Essays on Systemic Banking Crises and Bank Regulation

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Summary

The 2008 Global Financial Crisis (GFC) provided the motivation for this dissertation and has arguably stimulated academic banking-related research to levels not seen since the Great Crash of 1929 and the Great Depression which followed. The main questions addressed are 1) How was it that the world appeared to be so ill-equipped to recognise the potential for such a crisis and so ill-prepared to deal with the consequences? 2) What signals usually presage systemic banking crises and were these signals observable in any way prior to 2008 and 3) What steps have been taken since the GFC and are they likely to prove sufficient deterrents or, at the very least, warnings as far as future systemic banking crises are concerned?

In Chapter 1 we analyse those factors which the literature has consistently shown to be associated with systemic banking crises. We commence by attempting to replicate the results of one of the most influential papers in the literature, i.e. that of Demirgüç-Kunt and Detragiache (1998). We examine whether the factors they identified as being of importance in 1998, i.e. low GDP growth rates, high real-interest rates, inflation and in regimes where deposit-insurance is explicitly available, retain their significance in the context of the GFC. We examine whether or not they remain consistent as systemic crisis determinants over a thirty year period or if the business cycle phase matters. The factors identified in 1998 were broadly macroeconomic rather than institutional (i.e. measured at the financial-sector level) in nature, thus falling generally outside the sphere-of-control of the regulatory community. For this reason we analyse bank balance-sheet variables in addition to traditional macroeconomic variables, making use of data innovations that have taken place since the outbreak of the GFC and which were not available in 1998. We establish a control cluster of such sectoral variables to enable the more comprehensive regulatory-effectiveness analysis to proceed in Chapter 2. This control cluster is shown to have at least equal systemic banking crisis explanatory power as the traditional macroeconomic determinants, such that meaningful policy recommendations may follow.

In Chapter 2 we take a combination of the control cluster established in Chapter 1 together with the most prominent regulatory response instruments of the Basel III accord (e.g. strengthened Tier-1 capital standards and liquidity measures such as the Net Stable Funding Ratio (NSFR)) to test their effectiveness and relevance in terms of their correlation with known systemic crisis-related factors. We show that, measured in levels, these regulatory-response measures are not associated with more robust banking sectors and provide a working hypothesis for why that may

be the case. We also show that such measures can be effective if countries take steps to grow the capital / reserves present within their banking sectors and that it is this growth that is important, not the level per-se, as was originally proposed by Goodhart (2008). We also make use of regulatory framework survey data (see Barth et al. (2013)) to highlight those aspects of the macro-prudential landscape which are most significantly associated with banking-sector stability. Thus future policy intervention recommendations may be made which are demonstrably associated with reduced levels of systemic risk.

Chapter 3 challenges the prevailing assumption, encompassed within the Basel Accords upon their inception, that the risk of the sum equals the sum of the risk. That is, if each bank in a particular sector satisfies its own micro-prudential obligations then the sector (and global financial system by extension) as a whole must be safe. That this was a fallacy was exposed during the course of the GFC and new SRMs (systemic risk measures) were proposed in its wake. These SRMs are geared to measure externalities, these being the costs to other banks flowing from the collapse of any one particular bank. Examples of the SRMs include Marginal Expected Shortfall (MES), Systemic Expected Shortfall (SES) and ΔCoVaR (pronounced delta covar, see Adrian and Brunnermeier (2010) and Acharya et al. (2011)). Currently, such externalities are not directly subject to regulatory control nor are banks required to take any measures to internalise them.[1] We test the relationship between these new systemic risk measures (SRMs) and the established determinants of systemic banking crises as set forth in Chapters 1 and 2.

