern Rock	UK	44%
112	Tokyo Tanshi	Japan	44%
113	Shinsei Bank Limited	Japan	44%
114	Banco Popular Espanole	Spain	44%
115	Anglo Irish Bank	Ireland	44%
116	Fannie Mae	US	50%
117	Bayerische Landesbank	Germany	50%
118	WGZ	Germany	50%
119	UBI Banca	Italy	50%
120	Banca Popolare di Milano	Italy	50%
121	Hokuhoku Fin Group	Japan	50%
122	National Bank Financial Canada	Canada	50%
123	Caja de Ahorros del Mediterraneo	Spain	50%
124	National Westminster PLC	UK	56%
125	Canadian Imperial Bank of Commerce (CIBC)	Canada	56%
126	BANIF SGPS	Portugal	56%
127	CAJA Madrid	Spain	57%
128	Citigroup Inc	US	60%
129	HSH Nordbank	Germany	60%
130	Banco Popolare di Sondrio	Italy	60%
131	Bradford and Bingley	UK	63%
132	Hypo Real Estate Intl	Germany	67%
133	Mizuho	Japan	67%

134	Hypo Real Estate Holding	Germany	80%
135	Caja de Ahorros de Valencia	Spain	83%
136	Dexia Credit Local	France	100%
137	Novacaixa Galicia	Spain	100%
138	Caixa d'Estlavis de Catalunya	Spain	100%
139	Tecnicredito SGPS	Portugal	100%

Source: Authors' calculations.

6.9. Conclusions and Traffic Light Summary

To synthesize all the previous applications from the vantage point of a regulator, we compiled this section. It is structured as follows: micro model overlay to previous applications; Traffic Light Summary with Micro Model; and Conclusion.

6.9.1. Micro Model Overlay to Macro Models

In order to better evaluate how the three previous applications map, we had one additional analysis component, in the form of a traffic light type analysis. As the three models are not expected to have the same results consistently, otherwise they would not be sufficiently different to be adding information to the decision making information set of a regulator. However, the confirmation of signals by the three models should raise the red alarm and the disagreement should point to an amber alarm, whereas the full agreement for a no crisis signal should be a green light that the financial system is robust. In this section, we overlay the findings of the micro model on the traffic light summary of the three previous models. The rationale is if on the micro level, banks are stressed, this should be another factor leading to financial instability.

We overlay the findings of the micro model by calculating the percentage of 1 signals issued to total signals issued by the each bank in each country (1 and 0). We then aggregate these findings on a country level to come up with a country risk ranking. For any ranking higher than 6, we add a 1 signal to the respective country in the traffic light matrix. Looking at 2007, Greece is highly ranked, this possibly is on the back of data and reporting issues, where results were overstated. Ireland, Italy, Spain, the UK and Germany exhibit clear signs of stress. Moving forward to 2010 rankings, Ireland is now highly rated as all risks have materialized, the sector is substantially undercapitalized and realizing negative returns, however the status is stable bankruptcy. Recall all models studied are designed to pick up on *build-up* of vulnerabilities.

Table 6.10: Sum of Micro Signals by Country (2007) Vs (2010)

Rank	**Country**	**2007**	**Rank**	**Country**	**2010**
1	Greece	16%	1	Ireland	6%
2	France	26%	2	Greece	11%
3	US	27%	3	Japan	14%
4	Portugal	27%	4	France	17%
5	Japan	28%	5	US	21%
6	Canada	28%	6	Canada	22%
7	Ireland	29%	7	Germany	25%
8	Italy	33%	8	Portugal	31%
9	Spain	35%	9	Spain	34%
10	UK	35%	10	Italy	35%
11	Germany	37%	11	UK	37%

Source: Authors' calculations.

Table 6.11 below, presents the forecasts for all three models, for the base case 50 basis points bundled calibration dependent variable.

Table 6.11 - Out-of-Sample Forecasts Macro Z-Score, Signal Extraction and Logit Models (50 basis points bundled dependent variable calibration) – for Micro Overlay

Country	1 Year (2006 base) Crisis Forecast (Prob %)	Crisis Likelihood	Signal Extraction Output (Theta4:1 SD, 5 Yr Rolling Mean, Out of Sample)	Z-Score Forecast (5 Yr Rolling Mean)	2 Year (2005 base) Crisis Forecast (Prob %)	Crisis Likelihood	Signal Extraction Output (Theta4:1 SD, 5 Yr Rolling Mean, Out of Sample)	Z-Score Forecast (5 Yr Rolling Mean)	3 Year (2004 Base) Crisis Forecast (Prob %)	Crisis Likelihood	Signal Extraction Output (Theta4:1 SD, 5 Yr Rolling Mean, Out of Sample)	Z-Score Forecast (5 Yr Rolling Mean)
Australia	0.0	Unlikely	1	0	0.0	Unlikely	1	0	0.0	Unlikely	1	0
Austria	0.0	Unlikely	1	0	0.0	Unlikely	1	1	0.0	Unlikely	1	0
Belgium	0.0	Unlikely	1	1	0.0	Unlikely	1	1	0.0	Unlikely	1	1
Cananda	0.0	Unlikely	1	1	0.0	Unlikely	1	1	0.0	Unlikely	0	0
Czech	12.8	Likely	1	0	0.0	Unlikely	1	0	0.0	Unlikely	1	0
Denmark	0.0	Unlikely	1	0	0.0	Unlikely	1	0	0.0	Unlikely	1	0
Finland	0.0	Unlikely	1	0	0.0	Unlikely	1	0	0.0	Unlikely	1	0
France	0.0	Unlikely	1	0	0.0	Unlikely	1	0	0.0	Unlikely	0	0
Germany	0.0	Unlikely	1	0	0.0	Unlikely	1	0	0.0	Unlikely	1	0
Greece	5.2	Likely	0	0	5.2	Likely	1	0	9.3	Likely	1	0
Hungary	0.8	Unlikely	1	0	0.7	Unlikely	1	0	2.3	Unlikely	1	0
Iceland	5.1	Likely	1	0	9.7	Likely	1	0	9.0	Likely	1	0
Ireland	0.0	Unlikely	1	1	5.4	Likely	1	0	0.0	Unlikely	1	0
Italy	0.0	Unlikely	1	0	0.0	Unlikely	1	0	0.0	Unlikely	1	0
Japan	0.0	Unlikely	1	0	0.0	Unlikely	1	0	0.6	Unlikely	1	0

**For Z-score model, countries not in current sample, get a calibration of 0*

Source: Authors' calculations.

Table 6.11 - Out-of-Sample Forecast Comparison Between Z-Score, Signal Extraction and Logit Models (50 basis points bundled dependent variable calibration) -) – for Micro Overlay - Continued

	1 Year (2006 base)				2 Year (2005 base)				3 Year (2004 Base)			
Country	Crisis Forecast (Prob %)	Crisis Likelihood	Signal Extraction Output (Theta4:1 SD, 5 Yr Rolling Mean, Out of Sample)	Z-Score Forecast (5 Yr Rolling Mean)	Crisis Forecast (Prob %)	Crisis Likelihood	Signal Extraction Output (Theta4:1 SD, 5 Yr Rolling Mean, Out of Sample)	Z-Score Forecast (5 Yr Rolling Mean)	Crisis Forecast (Prob %)	Crisis Likelihood	Signal Extraction Output (Theta4:1 SD, 5 Yr Rolling Mean, Out of Sample)	Z-Score Forecast (5 Yr Rolling Mean)
Korea	0.0	Unlikely	1	0	0.0	Unlikely	1	0	0.0	Unlikely	1	0
Luxembourg	1.1	Unlikely	1	1	0.0	Unlikely	1	0	10.3	Likely	0	0
Mexico	0.0	Unlikely	1	0	0.0	Unlikely	0	0	0.0	Unlikely	1	0
Netherlands	0.0	Unlikely	1	0	0.0	Unlikely	1	0	0.0	Unlikely	1	0
Norway	0.0	Unlikely	1	0	0.0	Unlikely	1	0	0.0	Unlikely	1	0
New Zealand	0.0	Unlikely	1	0	0.0	Unlikely	0	0	0.8	Unlikely	1	0
Poland	0.0	Unlikely	1	0	0.0	Unlikely	1	0	0.0	Unlikely	1	0
Portugal	0.0	Unlikely	1	0	0.0	Unlikely	0	0	0.0	Unlikely	0	0
Slovenia	38.0	Probable	1	0	24.1	Probable	1	0	63.4	Probable	0	0
Spain	0.0	Unlikely	0	1	0.0	Unlikely	1	0	0.0	Unlikely	1	1
Sweden	0.0	Unlikely	1	1	0.0	Unlikely	1	0	0.0	Unlikely	1	1
Switzerland	0.0	Unlikely	1	0	0.0	Unlikely	1	1	0.0	Unlikely	1	0
Turkey	8.5	Likely	0	0	10.4	Likely	0	0	12.7	Likely	0	0
UK	1.3	Unlikely	1	0	0.0	Unlikely	1	0	0.0	Unlikely	1	0
US	0.0	Unlikely	1	0	0.0	Unlikely	1	0	0.0	Unlikely	1	1
			27	6			26	4			24	4

**For Z-score model, countries not in current sample, get a calibration of 0*

Source: Authors' calculations.