We show that each of these SRMs has a useful role to play, but which is "best" depends very much upon the country in question and the purpose for which the SRM is being used. For instance future levels of systemic risk, measured by ΔCoVaR, may be inferred from bank balance sheet data and forecasts are reasonably reliable. Alternatively, systemic risk measured by MES is shown to be the most significant determinant of systemic banking crises resulting from bank funding shortfalls. We compare and contrast these SRMs and highlight their relative contribution to our understanding of systemic risk. In doing so we demonstrate that there is currently no

[1] Plans are in place to introduce additional capital buffers associated with systemic risk, systemically important institutions and counter-cyclicality but these are at an early stage of implementation and won't become fully mandatory in all countries falling under the auspices of the Basel accords until after 2018.

single globally-consistent measure of systemic risk and that prudence requires multiple measures to be maintained and monitored at both banking system and institutional-contribution levels.

Contents

Chapter 1

Long Run Macroeconomic and Sectoral Determinants of Systemic Banking Crises

Abstract

In a panel comprising 61 countries covering the years 1980-2010 we show that macroeconomic variables such as GDP and deposit insurance remain statistically significant crisis determinants in the long run but that variables such as real-interest rates and inflation are not reported as systemic banking crisis determinants when estimated over a full business cycle. When studies such as these are conducted we find that the choice of panel time-span is highly relevant. Using a shorter panel (1998-2011) involving 75 countries, we show that sectoral variables such as Bank Z-Score, private-credit-to-GDP ratio, bank credit-to-deposit ratio and non-performing loan levels yield improved in-sample crisis predictions. Whereas sectoral-centric models may over-estimate the likelihood of systemic banking crises this does not constitute a model weakness if not overlooking embryonic crises is the key objective. Future research is facilitated via the establishment of a control cluster of determinants with both sectoral as well as macroeconomic constituents.

1.1. Introduction

There is strong empirical evidence of the financial damage caused by the 2008 Global Financial Crisis (GFC), even though there are also signs of economic recovery. The Dow Jones Index currently stands 20% higher than it did at its 2007 zenith and the NASDAQ index shows a 60% gain over this period. Nevertheless many economic legacy problems persist. In the USA there were 12 million people officially registered as unemployed in July 2013, compared with 7.4 million people as of July 2007. It is estimated that up to $13tr of America's wealth was destroyed, $7tr of that in home equity alone.[2] In national debt terms the USA now owes $8tr more than it did in 2007 with its 2012 debt-to-GDP ratio of 101% considerably higher than the 76% level recorded for 2008 and current debt-per-capita levels exceed $54,000. The GFC hangover is not simply an American phenomenon. In the EU unemployment levels are 4% higher now than they were pre-crisis. In the worst-affected peripheral EU states GDP per-capita has still not recovered and remains below pre-crisis levels in countries such as Portugal, Ireland, Greece, Cyprus, Italy and Spain.[3] Despite several attempts to restructure the Greek economy, the dual prospects of a Euro exit coupled with sovereign default remain a serious concern, anchoring the Euro's value.

Academics and analysts have studied how the collapse of one particular bank, Lehman Brothers, in 2007 triggered such widespread and long-lasting financial chaos, resulting in systemic banking crises in many countries (see Mody and Sandri (2012) and Connor et al. (2012)). Could the 2008 crisis have been better anticipated given our knowledge of the factors historically associated with financial industry collapse? (see Demirgüç-Kunt and Detragiache (1998), Akerlof and Romer

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[2] Market Indices are sourced via Yahoo finance, US unemployment figures are sourced via the Bureau of Labor Statistics and wealth loss data is sourced via Bettermarkets.com

[3] US Debt per capita data comes from Ycharts.com, EU unemployment and GDP per capita stats have been sourced via Eurostats.

(1994), Allen and Gale (2003) and Beck et al. (2006)). Or, given the pace of technological advancement, increasing bank interconnectedness and product innovation, is it possible that new factors now play a central role in facilitating crisis-enabling conditions? Those responsible for financial-industry stability, i.e. central banks, regulatory authorities and organisations such as the IMF, had myriad early-warning-systems at their disposal. Nevertheless the crisis appeared to catch most academics and analysts off-guard (see Rajan (2005)).[4] Given such a failure in their primary function it is important to re-appraise the theory underpinning these systems and to identify potential areas for enhancement.

This paper re-examines the determinants of systemic banking crises in the wake of the GFC placing a particular emphasis on identifying those sectoral factors most closely associated with such crises. These factors have not received a lot of attention in previous studies where greater attention was instead paid to macroeconomic variables. We believe data availability concerns played a role in the historical bias towards macroeconomic variables, however new banking-sector databases help overcome this data-shortage issue, facilitating more comprehensive sectoral analysis than was possible until recently (see Laeven and Valencia (2013), Barth et al. (2013) and Cihák et al. (2013)). Our results should provide guidance towards the recalibration of stress-tests and other early-warning systems as the lessons of the GFC continue to be absorbed.[5] We assess whether those macroeconomic factors which, pre-2007, were most closely associated with crises retain their significance or whether new variables, drawn from these new banking-data sources, should feature more prominently. Our rationale for adopting a sectoral focus is grounded in the

[4] In a March 2010 interview Alan Greenspan, former head of the Federal Reserve claimed, in relation to the US housing bubble that "everybody missed it, academia, the Federal Reserve and all regulators".

[5] Throughout the paper a reference to a crisis or bank crisis is intended to mean a *systemic* bank crisis. The shorter form is used for readability purposes. The definition of what constitutes a systemic bank crisis is described in the literature review of Chapter 2 (see section 2.2).

pragmatic view that regulators safeguard the financial services industry by wielding control over *sectoral* variables whereas they have only a limited ability to influence historical *macroeconomic* crisis determinants such as GDP growth, real-interest rates and inflation. Therefore future macro-prudential policy measures may be directed towards those variables most closely associated with systemic banking risk.

More specifically, our goals are as follows: 1) to examine whether or not the previously-established macroeconomic determinants retain their significance over a longer period (30 years) than has been examined to-date, 2) to identify the most significant sectoral crisis factors, 3) to compare and contrast the performance of macroeconomic versus sectoral variables as in-sample crisis predictors and 4) to establish a "*control cluster*" of variables that can be used in future research (see Chapter 2).

The paper makes several important contributions to the literature. We find that previously-established macroeconomic crisis determinants lose explanatory power in the long run and that inflation loses its significance entirely. Whereas in the short run (i.e. over a 14 year period spanning the GFC) macroeconomic factors remain significant, in models where they are augmented / replaced by sectoral variables such models perform at least equally as well in terms of predicting in-sample crises. We demonstrate that where shorter panels are used the choice of time-span / business cycle is highly relevant. From a sectoral perspective we find the most important determinants to be: 1) levels of private credit extended to borrowers, 2) bank distance-to-default as measured by aggregate Z-score and 3) bank non-performing loan levels.

As part of global efforts geared towards avoiding any recurrence of a crisis on the scale of the GFC researchers are adopting new systemic banking risk measures. A useful leading signal of crises ought to reflect and quantify the accumulation of systemic risk over time ***prior*** to the onset of a crisis and thus could augment future stress-test models. New measures to enhance /

supersede value-at-risk (VaR) have been proposed.[6]Acharya et al. (2010) recommend Systemic Expected Shortfall, whereas Adrian and Brunnermeier (2011) favour a measured they term ΔCoVaR (pronounced Delta Covar).[7] Brownlees and Engle (2010) suggest a measure called marginal expected shortfall (MES). Our contribution lies in enabling researchers to ascertain the empirical relationship between any proposed systemic risk measure (SRM) and the sectoral crisis determinants we identify. In turn this will help establish which SRM is most appropriate for a particular country based upon the composition of that country's banking sector (see Chapter 3). Our final contribution is to establish what we term a "*control cluster*" of up-to-date crisis determinants which will facilitate an in-depth analysis of the effectiveness of the regulatory communities' response to the GFC (see Chapter 2).

To achieve our results we use two separate but related panels. Panel A comprises 61 emerging and established economies, covering the period 1980-2010, wherein 57 systemic banking crisis episodes were observed (see Table 1.1). We use panel A to analyse the long-run reliability of ex-ante (i.e. pre-2007) known crises determinants. Due to the unavailability of sectoral data prior to 1998, panel B is broader but shallower than panel A, encompassing 75 countries over the period 1998-2011 and incorporating 36 systemic banking crises. We use panel B to perform the sectoral analysis described above.