6.9.2. Traffic Light Summary with Micro Model

Table 6.12, presents the traffic lights signal to regulators using the decision rule explained above. Note that the traffic signals panel is somewhat similar to a risk heat map and could be easily scaled to include other models as well or calibrated to modify output based on regulatory objective functions/ thresholds for intervention.

Table 6.12: Traffic Light Summary for Macro-Micro Overlay 50 Basis Points Dependent Variable Bundled Calibration

Country	1 Year	2 Year	3 Year
Australia	A	A	A
Austria	A	R	A
Belgium	R	R	R
Cananda	R	R	G
Czech	A	A	A
Denmark	A	A	A
Finland	A	A	A
France	A	A	G
Germany	R	A	A
Greece	A	R	R
Hungary	A	A	A
Iceland	R	R	R
Ireland	R	R	A
Italy	R	A	A
Japan	A	A	A
Korea	A	A	A
Luxembourg	R	A	A
Mexico	A	G	A
Netherlands	A	A	A
Norway	A	A	A
New Zealand	A	G	A
Poland	A	A	A
Portugal	R	G	A
Slovenia	R	R	A
Spain	R	A	R
Sweden	R	A	R
Switzerland	A	R	A
Turkey	A	A	A
UK	R	A	A
US	A	A	R

Looking at the traffic light signals issued by the synthesis of the macro and micro model outputs, most of the countries for the three years have amber signals, which is expected as most systems would be in flux with various variables moving picked up by the three models, although we have an increase in red signals to 25, versus 21 in the macro synthesis. The model design is based on capturing movement and volatility in the system, whereby bigger movements translate into larger signals. Canada still has a ‘Green’ signal in 2007 after adding the micro model, confirming that the financial system, other explanatory variables and largest banks in the system were stable and the system as a whole was resilient in terms of stocks and flows.

Source: Authors’ calculations.

Other countries that have green signals include Mexico in 2006, New Zealand in 2006, and Spain in 2005 and Portugal in 2006. This again reflects a period of relative tranquility in the system, as the macro and micro models are based on movement. The implication of this is that the traffic lights need to be monitored not only at a point in time, but also within the perspective of a rolling window.

Finally, the countries that have red signals associated are correctly called by the synthesis of these macro and micro models, and improve on just the use of macro models. The overlay of the financial strength of the top five banks in each country, which capture more than 75% of total sector assets in the 11 OECD countries in the smaller micro sample, improves the traffic lights substantially.

The UK is now flagged based on the micro overlay, while others with red flags are Austria (2006), Belgium (2005, 2006, 2007), Canada (2005, 2006), Greece (2006,2007), Iceland (2005, 2006, 2007), Ireland (2005, 2006), Italy (2005), Luxembourg (2005), Portugal (2005) and Slovenia (2005, 2006), Spain (2005), Sweden (2005, 2007), Switzerland (2006), UK (2005) and the US (2007). In addition, the two significant explanatory variables, banking assets to GDP and banking sector asset growth, in all these countries again were either very high as a percentage of GDP (ranging from a low of 2 times to a high of 30 times GDP), while banking sector asset growth in the year prior to a signal being issued was close to 20%.

The three macro models however, did improve by picking up on some of the countries, including the US which should have had red signals in hindsight in the two model synthesis. The UK is still in amber mode for this synthesis as it had the smallest equity index movements, another significant explanatory variable. This improves substantially with the micro-model overlay for the final traffic lights synthesis which incorporates the health of the top five banks in this picture.

The overlay of the micro model improves the traffic lights matrix substantially, these findings reinforce the need by regulators to use different models and to look at all of them in judging the build up of vulnerabilities, even within the same system / country. Also to look at the evolution of signals in a time series fashion.

6.9.3 Conclusion

Using a Merton type Z-score framework and looking at OECD countries, movements in PD by more than one standard deviation in member banks in the sample which were aggregated were found to be significant in predicting crises. The PDs were calculated using a Merton type Z-score framework, where the Z-score is a capital adequacy measure plus returns on average assets all divided by the standard deviation of returns.

The output model shows that as early as 2004, clear signals were being given for a number of countries that vulnerabilities were building up across their banking sectors. The countries signaled to have crises in the previous applications do not map one to one in all three applications and some key countries called by the signal extraction to be susceptible to crises are not called by the Logit model but are called by the Z-score model, but the Logit model raises the alarm bell for other countries.

Different models will invariably have different output in some aspects, one way to summarize the results is by looking at EWS models as a traffic light system, where a system is considered to be in the 'Red' if more than two models used as decision making tools indicate a crisis, whereas in Amber mode, the system is in flux and needs to be monitored closely, while for Green mode, the system is robust with all models showing no signals. This traffic light approach is comparable to the risk heat maps adopted by global institutions analysing financial stability and is scalable to incorporate as many models as required by regulators. Also micro model improves the EWS system considerably.

This section overlays the micro model findings to the previous suite of models, Z-Score, Logit and signal extraction and points to a measured improvement resulting from combining the micro and macro analysis. Regulator objective functions do have an impact on model performance, and therefore EWS should always be designed with a set of objective functions and crises evaluated for each set as evident from the output of the three previous methodologies based on the three scenarios for the magnitude of change in the dependent variable that is deemed systemic. Similarly the micro model is a valuable overlay to complete the picture. Also, regulators should use a number of models simultaneously to monitor changes in their respective systems and the impact from spill-overs from other interconnected systems as each model has strengths and weaknesses. In addition, there is a lot of value in the initial data searching exercise for variables, because this helps determine at any one point in time on a dynamic basis as these are the factors that are 'moving' in the system and could cause vulnerabilities. Also as evident from the micro model, building robust databases on the micro level and the macro level are elementary to setting up an effective EWS. Lastly, regulatory oversight and judgment need to be exercised at all times without over reliance on models as clearly, the outcomes must be then mapped onto real life by the regulator and also assessed in terms of cost of intervention versus cost of waiting for certain further critical triggers and regulators need to exercise vigilance and prudence consistently.

7. Chapter Seven: Conclusions, Regulation, Macro-prudential Analysis and EWS and Regulatory Challenges Ahead

7.1 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 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 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 and 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 and Shin (2003) prove that low capital adequacy and a fragile banking sector is a leading indicator of banking distress, signaling a high likelihood of near-term bank failure. Furthermore, Cihak and 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 or 'Near Failure' or 'Fragility' on the micro/ individual institution level. 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 behavior 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 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 research we use signal extraction, logit and Z-score methodologies, in macro and micro applications. This research 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. 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 banking sector prior to the crisis was highly concentrated, and after the crisis it will become more concentrated, give the implementation of Basle III requirements, which in effect would force a number of institutions to merge and result in even bigger entities. This has a number of implications for the design of EWS and their use to help implementation of countercyclical measures for LCFIs. The scope of changes in regulatory issues is sizable in both Europe and in the US.

EWS and analytic tools in light of the aforementioned need to take into account that each crisis will be different, have different triggers and unravel in a different manner to its predecessors, yet it will also be similar in other ways to previous crises. Therefore the best way to prevent a crisis is to ensure that the 'system' is as healthy as possible by attacking imbalances before they accumulate which is what this research focuses on by the innovation in dependent variable.

The EWS in itself is a necessary starting point, however it is nowhere near sufficient, it has to be approached as part of a set of decision suites to be used as demonstrated throughout this research. The importance of a strong macroprudential surveillance and systemic regulator function with wide reaching powers to safeguard against financial instability is paramount. Having a robust early warning signals system (EWS) in place is the core 'brain' component of such a system. It will serve in satisfying two key goals in the oversight of systemic financial stability: a) limiting financial system-wide distress, and b) avoiding output or GDP costs. The earlier and more reliable this system is in predicting instability - and the more easily understood, mapped and shared with a high degree of transparency among the parties concerned with safeguarding financial stability in any country and indeed across borders – the more likely it will achieve its objectives by allowing sufficient lead time for action. The past crisis highlighted the global nature of shocks and thus a global EWS is needed to assess and disseminate key threats to financial stability and information on systemic vulnerabilities in a quantifiable manner. By so doing the EWS will assist policy makers in preventing crises, in a financial world with more integrity and more ethics.

This rest of the chapter is structured as follows: 7.2 Conclusions for macro and micro applications; Macro-Micro Combined Application; and Conclusion and Traffic Lights Summary. While section 7.3 covers Regulation, macroprudential Analysis and EWS, section 7.4 covers Regulatory Challenges Ahead and Basle III; and finally section 7.5 concludes.

7.2 Summary Conclusions

7.2.1 Signal Extraction

Using a signal extraction framework and looking at OECD countries over a 30 year period two variables were found to be significant in predicting crises. These include growth in pension assets (positive and significant at the 5% level) and equity market dividend yield (positive coefficient, 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, and also as free cash flows to equity shareholders, after debt service, are available.

Banking sector assets growth was also significant, indicating a strong relationship between rapid growth in the sector, its relative size to GDP and the development of vulnerabilities (positive coefficient).