This paper proceeds as follows. In Section 1.2 we present a review of the most important and relevant literature. In section 1.3 the econometric methodology is described in detail. We

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6 Traditionally VaR was and remains and important micro-prudential risk metric. However VaR does not provide guidance to the extent of potential losses in shocked scenarios. The crisis demonstrated that the risk of the sum is not the same as the sum of the risks; therefore VaR's reputation has been damaged as a macro-prudential tool.

7 Systemic Expected Shortfall attempts to estimate the degree to which banks may be undercapitalised during crises periods. Delta-CoVaR measures the value-at-risk distributional shift that occurs within the returns of the financial sector as a whole conditional upon Institution "i" meeting or exceeding its individual 1% value at risk.

describe our data in section 1.4 and our approach in section 1.5. Detailed results are provided in section 1.6. An outline of the robustness checks carried out is provided in section 1.7 with section 1.8 concluding.

1.2. Literature Review

Systemic banking crises are not a new phenomenon. The Wall Street crash of 1929 led to the collapse of thousands of small banks and was one of the principal causes of the global depression in the 1930s. The Glass-Steagall Act (1933) was enacted to comprehensively regulate the US banking system and to separate retail from investment banking activities with a view to guarding against a recurrence of the events of 1929. As our paper is primarily concerned with recent systemic crises, i.e. those occurring in the era of technological advances and financial product innovation, we focus on literature published in the wake of the eventual supersedure of the Glass-Steagall Act (1933) by the Gramm-Leach-Bliley Act (1999). This latter act of financial deregulation is believed by some to have ushered in an era of unprecedented risk-taking by bank managers, culminating in the GFC (see Allen (2005), Verschoor (2009), Crotty (2009) and Frank (2010)).

One of the most important studies of systemic banking-crisis determinants is that of Demirgüç-Kunt and Detragiache (1998). As well as establishing the benchmark logit-based econometric model for such studies (see section 1.3 below) the authors find that systemic crises emerge when the macroeconomic environment is weak, particularly when GDP growth is low and where real-interest rates or inflation (or both) are high. They also find that vulnerability to balance-of-payments crises plays a role. In contrast to Diamond and Dybvig's (1983) seminal theoretical paper, which argues for the adoption of explicit deposit-insurance as a policy measure to deflect bank runs, they find that implementing such a policy actually destabilises banking systems. In a follow-up paper the same authors consider deposit-insurance in more detail and re-assert their finding that deposit-insurance increases the likelihood of systemic crises, especially in circumstances where bank interest rates are deregulated and the institutional environment is weak (see Demirgüç-Kunt and Detragiache (2002)). This finding supports the view that bank managers tend to adopt riskier loan-book positions than they would otherwise have done because they know a-priori that deposits are guaranteed by the sovereign.

Kaminsky and Reinhart (1999), using a signals approach to study crises, identify low GDP growth-rates, appreciation of real exchange rates, low export growth-rates and rapid financial liberalisation as significant factors signalling the onset of a financial and/or currency crisis. Using logit as well as signalling models Davis and Karim's (2008) findings support those of Kaminsky and Reinhardt (1999). Hoggarth et al. (2005b) adopt a vector auto-regression model to explore the interconnectedness of UK bank loan write-off levels with the wider economy and find that total write-off ratios are strongly linked to deviations from GDP potential, whereas mortgage arrears are linked to private income-gearing ratios.

Honohan (1999), in a theoretical model, demonstrates how bank crises can arise as a result of risky lending activities carried out by bank managers who take advantage of "informational externalities", i.e. the asymmetric information they possess relating to the risk-level incorporated in their loan books and the put-option inherent in explicit state-backed deposit-insurance schemes. Von Hagen and Ho (2007) develop an index of money market pressure and use this index as a banking crisis signalling device. They define bank crises as periods during which there is an excessive demand for liquidity. In line with earlier studies they find that crises are more likely in periods of low GDP growth and high inflation. However, in contrast with Demirgüç-Kunt and Detragiache (1998), they find that low real-interest rates increase the likelihood of crises.