The output model shows that as early as 2004, clear signals were being given for a number of countries that vulnerabilities were building up across 144 runs for an unbundled dependent variable of four components, with three cases: a base case, a high change dynamic threshold case and a low change dynamic threshold case. For the base case dependent variable runs, the consolidation run shows the best in-sample model, is the 3-year rolling one standard deviation, very closely followed by the 10-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 1.60 to 0.6. 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 NTSR in Borio and 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%.

This research 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, is the 10-year rolling one standard deviation specification with a Type I error of 0% and a noise-to-signal ratio of 0.6. These results show a significant improvement compared to earlier work. Using an adapted crisis definition as measured by a solvency proxy, in itself an innovation, has improved the performance of the model in terms of minimizing Type I errors over a three year period and NTSR out-of-sample. Furthermore out-of-sample performance is better than in-sample performance. A major improvement to previously existing models.

Furthermore, an evaluation of model performance had it been calibrated using the crises definitions in earlier literature compared to the near-crises definition proposed by this research, 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 (NTSRs).

7.2.2 Macro Applications Conclusions

Logit Model

For the Logit framework, looking at OECD countries over a 30 year period a number of variables were found to be significant in predicting crises. These include growth in pension assets (positive and significant at the 5% level) and equity market dividend yield (positive coefficient, 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, and also as free cash flows to equity shareholders, after debt service, are available.

Banking sector assets growth was also significant, indicating a strong relationship between rapid growth in the sector, its relative size to GDP and the development of vulnerabilities (positive coefficient).

The output model shows that as early as 2004, clear signals were being given for a number of countries that vulnerabilities were building up across a dependent variable with three cases: a base case, a high change dynamic threshold case and a low change dynamic threshold case. Performance out-of-sample, is better than in-sample in terms of overall noise to signal ratios. These results show a significant improvement compared to earlier work, in terms of NTSR and Type I and Type II errors for all calibrations, with the exception of the 100 bps dependent variable calibration. Again a point to support the importance of the dependent variable regulator objective calibration and the inherent feedback loop to actual model performance.

Z-Score Macro Model

Using a Merton type Z-score framework and looking at OECD countries, movements in PD by more than one standard deviation were found to be significant in predicting crises. The PDs were calculated using a Merton type Z-score framework, where the Z-score is a capital adequacy measure plus returns on average assets (the latter defined as NI before provisions/average assets) all divided by the standard deviation of returns (same definition, NI before provisions/average assets).

The output model shows that as early as 2004, clear signals were being given for a number of countries that vulnerabilities were building up across the base case dependent variable calibration. The model performs well compared to World Bank published Z-Score indicators to calculate migration matrices in PDs.

This research focuses on the migration matrix rather than absolute thresholds, because this is the crisis indicator utilized. Comparing the migration matrices using the same methodology, a shift by more than 1 SD over a 5 year rolling mean, shows that for 14 countries the migrations using both the WB data and data in this paper are the same in count, but with a small difference in timing (+/- 1 year). Also the indicator used in this application signals a ‘crisis’ or a ‘migration’ to a higher probability of default, one period before the migrations calculated using World Bank data (i.e. outperforming World Bank results). The migrations are dissimilar for six countries, for which one country there is no WB data and for the research the data was compiled (namely Korea).

7.2.3. Micro Application Conclusion

The Z-Score micro-application results show similar performance in-sample and out-of-sample, unlike the previous three macro applications which showed better out-of-sample performance and better lead time. This is explained by the length of the data series for the micro application. However, Type I errors for the 2-Year and 3-Year horizons are 14% in-sample and 17% out-of-sample, which out-performs earlier literature. This compares to higher Out-of-Sample Type I errors for the 2 and 3 year forecast horizon in the Z-Score macro application that are slightly higher than the micro application, so there is an improvement here. The Signal extraction macro methodology remains the best performing methodology in terms of Type I errors, while the Logit macro methodology is the best in terms of NTSRs.

The output model shows that as early as 2004, clear signals were being given for a number of banks that vulnerabilities were building up across the base case dependent variable calibration. Performance out-of-sample, is better than in-sample in terms of overall noise to signal ratios. These results show a significant improvement compared to earlier work, in terms of NTSR and Type I and Type II errors for all calibrations. Signal extraction performed best in terms of Type I errors, the Logit model in terms of NTSR and the Z-score model in terms of Type II errors.

7.2.4. Macro-Micro Combined Applications

The overlay of the micro model improves the traffic lights matrix substantially, with countries like Portugal, Italy, Ireland and the UK in 2007, which were in ‘Amber’ mode before, moving to ‘Red’. These two findings reinforce the need by regulators to use different models and to look at all of them in judging the build up of vulnerabilities, even within the same system / country.

7.2.5. Conclusion

The models presented in this research on the macro and micro levels provide significant improvement to earlier research in terms of dependent variable specification, model design, out-of-sample performance, NTSR and most importantly Type I errors. Furthermore they are locationally and temporally consistent due to the dynamic research design and do suffer from over fitting. By using an innovation in the dependent variable specification to focus on near crises, lead time is improved and information disregarded in previous analysis on vulnerability build up is also incorporated.

The choice of dependent variable selection affects the overall performance of the model and thus the difficulty inherent in calling crises correctly and the impact of the choice of dependent variable on the model. The key take away is that we need a range of dependent variable triggers for which results to be presented consistently to regulators to enable sound decision making. Or in other words, the inherent feedback loops between the choice of the regulator objective and the output of an EWS.

For the various models, the countries signaled to have crises do not map one to one in all three applications and some key countries called by the signal extraction to be susceptible to crises are not called by the Logit model but are called by the Z-score model, but the Logit model raises the alarm bell for other countries. These two findings reinforce the need by regulators to use different models and to look at all of them in judging the build up of vulnerabilities, even within the same system / country.

Also, in line with Staikouras (2004) and Staikouras and Kalotychou (2005), the interplay between banking and currency crisis, is an important dimension to focus on for emerging market applications. While given the growth in banking exposure to international lending, this factor has and will continue to gain more prominence in the build up of financial vulnerability. Finally, the development of new products and innovation in the financial sector which is continuous, has implications for any EWS in the need to incorporate non-bank financial institutions on the one hand (this research incorporates one indicator, pension fund assets) and off-balance sheet activity.

7.3 Overview of Regulatory Regimes and Response to the Crisis of 2007-2010

José Viñals, IMF Financial Counselor and Director, Monetary and Capital Markets Department, (Berlin, 20 May 2010) outlines five key areas for effective financial market regulation, where a delicate balance needs to be maintained in the redesign of regulatory frameworks: macro-prudential and micro-prudential dimensions; regulation and supervision; banks and non-banks; safety of the system versus its efficiency; and regulations which are tailored to national requirements, without compromising consistency with international regulation, versus international regulation. Other prominent figures with government mandates such as Hank Paulson comment on how the regulatory structure had not kept up with the changes in the financial markets and as a result a 'patchwork' system of regulation existed, with similar patterns in other major financial centers. Markets and players outpaced regulation. A challenge for regulators that will persist is how to cope with market growth and promote its efficiency, while ensuring the system's safety and stability. In Mohamed El Erian's book When Markets Collide, he endorses this view 'The modern financial complex has morphed into something unrecognizable to many astute market veterans and academics'.

The past and ongoing crisis has brought this regulator dilemma to the forefront, and the question of which regulatory regimes were the most effective or minimized losses during the downturn and how this impacts future design of regulation, needed to be studied. How regimes reacted to the past crisis, the actions taken, the set of policy tools and the impact of these on losses realized and on the speed of crisis unraveling and its resolution all hold lessons to be learnt. The debate will shape the face of financial regulation over the coming decades and how to approach regulation in general whether through a 'light touch' or more 'intrusive' measures. This section is structured as follows: the architecture of the existing regulatory regimes pre-crisis; highlights the losses by type of regulatory regime; the various policy responses and tools on a country and global level; and highlights planned policy changes triggered by the crisis.

7.3.1. Existing regulatory regimes pre-crisis

Nier (2009) reviews financial stability and regulatory frameworks architecture and the costs and benefits associated thereof, against the backdrop of the recent crisis. He weighs the strengths and weaknesses of existing structures including the integrated model, the twin peaks model and hybrid models. The single-integrated regulator (SIR) model has one regulator overseeing market regulation (commercial banks, mutual funds and pension funds and insurance companies) and the central bank overseeing lender of last resort (LOLR) activities and payments oversight. Examples of SIR-type models were the UK before the abolishment of the FSA, Germany (although it had announced the abolishment of BaFin, it retracted and maintained the supervisory body), Denmark, Norway, Sweden and Switzerland, among others. Twin peaks models have the central bank overseeing systemic risk, including LOLR and payment systems and all potentially systemic institutions and another regulatory body handling regulation of financial services. Examples of TP-type systems include the UK currently, Netherlands, Bulgaria and South Africa, France, Italy, Portugal and Spain.

7.3.2. Losses by type of regulatory regime

In some preliminary empirical results covering the period from 2Q07 to 2Q08, Nier (2009) classifies the losses associated with each main type of regulatory regime (single-integrated regulator, SIR versus twin peaks, TP) in Europe and finds greater losses associated with the SIR model. While total losses in TP countries booked around USD40 billion, the comparative figure for SIR countries is USD126 billion. The overall loss to credit ratio also draws a similar picture with the total for TPs at 0.5%, compared to SIRs at 2.9%. These findings support the argument that having a twin peaks-type regulatory setup is more effective. With the previous SIR setup in the UK for example, there was potential for a lot of 'lost' information in having the Bank of England only regulating LOLR activities as it is relatively detached from the banking supervisory function and all the information bank supervisors are privy to, including regular discussions with market players. Therefore, twin peak systems have been found to be more effective in ensuring that regulators have a broader perspective and information is not compartmentalized.

7.3.3. Policy response

Regulatory policy response to the crisis has been far-reaching, from direct intervention in the financial sector through capital injections, purchase of assets, central bank provision of liquidity and guarantees, in addition to traditional coordinated monetary action and fiscal stimulus and last but not least quantitative easing. These measures have collectively ranged from less than 1% of GDP to almost 20% in the UK.

In 2008 the IMF's GFSR identified three interrelated areas that authorities need to continue to address as the global financial system deleverages: firstly insufficient capital, second falling and uncertain asset valuations and third dysfunctional capital markets. This is challenging given that monetary policy tools were mostly exhausted, not only because of some of the characteristics of balance sheet recessions which were applicable, but more importantly, because rates are at very low levels and as such transmission channels were partly severed. Transmission channels were affected by the increasing importance of the shadow banking system, which was affected much less by changes in reserve requirements and base interest rates. Banks moved away from a stable deposit base to larger proportion of short-term funding through wholesale funding markets and their cost of funding in these markets was not strongly linked to monetary policy actions. Governments have responded as such by directly pumping liquidity into their banking systems in the form of capital, thereby part or fully nationalizing failed institutions; providing asset protection, liquidity extension and guarantees to banks and instruments issued by banks; and attempting to enhance transparency in financial markets and kick start the securitization markets using various tools.

With the onset of the crisis, policy makers fell back on the traditional monetary policy tool: cutting interest rates. The dramatic evolution of interest rate cuts to almost zero percent in developed economies and the degree of coordination during the implementation between the various authorities since 2007 was exceptional. Having exhausted this tool, and with the disconnect between base rates and interbank and other market rates – because of the shift in risk premiums (in general investors discovered they had been underpricing risk), with London Interbank Offer Rate (LIBOR) spreads hiking to as high as 360 bps in April 2009 up from an average spread of a few basis points to base rates prior to the crisis (banks were seen as having credit risk higher than previously thought, as evidenced by the failure of some institutions). The Fed announced USD1.2 trillion in March 2009 in quantitative easing and the Bank of England GBP75 billion, respectively – the latter was raised to GBP200 billion subsequently. A number of other not-so-mainstream liquidity-creating tools were used such as asset swaps. Collectively these led to the growth of the Fed's balance sheet by more than 250% and the Bank of England's balance sheet by more than 220% from March 2007 to end of 2010.

Fiscal stimulus in G-20 countries in 2009 was projected to be around 1.5% of GDP according to the IMF, while overall fiscal balance in advanced economies was projected to deteriorate by 3.25% to -7% percent of GDP in 2009. The US has announced a stimulus package to the tune of 2% of GDP in 2009 and for a total of 4.6% until 2011 (or USD787 billion). The banking losses were transferred onto the sovereign balance sheets, which resulted in the loss of the US of its Triple AAA credit rating by S&P, while a number of countries, Greece and Ireland, have received full fledged bail outs, with

Portugal, Spain and Italy being watched closely for any signs of deterioration and have announced their own austerity packages to appease the markets.

While some countries had a better fiscal standing at the beginning of the crisis, the bailed out nations did not. Canada, China, France, Germany, the UK and the US had smaller levels of deficits, public debt and interest rates. Others, like India and Italy, had higher real interest rates and debt levels. Japan had the highest level of debt among developed countries, standing at almost 200% of GDP and was recently downgraded by Moody's as a result. The size of the increase in public debt, however, was largest for the UK and the US, for the former increasing by half the amount outstanding and by a third almost for the US.

The increase in government debt has had significant crowding-out effects: for every 10% of increase in government debt, global GDP is forecast to drop by 1.3% (1.2% for the US, respectively, IMF). Furthermore, fiscal deterioration in advanced economies poses an additional threat to future global growth, as these very same nations have to deal with the effects of a rapidly ageing population and the consequences on pension funding deficits, among others.

From crisis onset to end 2010, the IMF has pledged USD1.1 trillion to help developing countries weather the crisis. From November 2008 to March 2009, the IMF has given assistance to Romania, Ukraine, Hungary, Pakistan, Belarus, Latvia, Iceland, Georgia, Armenia and Serbia of more than USD60 billion, ranging from 1% to 11% of GDP for these countries. The Institute of International Finance (IIF) has estimated that capital flows to emerging economies in 2009 will be 80% lower than in 2007. The G20 meeting in April 2009 in London saw global leaders pledging some USD500 billion to USD750 billion in additional resources for the IMF to fund these measures and others. The IMF has also introduced a new instrument, a Flexible Credit Line (FCL). This instrument is in effect a contingent line of credit and the first one has been requested by Mexico for USD47 billion.

7.3.4. Regulatory challenges and proposed changes

The IMF identified a set of policy challenges ahead that would require addressing. These include policies to: secure a backdrop for economic recovery; strengthen the banking sector and promote resumption of lending; revive securitization markets; prevent crises in emerging markets in Europe which remain vulnerable to deleveraging; ensure orderly disengagement or exit strategies for regulators; and to manage the recent transfer of private risks to sovereign balance sheets. It proposes the following priorities for reform: i) restoring market discipline, ii) addressing fiscal risks caused by financial institutions (the idea of a 'systemic tax'), iii) living wills, iv) a macroprudential approach to policy making and v) integrating the oversight of LCFI's into the global financial market. There are a number of structural issues which pose challenges to the global reform agenda, these are outlined below.

Banking sectors and individual institutions are too big to fail. The current size of the banking sectors in a number of countries and the size of selected banks relative to the GDP of their host countries range from 100% in the US (this excludes Fannie Mae and Freddie Mac and other specialized institutions, which if they were to be included would render a ratio of 232%) to more than 800% in Switzerland. Banks should support economic growth rather than economic growth supporting bank growth which seems to have been the case here given these size comparisons.

Moreover, the ratio of a single bank's assets to a host country's GDP should not be greater than a small percentage of its national GDP, deemed reasonable to ensure a fairly diversified, non-concentrated sector in any given country. These ratios of more than 500% in the case of Icelandic Bank Kauphthing, Credit Suisse 250% and Dexia 200% explain why when two of these banks collapsed, they had to be rescued not by their hosts, but by cross-border coordinated efforts. The case of financial centers is even more complicated and different rules will have to apply with the caveat being always how to safeguard the national system in the case of the unwinding or failure of any or a number of the international institutions operating in the host country or financial hub, examples are Switzerland as mentioned above with banking assets being 8xGDP and Bahrain, with banking assets at 11 times GDP.

Many countries have now, on the national level, undertaken overhauls of their regulatory arrangements: Germany recently abolished BaFin and delegated all its responsibilities back to the Bundesbank (this decision was later reversed), the Fed has been also mandated with systemic regulation in the US and in the UK, the FSA was abolished– and the Bank of England established systemic regulation functions.

In its April 2009 summit the G7 broadened the mandate of a previously established body, the Financial Stability Forum (FSF) established in 1999 and renamed the entity the Financial Stability Board (FSB). The membership of the board includes national financial authorities (central banks, supervisory authorities, finance ministries); international financial institutions (BIS, ECB, EC, IMF, WB, OECD), international standard setters and committees of central bank experts (BCBS; IAIS; IOSCO; IASB; CGFS; CPSS). The board's mandate is to

1) assess vulnerabilities affecting the financial system, 2) identify and oversee action needed to address them, 3) promote coordination and information sharing among authorities responsible for financial stability, 4) monitor and advise on market developments, 5) advise on and monitor best practice in meeting regulatory standards, 6) collaborate with the IMF, including in conducting early warning exercises, 7) undertake joint strategic reviews of the policy development work of the international standard setting bodies, 8) set guidelines for and support supervisory colleges and 9) come up with contingency planning for cross-border crisis management (particularly for systemically important firms). Two key issues are underscored by the board: first that 'there is no single silver bullet', that a combination of approaches to assess and address systemic risks is needed. Second: 'no one size fits all' – the choice of policy action has to be determined by the structure, the size of the financial system, nature and extent of domestic and cross-border linkages and the status of the institution as being subject to the 'home' or 'host' jurisdictions (i.e. it is an independent subsidiary, with the mother company not liable for its deposits or liabilities, or merely a branch, with all the regulatory implications thereof).