One important paper that examines systemic crises over a long run (1870–2008) is that of Schularick and Taylor (2012). They identify specific eras in the history of finance (mainly pre-1945) where control and monitoring over the supply of money supply was considered sufficient to help prevent crises but that in recent decades there has been a break in the long-term relationship between the growth rates of credit and money. They argue that nowadays, control over excessive credit growth (termed "credit booms") is more fundamentally important, something which our results support (see also Drehmann (2013)). However, given the nature of their dataset the number of countries included is limited to those 12 advanced economies for which long-term data is available, and balance sheet analysis is not possible.

Additional support for the idea that systemic banking crises are credit booms gone wrong can be found in the work of Boissay et al. (2013) where they characterise the differences in credit distributions in years leading up to crises with their full-sample counterparts.

Johnson et al. (2000) draw upon well-established corporate governance guidelines (see Shleifer and Vishny (1997)) to show how failures in bank governance were instrumental to the emergence of the 1997 Asian Financial Crisis. Brunnermeier (2008) highlights how banks evolved from loan-origination and fulfilment agencies into institutions which originated, securitised and distributed loans, resulting in reduced incentives for careful monitoring of loan portfolios by managers (and by extension regulators). This in turn contributed to a US housing bubble, resulting ultimately in the Savings and Loans crisis (1986-1995).

More recently Eichler and Sobański (2012) investigate bank fragility at a micro-prudential level in the Eurozone. They apply a variant of Merton's (1974) model to a panel comprising high-frequency stock market data, wherein bank stability is measured on a "distance-to-default" basis.[8] Their results support the view that bank fragility is associated with periods of high real-interest and credit growth-rates. They also show that crisis likelihood increases where bank concentration levels are low.[9] However they find that high inflation levels are not significantly associated with bank fragility in contrast with Demirgüç-Kunt and Detragiache (1998, 2002) and Von Hagen and Ho (2007). Their paper also provides a survey of several important banking-crisis studies, providing details on the methodologies employed, the countries studied and key findings.

It should be noted that relatively few studies include the core GFC years (2008-2010) as part of their analysis. Those that do include them are frequently restricted in terms of panel-country composition[10]. In addition, the panels themselves are invariably "shallow" and generally do not cover a full business cycle. As such, whether their reported crisis determinants retain their significance in the long run is not clear. Also, even a cursory review of key findings reported in the literature demonstrates how past crisis-determinant studies tend to lean towards macroeconomic variables with relatively little attention paid to sectoral data generally.

1.3. Methodology

To test whether a regulatory measure constitutes a systemic banking crisis determinant we use a pooled logit model (see Demirgüç-Kunt and Detragiache (1998, 2002), Beck et al. (2006), Von Hagen and Ho (2007), Davis and Karim (2008) and Schaeck et al. (2009)). Here the dependent

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[8] Merton (1974) uses a variant of the Black-Scholes option pricing model to determine average distance-to-default of an individual bank using monthly stock market data.

[9] Bank concentration measures the proportion of the total assets held by all banks in a sector which are held by the three largest banks in that sector.

[10] For example Barrel et al. (2010) look at 14 OECD countries whereas Büyükkarabacak and Valev (2010) examine a panel of 37 countries.

variable $P_{i,t}$ is a dummy variable that has a value of 1 if country "i" experiences a systemic banking crisis in year "t" and 0 otherwise. The fact that the response (or crisis) variable is limited to only two discrete values is crucial. If our goal is to model / predict the probability of a crisis, based upon a function of observed variables (vector $X_{i,t}$) we might proceed as follows:

$$\Pr(P_{i,t} = 1 | X) = F(X_{i,t}, \beta), \quad \textbf{(1.1)}$$

where F is a function of several explanatory variables as represented by vector X and parameters β. From this it follows that the probability of a no-crisis observation would be:

$$\Pr(P_{i,t} = 0 | X) = 1 - F(X_{i,t}, \beta). \quad \textbf{(1.2)}$$

A simple functional form for $F(X_{i,t}, \beta)$ might be a linear function of the observed variables of the form:

$$P(i,t) = \beta' X_{i,t} + \varepsilon_{i,t}, \quad \textbf{(1.3)}$$

where $\varepsilon_{i,t}$ represents an error term with the following desired properties:

$$E[\varepsilon_{i,t} | X_{i,t}] = 0, \quad \textbf{(1.4)}$$

$$\mathrm{Cov}[\varepsilon_{i,t}, X_{i,t}] = 0 \text{ and} \quad \textbf{(1.5)}$$

$$\mathrm{Cov}[\varepsilon_{i,t}, \varepsilon_{j,s}] = 0 \text{ for all i,t,j and s} \quad \textbf{(1.6)}$$

The equation represented by (1.3) is defined as the linear probability model. The parameters β are estimated using ordinary least squares (OLS) regression by minimising the sum of the least squared errors across all observations with respect to β. However the choice of a linear probability model raises two difficulties. Firstly the values for our independent variables can take on very large or very small values, consequently the linear combinations of such values could lead to values of the crisis probability taking on equally small or large values, especially when the model is used to predict crises. A probability should lie in the interval [0,1] but the linear probability model is not bound by this requirement. Secondly, under OLS we require our error terms to be homoskedastic and to demonstrate no covariance between the error terms, or between the error term and the vector $X_{i,t}$ as described by equations (1.5) and (1.6). This requirement also does not hold in circumstances where we don't actually observe the dependent variable as crisis probabilities but instead only observe binary outcomes where either a crisis occurs or not as the case may be. Thus the error terms will be heteroskedastic because the dependent variable only takes on two values, rather than a continuous range of values we typically observe in an OLS specification.[11]

An obvious solution is to replace the linear probability function F of (1.1) with a non-linear transformation of the linear probability model which then yields the first of the properties we require. One such transformation is given by the logit function where $F(X_{i,t},\beta)$ takes the following form:

$$\Pr(P_{it} = 1 | X_{i,t}) = \frac{e^{\beta' X_{i,t}}}{1 + e^{\beta' X_{i,t}}} \tag{1.7}$$

Note that if $\beta' X_{i,t}$ is very large then the probability of a crisis tends to 1, likewise if $\beta' X_{i,t}$ is small the probability of a crisis tends to zero. Also, all values returned by (1.7) will be positive regardless of the values of $X_{i,t}$ or β, another required feature. We overcome the second linear probability model difficulty by using maximum likelihood estimation to estimate the coefficients, instead of OLS. To understand how this proceeds consider the observed dependent variables in

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[11] As $\beta'X+\varepsilon = 1$ or 0 then $\varepsilon = 1-\beta'X$ with probability F or $\varepsilon = -x'\beta$ with probability (1-F) leaving us with a heteroskedastic distribution of error terms in such a model.

a random sample. The probability of observing a 1 is F(X,β) as per (1.7). The probability of observing two 1s in a row is thus $F(X,\beta)^2$. The probability of observing a 1, followed by a 0 is F(X,β) * 1- F(X,β) and so on. Therefore, in a given sample where we observe a sequence of 0s and 1s we recognise that particular sequence is just one possible sequence drawn from a random distribution of many possible sequences. Consequently the probability that such a sequence is observed can be modelled as a Bernouilli random variable according to the following function "L", known as a likelihood function:

$$\Pr(Y \mid X) = L = \prod_{t=1}^{T}\prod_{i=1}^{N}[F(X_{i,t}\beta)]^{Pi,t}[1 - F(X_{i,t}\mathrm{B}]^{1-P_{i,t}} . \qquad \textbf{(1.8)}$$