Other 'super' regulators also set up in 2009, include the European Systemic Risk Board at a European level, while in the US more powers were delegated to the Fed. The mandate of the ESRB is the macroprudential oversight of the financial system within the European Union. It aims to prevent and mitigate systemic risks in the financial system within the European system to prevent financial distress. It is also charged with issuing risk warnings, giving recommendations on measures and following-up on implementation. The Risk Board will have 33 full members: the 27 EU central bank governors, the ECB president and vice-president, a Commission member and the three chairs of the new

European Supervisory Authorities - the European Banking Authority (EBA), the European Insurance and Occupational Pensions Authority (EIOPA) and the European Securities Authority (ESA). A representative from one national supervisory authority or each EU country may attend the meetings of the ESRB, but - to ensure close cooperation - will have no voting rights. The EBA has been under the spotlight with its mandate of publishing periodic stress testing results for European banks, albeit it has been under criticism as well with respect to the severity of scenarios used and tests design.

A centralized clearing house for a segment of the CDS market was expected to be fully operational towards the end of 2009. However, this has not materialized. The clearing house was to ensure that for any given participant, all transactions on the same underlying entity would be netted to a single position, and single margin account maintained on its entire portfolio of CDS. Bringing OTC derivatives on to regulated exchanges and standardizing the instruments, should help enhance transparency and market discipline. The reasons possibly for this initiative not being implemented are some of these instruments are highly structured or tailored to the needs of specific investors, so standardization might not be feasible and/or desirable.

In 2009 the Basle Committee for Banking Supervision (BCBS) and the International Association of Deposit Insurers (IADI) proposed the following changes to restore the level and quality of bank capital in 2009:1. Higher (and better quality) risk-weighted capital requirements: capital adequacy requirements should dictate banks holding more capital as compared to the risk profile of their assets not only in terms of the ratio of capital to be held but also the quality of this capital. 2. Countercyclical credit-loss provisioning: provisioning rules that would require banks to take more provisions in ‘good’ times, at the upturn of the credit cycle and ‘less’ provisions when times are bad, at the downturn of the credit cycle. 3. formal leverage ratio and formal Liquidity Coverage Ratio: Formal leverage ratio to ‘cap’ the extent of leverage banks can engage in, in addition to the minimum capital requirements. A liquidity coverage ratio ensuring banks keep sufficient, good quality liquidity. These ratios are commonly used by multi-lateral development institutions and domestic development institutions; 4. Mandatory capital insurance or contingent capital: Capital reserves that could be ‘called upon’ when they are needed, whether it be in the form of insurance, capital notes with a certain structure, or reserves of a special nature. 5. Convertible capital: Hybrid debt or hybrid capital notes,

convertible to capital. 6. Subordinated debt issuance frequency: Put policies in place for the use of subordinated debt and its issuance frequency, again subject to leverage limits.
7. Prefunding of deposit insurance: That deposit insurance be prefunded not on a 'pay as you go' basis, or the money to be provided in the case of a crisis. 8. Capital charges linked to systemic risk (Acharya et al.): This is similar in concept to a systemic tax or that institutions with a large contribution to systemic risk pay an 'insurance' premium to the regulator. This tax or premium could fund a 'systemic risk fund' of sorts. A detailed discussion of Basle III and phasing arrangements is discussed in Section c.

Other key concepts for the new global architecture design are countercyclical regulation and lean against the wind (LATW) policies, with the main causes of the previous crisis being an asset price bubble and a credit boom. Tax havens: streamlining regulation to ensure taxing of high earners and improve tax yield. Bank bonus structures and pay caps: including longer vesting periods and stronger claw back provisions. Bank living wills: banks have to draw their own resolution plans for key strategic businesses which kick into action when and if their resolution is needed. Bank systemic tax: A systemic tax on large institutions with a high systemic impact is proposed by leading academics - an institution which contributes more to overall systemic risk should pay a mandatory 'systemic insurance premium'. This is the same as the BCBS proposition. Taxation of financial transactions A proposal was made to impose taxes on financial transactions by the various regulators to generate some USD150 billion in the US. Similar proposals were made in Europe (France) but have not been approved. Finally, IOSCO proposed regulation of financial products and is considering expanding its regulatory scope to include more direct supervision of investment products, credit rating agencies and hedge funds.

7.4. Macroprudential Analysis and Early Warning Systems

Turner (2009) and IMF analyses indicate that the length of the recession post a banking stress episode is eight quarters on average, versus only three quarters for recessions which are not preceded by financial stress. So in addition to the motivation presented for this course of research on EWS, this further highlights the impact of large imbalance build-up on cost and duration of a crisis and hence the need to identify a crisis at a 'pre-crisis' time, namely the build-up of imbalances at the stage of financial fragility by focusing on a near crisis innovative dependent variable. This is the role early warning systems (EWS) should play. This section starts with a general conceptual discussion of early warning systems for crises and the required elements for a robust system, linking through to the research undertaken and highlighting innovations. This is followed by a historical survey of EWS design and an evaluation of how well existing models predicted the past crisis and how this research improves on this.

7.4.1. General conceptual design and elements of a robust and applicable EWS

A robust and applicable EWS is a cornerstone of any sound framework for ensuring financial sector stability. S. Lall et al. (2008) identify the following elements: pre-crisis sanctions on undercapitalized financial institutions that pose systemic risks (in this respect the importance of a thorough stress- and back-testing framework directly linked to macroprudential regulation is needed. During the past crisis, the usefulness of this tool was abandoned prematurely); legal and institutional mechanisms to deal quickly with weak financial institutions; and an effective deposit insurance system.

The IMF cautions though that EWS systems are not a substitute for sound and balanced judgments on financial weaknesses. The EWS also needs to be usable by policy makers in a practical manner. Borio and Drehmann (2009) underscore the importance of applicability and the need to take the policy maker's objectives into account when designing an EWS. Thus the choice of models and the selection of thresholds taking into account the trade-off between correctly calling crises and false alarms (NTSRs) should be tailored to the policy makers' objectives. They also identify that one of the design features of an effective EWS should be the clear quantitative delineation of the definition of a crisis (e.g. indirect cost of failures as a percentage of GDP, a bank run on a specific percentage of bank deposits is what the system would classify as a crisis, or others, but a clear 'crisis' objective which can be measured). The advantage of a quantifiable objective as such is that it would also enable cross-border objective comparisons as well as standardized time series analysis. Karim and Davis (2008) stipulate two further conditions for an effective EWS: having sufficient lead time to allow the policy maker to take action and that it is simple enough to be understood by policy makers at all levels. The usefulness of such an EWS, the authors continue, is that it would enable authorities to warn financial market players of potential risks in speeches and various publications and also alert bank examiners that they need to do more thorough examinations at times of elevated stress. A credible EWS would also justify direct policy action to avoid a crisis by policy makers through the use of prudential measures on lending to certain sectors or in the form of monetary and macro action.

In this research we delineate this objective as bank capitalization changing by a given number of basis points deemed suitable by the regulator and bank profitability dropping by a certain number of basis points deemed to signal by the regulator an unhealthy development in the system. As another cross check on the sources of data and the way the analysis is conducted and to ensure that institutions which are not profitable but do not see changes in this poor profitability status, if institutions have profitability of below a certain number of basis points deemed by the regulator to indicate that these institutions are unhealthy, this also is a quantifiable measure of near crisis in the system. All analysis in the macro applications is conducted on a super balance sheet approach, whereby the financial system is summarized by the aggregate balance sheet of the system compiled by regulatory bodies.

7.4.2. History of EWS design and this research

EWS are used to i) identify the macro states where policy action is needed (macro-models), ii) provide a rating system of individual institutions for a peer group or financial system in a country or indeed globally (micro-models), and iii) map the choice of policy tools to reduce crises costs. The evolution of EWS historically follows through from the evolution of their theoretical underpinnings which dictate the design to trace the hypothesized causes of crises. The theory on banking crises is usually categorized according to four generations (Breuer 2004). First-generation models (for example Mishkin, 1978), hypothesize that a poor macroeconomic setting adversely affects banks' borrowers and in turn impacts the depositors themselves, resulting in bank runs which ultimately lead to the closure of financial institutions. Second-generation models focus on depositor behavior and regard banking crises as 'sunspot' events or self-fulfilling prophecies, unrelated to the business cycle. Third-generation models highlight the role played by boom and bust cycles in the economy (and twin crises – a twin crisis is when there is a simultaneous balance of payments or currency crisis coupled with a banking crisis, e.g. the Asian crisis in 1998), with banking problems arising on the asset side of the institutions being fuelled by excessive lending against collateral such as real estate and equities. A bust cycle then causes asset prices to fall, financial institutions to lend less and a credit crunch to develop, which leads to further economic slowdown and more borrower defaults. Finally, fourth-generation models seek to identify the features of the institutional environment that set the stage for the build-up of macroeconomic imbalances, which then gives rise to banking problems.

From the literature review, a multitude of empirical models to assess such indicators have been developed in two main strands: models which rely on macroeconomic indicators as key explanatory variables and models that asses how microeconomic factors contribute to banking crises. These were followed by a number of integrated empirical models which took both types of explanatory variables into account. These models use different methodologies and either predict individual bank failure or look at systemic banking crises as a whole. The methodologies mainly fall into four categories: a) signals models (which include sub-branches of first-generation, second-generation and third-generation type models), b) logit/probit models, iii) Merton-type models and a less-used class of models, and d) binary recursive trees.

In this research, some features of all the above are used, with innovations in near crisis definitions, explanatory variables, model design, model applicability to different time periods and to different countries and regions, among others. This model can be used by regulators on a global or regional level, or by individual country regulators on an aggregate system level or on a micro level for individual banks. This links through and would complement two best practice models used by the OeNB and by the Bank of England.

In Austria the Oesterreichische Nationalbank (OeNB) uses a proprietary model for systemic risk analysis and stress testing of the banking system. Boss, Krenn, Puhr and Summer (2006) outline the key features of this model with the building blocks comprising market risk, non-interbank credit risk and an interbank network model. The factors chosen for each building block are the ones which maximize out-of-sample performance. The output of this model consists of problem statistics of the banking system, identification of fundamental versus contagion-type potential problem events and a value at risk for the lender of last resort or ‘price tag’ for intervention. This model could be improved in design by using a dynamic set up, and/or some inputs or outputs of this model could feed into the EWS discussed in this research or could be fed from the EWS discussed in this research.

In the UK, the Bank of England also uses a network type model, but focusing on a set of six identified vulnerabilities, while recognizing that other vulnerabilities might not be identified or measured. The model then attempts to analyze the ways that a potential shock could trigger each vulnerability and identify which sub-sectors of the financial and non-financial sector will be affected It also seeks to find out what the second-order effects and feedback effects between the real economy and the financial sector are and the impact of the combined effects of transmission channels. Similarly for this model, it could be improved in design by using a dynamic set up, and/or some inputs or outputs of this model could feed into the EWS discussed in this research or could be fed from the EWS discussed in this research.

Moving on to Micro-models, which identify states where policy action is required and whose output is mainly the identification of systemic hot spots, were supplemented by central banks and agencies to provide rating systems of institutions within their jurisdiction on a micro-level. These include, but are not limited to, analyses of capital adequacy, asset quality, management, efficiency, liquidity and sensitivities to various risks, commonly called CAMELS for short, analysis rankings of financial institutions, and all derivatives thereof. As shown by the application to 139 banks in this research, the model presented here easily renders itself to provide an internal ranking of banks within a system or across a sample in a number of countries.

Poghosyan and Cihak (2009) provide a comprehensive survey of EWS used by European regulators, utilizing a unique database of individual bank distress across the European Union from the mid-1990s to 2008 on the basis of which they identify a set of indicators (CAMELS based) and thresholds to distinguish between sound banks and banks vulnerable to financial distress. They highlight the usefulness of an EU-level early warning system based on this model, with published results by banks compared by benchmarks to enhance market discipline. The dataset is based on Bankscope data, on 5,708 banks, plus information obtained from NewsPlus/Factiva on each bank with regards to any financial support or other forms of rescue or merger. The authors identify 79 distress events for 54 banks. Using a Logit model they find that the model would have correctly called more than 55% to 68% of distress cases correctly. The explanatory variables they find most useful are: capitalization, asset quality and profitability. While cost-to-income ratios and basic liquidity indicators failed poorly (a liquidity indicator which measures wholesale percentage financing of liabilities was useful, however). They also find depositor discipline has an important signaling effect (if a bank pays higher rates on its deposits than its competitors, it has a higher probability of distress). This research uses both capitalization and efficiency metrics as the dependent variable and link through to how to predict this, as such because the prediction is for the variables which lead to distress as per this discussion, it has proven empirically and also intuitively that it does improve on lead times and help identify vulnerability build ups, before they develop into full fledged crises.

7.4.3. Performance of EWS models in the past and this research

As stated clear motivation for this research, EWS models described in the literature had failed in predicting the global meltdown of 2007-2010. In addition to research design issues discussed, there are possibly other non-quantifiable aspects such as ‘gambling and looting’ and other behavioral issues that might not have been possible to map. Asli Demirgüç-Kunt and Enrica Detragiache (2005), Kane (1989) and Akerlof and Romer (1993) had dubbed the US savings and loans crisis in the 1980s as such an episode. They demonstrated how the erosion of bank capital following financial liberalization, generous deposit insurance and ineffective regulation conspired to make ‘gambling and looting’ an optimal strategy for scores of bank managers. Other cases of systemic wide crises which resulted from fraud are Venezuela (1994), and Guinea in 1985 where the six main banks, accounting for over 95% of the system, were closed on a single day on the back of widespread bank fraud (Honohan 1997). In the design of the dependent variable, this research addresses this by looking at symmetric changes in capital, meaning that also increases in capitalization of the system by a certain number of basis points could be the sign of vulnerabilities which built up, bankers know that they have taken risks which have not yet been reflected on their balance sheets. A banker’s optimization function is to minimize capital and maximize returns, if bankers increase capital, it is not to hedge against future risk they will take, but to cover for risk they know they have already taken.

Recall Davis and Karim (2008) assessment on whether EWS based on a) logit and b) binomial tree, binary recursive trees (BRT) approaches for the UK and US economies could have helped raise the alarm about an impending crisis before the recent crisis. Using a sample of 105 countries and covering the years 1979 to 2003, Davis and Karim (2008) apply the models to US and UK data to test for out-of-sample performance from 2000–2007 (they partition the sample first into a sub-set until 1999, and the rest). In both cases, they set the start date of the crisis as 2007. They find that for the US, both models fail miserably with a probability of a crisis occurring in 2007 of 1% predicted by the logit model and 0.6% predicted by the binary tree model. For the UK, the results were similar, with logit model predicting the probability of a crisis at 3.4% in 2007 and the binary tree model assigning a 0.6% probability of a crisis occurring.. The authors identify a short checklist approach for detecting financial instability, including a) regime shifts, b) entry conditions, c) debt accumulation, 4) innovation in financial markets, and 5) risk concentration.

More interestingly, Davis and Karim (2008) also considered a ‘checklist approach’ of indicators previously used. They find that the models were not largely successful and as such suggest a broadening of the approach to a more comprehensive set of macroprudential analyses. They start with a survey of the various financial stability reviews (IMF, ECB, Bank of England and BIS) in the spring of 2007 to gauge whether any of them showed concern over an impending crisis. They find that collectively these reports did point out: deterioration in credit quality of US subprime mortgages; high European institutions’ exposure to the US subprime market; rising corporate leverage; rising household indebtedness; rising capital flows into emerging markets; concerns about credit-risk transfer between markets; high asset prices and irrational exuberance; complacency by LCFIs; poor perception of risk due to the ‘originate and distribute’ model; the potential of liquidity ‘vanishing’ from markets; a likely rise in investor’s risk aversion in the case of a shock and most importantly a significant deviation from historic norms for many of these indicators. The BIS concluded that ‘a tail event affecting the global economy might at some point have much higher costs than is commonly supposed’. Thus while the features of the crisis were correctly recognized on a collective level, the extent was not. It is worth noting, however, that the Bank of England’s FSR of April 2007correctly identified most of the key vulnerabilities to include the major causes of the recent crises and estimated a potential loss of UK bank’s tier I capital of up to 30%

to 40% (or GBP47 billion to GBP62 billion), given certain scenarios, an estimate which was very accurate for the first-order-effects of the crisis in the first stages.

If these bodies had conducted a combined stress test with all the fragilities identified, perhaps they would have they been able to predict the crisis, this view is supported by Borio and Drehmann (2008) who identify crucial features of an operational framework to address financial instability as including setting up institutional arrangements that leverage the comparative expertise of the various authorities involved in safeguarding financial stability. It is worth mentioning that none of these bodies included an analysis of SIVs, a key feature in this crisis nor other off-balance sheet items or a proxy for them thereof. In this research, this is also not addressed explicitly, but indirectly the effects are captured through development of asset price bubbles gauged by both a stock market index and a housing price index and growth of pension fund assets. The rationale is these variables are a reflection of the amount of liquidity available in the system to chase investments, and this liquidity, if it is not on-balance sheet, which is being measured explicitly, then it must come from off-balance sheet sources.

A 2006 IMF review of EWS in use and the next steps forward concludes that EWS models have shown mixed results in terms of forecasting accuracy, but nevertheless offer a systematic, objective and consistent method to predict crises which avoids analysts' biases. It also stresses the importance of developing a set of building blocks to predict foreign exchange crises, debt crises, sovereign risk, banking crises, financial market linkages/spillovers, and contagion and cross-country linkages. Bell and Pain (2000), after reviewing the existing EWS models up till 2000, with a special application to the Asian crisis, conclude that the models are subject to some significant weaknesses and limitations, especially as potential tools for policy makers.

Gunther and Moore (2002) analyze EWS in real time using a probit approach and identify as such one reason why EWS have performed so poorly. This study is interesting in that it uses a unique set of banking data over 1996 through to 1998 which includes both originally reported and revised financial variables for 12 financial ratios based on CAMELS. They find adverse revisions to initially reported data to be associated with downgrades in supervisory ratings. As such these results highlight the auditing role of bank exams and the implications thereof on a realistic assessment of EWS model accuracy. If the data on which an EWS is based is revised, then naturally the original output of the model was distorted. In a related study, O'Keefe et al (2003) stress the importance of loan underwriting practices in the determination of bank credit risk and study the relationship between examiners' assessments of the riskiness of bankers' lending practices and subsequent changes in the riskiness of bank portfolios. The authors investigate whether examiner assessments should as such serve as aids to an EWS which is based on real time data. They find that higher (lower) risk in underwriting practices is indeed associated with subsequent increases (decreases) in non-performing assets generally. This research addresses links through and addresses some of the weaknesses described above, as such it improves on previous research.

7.5. Regulatory Challenges Ahead and Basle III

7.5.1. Regulatory Challenges Ahead

Global leaders in the aftermath of the current crisis have underscored the importance of an EWS. 'An early warning system must be established to identify upstream increases in risks...' Heads of State or Government of European Union, November 7, 2008. While the De Larosière Report, on 25 February, 2009 states 'The Group recommends that the IMF, in close cooperation with other interested bodies … is put in charge of developing and operating a financial stability early warning system, accompanied by an international risk map and credit register. The early warning system should aim to deliver clear messages to policy makers and to recommend pre-emptive policy responses ...' This links through to the importance of EWS in directing policy action design and tools.

Given the prohibitive cost of crises, a number of studies were conducted to empirically assess cross-country intervention policies to determine which policies could minimize the costs of crises and should therefore be utilized once the alarm has been raised by an EWS, and which measures increase the costs and should be avoided. Honohan and Klingebiel (2003) constructed a database with 40 banking crises and the respective policy responses by governments according to five categories: a) blanket guarantees to depositors, b) liquidity support to banks, c) bank recapitalization, d) financial assistance to debtors and 5) forbearance. The authors link the various intervention policies and the fiscal cost of the bailout and find that the more generous bailouts had higher fiscal costs as expected. Claessens, Klingebiel and Laeven (2004) find that these generous bailouts do not reduce the output cost of banking crises as measured by the output loss relative to trend during the crisis period. Both studies endorse the view that the high moral hazard associated with bailouts which are too generous is more detrimental than effective.

Hoggarth and Reidhill (2003) survey various measures of reducing the net costs of crisis resolution and of reducing the probability of future crises. They outline a number of qualitative measures including the preferable use of private sector solutions, loss imposition on bank stakeholders and shareholders to reduce moral hazard (Greece is a good example but in a sovereign application), increasing transparency and disclosure of resolution programs in general, minimizing forbearance and expediting resolution. They also explore the various resolution strategies and their cost impact including: unassisted resolutions (bank status remains the same or is changed/private sector merger), liquidation and assisted resolutions (bank status remains the same, open bank assistance, bank status changed, bridge banks, outright government ownership). Santomero and Hoffman (1998) provide a similar survey that focuses on three distinct case studies in this respect, US banks, Scandinavian banks and French banks, arriving at the same conclusions as Hogarth and Reidhill,.

EWS design should help regulators test which policy tools are necessary and which will be sufficient to avert a crisis. Kaufman (2001) notes that in times of credit crunch, the whole economy contracts. If the government tries to force it out of a contraction through too much intervention using policy tools, coercing banks to increase lending could have negative consequences because it only weakens the banks further by making them extend excessively risky loans and exacerbates the size of the problem in the long run. He depicts the lifecycle of market-government regulation as follows:

Market regulation ⇒ market failures ⇒ ‘horror stories’ ⇒ government intervention (regulation) ⇒ government failures ⇒ government deregulation ⇒ market regulation ⇒ market failure.

While government policy actions are necessary, as seen from Kaufman’s depiction, they are not sufficient. Sufficiency would stem from the revamping of financial stability frameworks and other structural reforms which will ensure a sounder and safer system in the long run. Also more streamlining of global financial stability frameworks and strengthening frameworks in developing and emerging countries is needed as where or when the next crisis will hit remains unknown. Even though here are a number of robust frameworks in developed countries; the need for streamlining and further cooperation cross-border has been highlighted by the cross-border evolution of the recent crisis. Also financial stability frameworks will need to be brought up to international best practice in developing and emerging markets, with the developed world in poor economic health and suffering from an ageing population, banks will have to start expanding more in these countries looking for growth. Banks have already indicated that they will start allocating more capital to less restrictive regulatory environments – i.e to engage in regulatory arbitrage for operations set up in countries with weak regulators compared to strong home country regulation. As the operations of banks grow in developing and emerging markets, ensuring developed countries' stability will in part have to be addressed by ensuring stability of developing markets. This is clearly demoNTSRated by the Dubai World credit-risk transfer example, with a 'problem' exposure by Standard Chartered and HSBC of USD26 billion. More recently, problems have emerged with a large Saudi business conglomerate, Al Saad Group, which reportedly has USD20 billion in problem loans owed to local and international players, for which it offered 8 cents to the dollar to its creditors during attempted settlement negotiations which broke down. This development is foreseen by Kaufman's (2001) empirical evaluation over three decades, whereby, he notes that since 1973, losses from banking crises as a percent of GDP were nearly four times as great in emerging economies which had poor financial stability frameworks - providing open-ended financial support to their banks - than countries that provided smaller or no such support.

Procyclicality and boundary problems in financial regulation dictate the need for a meta-theory for guiding new EWS design. Goodhart et al have written extensively on the subject. This meta space has implications for the design of an effective EWS and there are tradeoffs. Four main elements of this meta-space are: a) regulator objectives: price stability versus financial stability, b) macroprudential versus microprudential analysis, c) procyclical versus countercyclical measures, and d) rules-based versus risk-based regulation.

7.5.2 Regulator Objectives: Price Stability vs Financial Stability

Goodhart et al (2006) present the various tradeoffs between central banks' objectives of price stability versus financial stability and the implications thereof. In terms of price stability, measurement and definition is established, the iNTSRuments for control are present, there is a high degree of accountability, there is a forecasting structure based on central tendencies and a simple administrative procedure is in place. In terms of financial stability there are many challenges in measurement and definition, control tools, accountability, forecasting and administrative procedures. Consequently, designing EWS which address the latter is a challenging task given the 'fluid' nature of the components. This would necessarily also imply that the 'optimal' EWS also be of a dynamic and 'fluid' nature within each sub-category in order to satisfy regulator objectives. This research takes these considerations into account.

7.5.3 Macroprudential versus microprudential analysis

Borio (2006) delineates the tradeoffs in both analysis approaches. A macroprudential approach takes into account correlations and common exposures among institutions, whereas a microprudential approach focuses only on individual institutions. For an EWS design to be effective, it has to take into account both types of analysis to ensure completeness and a comprehensive mapping of risk on a 'gross' and 'net' basis, after taking into account the eliminated or offset risks within a system, and the positive or negative impact of having a strong or weak regulator, respectively. This research takes these considerations into account.

7.5.6 Procyclical versus countercyclical measures

Goodhart (2008) explores procyclical versus countercyclical measures through a discussion of the boundary problem in financial regulation. He reiterates his proposal that state and time-varying capital adequacy requirements are needed (similar to the Spanish model) through a discussion of how and where to set the boundary for regulation. Too much regulation could result in disintermediation, competitive inequality (no level-playing-field), and inefficiency and higher spreads. Wadhwani (2008) finds that there are strong theoretical and empirical reasons for considering a 'lean-against-the-wind' (LATW), countercyclical tilt to monetary policy to enhance macroeconomic stability. He discusses Bernanke's proposition on the difficulty of 'safe popping' an asset bubble without grave consequences on the economy. He also cites one case, Sweden, where

LATW actually worked. With house prices increasing drastically in Sweden, on a few occasions in 2004-5, the Riksbank did for that reason lean against the wind and did not take rates down as quickly as they could have considering the outlook for inflation alone. Thus for an EWS to be 'implementable', it has to give sufficient lead time to enable countercyclical/LATW policy action and also identify the most effective tools for policy action as such. This research takes these considerations into account.

7.5.7 Rules-based versus risk-based regulation

The roll-out of Basle II in 2004 and its global adoption by banks starting 2007, with full compliance originally expected by 2010, has been blamed for increasing procyclicality and hence exacerbating the recent crisis. However, if Basle II had been adopted in its entirety, before the crisis had developed, it would have achieved its initial objectives of a introducing a more risk-sensitive capital measurement and minimum regulatory capital requirement and a 'risk-based' regulations and supervision framework as opposed to a 'rules-based' framework of regulation and supervision. Basle II's three pillars are a self-contained framework with its own internal checks and balances. The main problem was that only Pillar I was being rolled out, while Pillars II and III were still 'playing catch-up'. Pillar II, on supervision, through the use of stress testing, gives regulators the tool to enforce minimum capital requirements on the basis of differentiated risk exposures of various institutions, discarding Basle I's 'one-size-fits-all' approach. Pillar III on market discipline would ensure that whatever is not addressed by Pillars, I and II is captured by the 'market'. For the most recent crisis, it's my view that we had a failure of pillars II and III, rather than pillar I. Pillar II's stress tests, albeit not sufficient without adding an additional component for liquidity stress tests and for back testing as well, never got the chance to be utilized, and regulators were still trying to fully comprehend the various models used by banks under the internal ratings based (IRB) approach. While pillar III on market discipline was undermined in two key ways. Firstly in scope, it was not generic enough to require that systemically significant markets in which banks are active must be subject to a minimum level of accepted transparency and disclosure on their operations. With notional outstanding value of the global derivatives markets at more than ten times global GDP and more than twenty times global banking assets, these markets should have been subject to minimum transparency and disclosure. Secondly, by not acknowledging the weaknesses inherent in markets given that the built-in assumptions of rationality and efficiency necessary for market functioning do not hold all the time. If we do not assume that markets are rational or efficient, then a world with market dislocations is possible and we always have to be on our toes so to speak – there is no room for complacency and for trusting the markets to continuously self-correct without financial collapses. Working on this basis, Pillar III would have signaled to regulators that shifts they saw in the market pre-crisis needed to be investigated more thoroughly or that 'something might be wrong' and the market is trying to tell us something. Basle III is an extension of Basle II, but with some fixed ratios more in line with a Basle I set up.

From this discussion, it also follows then that in a risk-based regulatory setup, the role of the regulator is far more paramount to the safe-guarding of a system's stability, much more so than in a simple rules-based setup. A weak regulator would in effect jeopardize a strong system and a strong regulator would strengthen a weak system.

7.5.8 Basle III

Basle III is an enhancement to Basle II with some fixed measures to specifically address key issues that led to the previous crisis of 2007-2010. Special emphasis on liquidity risk, the procyclicality in Basle II by bringing back some static capital requirements and a systemic surcharge on all institutions. Basle III also puts more emphasis on the quality of the capital held by banks, rather than just levels, while the introduction of new contingent capital to 'automatically' be converted to capital based on pre-defined triggers ensures that capital can be shored up automatically in times of need. Formal leverage and liquidity ratios are introduced along with a stable funding requirement. Off-balance sheet activities are scrutinized in more detail and there are increased requirements on counterparty credit risk. Finally, Basle III aims to improve transparency across the board. Basle III still has the three main pillars of Basle II, however, with enhancements applied as discussed. Table 7.1 discusses the regulatory elements of Basle III and the proposed requirement. The net result is the recognition of more risk weighted assets, recognizing less instruments as eligible for capital and increasing capital requirements as well based on the modified measures. Banking industry activities will be severely curtailed and profitability impacted, but safety should be improved substantively.

Table 7.1 Basle III Regulatory Elements and Requirements

Higher Minimum Tier 1 Capital Requirement	-Tier 1 Capital Ratio increases from 4% to 6% -The ratio will be set at 4.5% from 1 January 2013, 5.5% from 1 January 2014 and 6% from 1 January 2015 -Predominance of common equity will now reach 82.3% of Tier 1 capital, inclusive of capital conservation buffer
New Capital Conservation Buffer	-Used to absorb losses during periods of financial and economic stress -Banks will be required to hold a capital conservation buffer of 2.5% to withstand future periods of stress binging the total common equity requirement to 7% (4.5% common equity requirement and the 2.5% capital conservation buffer) -The capital conservation buffer must be met exclusively with common equity -Banks that do not maintain the capital conservation buffer will face restrictions on pay-outs of dividends, share buybacks and bonuses.
Countercyclical Capital Buffer	-A countercyclical buffer within a range of 0% to 2.5% of common equity or other fully loss absorbing capital will be implemented according to national circumstances -When in effect, this is an extension to the conservation buffer.
Higher Minimum Tier 1 Common Equity Requirement	-Tier 1 Common Equity Requirement increase from 2% to 4.5% -The ratio will be set at 3.5% from 1 January 2013, 4% from 1 January 2014 and 4.5% from 1 January 2015.
Liquidity Standard	-Liquidity Coverage Ratio (LCR) to ensure that sufficient high quality liquid resources are available for one month survival in case of a stress scenario, 1 January 2015. -Net Stable Funding Ratio (NSFR) to promote resiliency over longer-term time horizons by creating additional incentives for banks to fund their activities with more stable sources of funding on an on going structural basis -Additional liquidity monitoring metrics focused on maturity mismatch, concentration of funding and available unencumbered assets
Leverage Ratio	-A supplemental 3% non-risk based leverage ratio which serves as a backstop to the measures outlined above - Parallel run between 2013-2017, migration to Pillar 1 from 2018
Minimum Total Capital Ratio	- Remains at 8% -The addition of the capital conservation buffer increases the total amount of capital a bank must hold to 10.5% of risk-weighted assets, of which 8.5% must be tier 1 capital. -Tier 2 capital iNTSRuments will be harmonized; tier 3 capital will be phased out

Source: Moody's Analytics, BCBS, BIS.

7.6. Conclusion

The banking sector prior to the crisis was highly concentrated, and after the crisis it will become more concentrated, give the implementation of Basle III requirements, which in effect would force a number of institutions to merge and result in even bigger entities. This has a number of implications for the design of EWS and their use to help implementation of countercyclical measures for LCFIs. The scope of changes in regulatory issues is sizable in both Europe and in the US.

The last crisis showed clearly that regulators need to better understand what is happening in their financial markets. One way to achieve this would be through greater market discipline, sharing more with participants and players on a national level and publicly warning against eminent threats. Sharing information publicly with the market through preset regular schedules via publications, presentations and hearings at national assemblies should ensure effectiveness. Greater market discipline should be used as a tool bearing in mind that for it to be effective, its scope should include all systemically significant markets and these need to have a minimum level of accepted transparency and disclosure. Also that markets are neither necessarily always efficient nor rational, deviations should be investigated diligently.

Regulators need to communicate closely with industry players to understand the businesses their players are involved in, how they are making their profits and the risks they are accumulating in the process. More importantly, they must be on very good terms with the leaders of systemically significant institutions on a personal level.

Another important design aspect is the governance structures of regulators, discouraging group think and protecting whistle-blowers, the more balanced to ensure a diversity of opinions, the better. Strengthening the whistle-blower channel means that differing views can and will be heard. Also ensuring adequate representation from the private sector on regulatory boards and sufficient ‘brainstorming’ open up discussions with the private sector on upcoming regulations and existing regulations. Listening to views from think tanks and independent economists is also crucial in ensuring regulators are not divorced from the market.

Businesses succeed or fail and the same applies to financial institutions. Each stakeholder in a business should always share the 'burden' commensurate to the nature of its stake holding. Thus equity shareholders, with unlimited upside, should also pay for the costs of getting wiped out. Likewise with debt holders, an investor - though only getting a fixed return on its debt - should expect repayment, prior to equity shareholders receiving any funds in the case of failure. Any exceptions will result in playing fields which are not level.

Investors, especially those in charge of money belonging to others, have a fiduciary duty not only to make the best investments for their clients on an absolute-return basis, but also on a risk-adjusted basis. Agents and principal investors should apply prudence and undertake necessary due diligence before embarking on an investment. An investor should understand what they are investing in, the mapping of the returns and the risks and if they don't then perhaps a degree of modesty is required and opportunities forgone if necessary.

Inclusion of a strong ethical code of conduct and ethics training for both regulators and private sector players is crucial – if anything the last crisis was also a clear crisis of ethics and governance. If mortgage brokers had not extended loans to people who could not repay them, then the subprime market would have not collapsed and the crisis would possibly not have occurred. If mortgage brokers had extended these loans, but we had much lower leverage levels because banks were not seeking extra yield at any cost, then the crisis would have been nowhere close to what it was in terms of magnitude. If investment officers were not overzealous in investing in products for which they did not perform sufficient due diligence because they were following the herd, the magnitude of the spillover would have been much less.

Ethics have a quantifiable value, and their value is derived from a complete default scenario. Without ethics, all contractual obligations would not be worth the paper they are written on and indeed markets cannot function.

EWS and analytic tools in light of the aforementioned need to take into account that each crisis will be different, have different triggers and unravel in a different manner to its predecessors. Therefore the best way to prevent a crisis is to ensure that the 'system' is as healthy as possible by attacking imbalances before they accumulate which is what this research focuses on by the innovation in dependent variable.

The EWS in itself is a necessary starting point, however it is nowhere near sufficient, it has to be approached as part of a set of decision suites to be used as demoNTSRated throughout this research. The importance of a strong macroprudential surveillance and systemic regulator function with wide reaching powers to safeguard against financial instability is paramount. Having a robust early warning signals system (EWS) in place is the core 'brain' component of such a system. It will serve in satisfying two key goals in the oversight of systemic financial stability: a) limiting financial system-wide distress, and b) avoiding output or GDP costs. The earlier and more reliable this system is in predicting instability - and the more easily understood, mapped and shared with a high degree of transparency among the parties concerned with safeguarding financial stability in any country and indeed across borders – the more likely it will achieve its objectives by allowing sufficient lead time for action. The past crisis highlighted the global nature of shocks and thus a global EWS is needed to assess and disseminate key threats to financial stability and information on systemic vulnerabilities in a quantifiable manner. By so doing the EWS will assist policy makers in preventing crises, in a financial world with more integrity and more ethics.

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