Here, for our purposes, N represents the number of countries included in our sample and T represents the number of years. $P_{i,t}$ takes on the value of 0 or 1 as stated. We are interested in finding the values for β which maximise the likelihood that such a sequence of 0s and 1s would have been observed across all country / time combinations as was actually yielded by our sample. This could be done in the usual way by differentiating the likelihood function with respect to β, setting the result to 0 and solving. However the product operators, coupled with the exponents nested within the function renders the problem relatively intractable. Instead, we take the log of "L" which overcomes several difficulties. As the log operator has no impact upon the optimised values for β the optimisation problem can be equally stated as follows:

$$\text{Argmax}(\beta): \quad LnL = \sum_{t=1}^{T}\sum_{i=1}^{N}\mathrm{P}(i,t)\ln[F(X_{i,t}\beta')] + [1 - P(i,t)]\ln[1 - F(X_{i,t}\beta.')] \qquad \textbf{(1.9)}$$

Finding the best solution to 1.9 is a maximum likelihood problem. Typically no closed form solution is available so the solution is usually determined by software packages availing of numerical techniques to determine those values vector β values yielding the maximum likelihood value of the log likelihood function. Remember, $X_{i,t}$ represents a vector of K explanatory variables (which can be either macroeconomic factors or balance sheet metrics), β is a vector of unknown coefficients and $F(X_{i,t}\beta)$ is a cumulative probability distribution function as per (1.7).

It is worth noting that, unlike in OLS, each individual coefficient "β_j" yielded does not represent the marginal increase in the probability of a country experiencing a systemic banking crisis given a unit change in one of the corresponding $X_{i,t}$ variables, i.e. variable X_j. Rather each β_j measures the effect of a unit change in variable X_j upon the log odds ratio of country "i" experiencing a systemic banking crisis in period "t". We rely upon (1.7) to calculate the probability of a systemic banking crisis and note that this figure depends upon the values contained in vector X at the time. The marginal effect of a change in a particular variable X_j can be shown to be:

$$\frac{\delta F(X_{i,t}\beta)}{\delta X_j} = \beta_j F(X_{i,t}\beta)(1 - F(X_{i,t}\beta) \qquad \textbf{(1.10)}$$

Thus the marginal effect of a change variable X_j depends upon the ex-ante value of the variables comprising vector X, which changes from year to year as well as from country to country. Thus we are dealing with non-constant marginal effects.

The use of the logit model, estimated using MLE, is widespread and remains preferred whenever country panels form the basis of the crisis-determinants analysis (see Davis and Karim (2008) and Schaeck et al. (2012)). The technique enables us to test the extent to which any regulatory, macroeconomic or sectoral variable is associated with bank stability. The sign of a given coefficient β_j illustrates whether a variable contributes positively or negatively to the odds of a systemic crisis and the p-value reported from the analysis for each β_j indicates whether or not the corresponding factor is statistically significant at 1%, 5% and 10% levels.

Fixed-effects regressions are not used because they force the removal of non-changing data (by country) from the analysis. Therefore a country would have to be excluded if it didn't experience a crisis or if a variable of interest, e.g. capital-to-asset ratio, remained constant. This restriction results in the loss of significant and relevant data (see section 1.7 for more details).

We sometimes compare the results from different regression specifications by assessing the value of the AIC (Akaike Information Criterion) score reported as part of the regression output. The formula for calculating AIC is given by:

$$AIC = 2K - 2\ln(L), \tag{1.11}$$

where K is the dimension of vector β and L is the value returned for the maximum likelihood as per (1.9). Thus the AIC value represents a trade-off between model fit (L) and information lost (gained) via the removal (addition) of another variable. In general, lower AIC scores are preferred to larger ones in models that rely upon the same sample datasets.

1.4. Data

To undertake the analysis we use two separate but related panels. Panel A aims to replicate, by country / year composition, the original panel formulated by Demirgüç-Kunt and Detragiache (1998) which covered the period 1980-1994. However panel A includes data up to 2010 so that long-run macroeconomic effects are assessed over a time-span that includes the GFC. We have altered the country composition of panel A slightly compared with that which formed the basis for Demirgüç-Kunt and Detragiache's (1998) results. Whereas Chile, Peru and Turkey formed part of the 1998 panel those countries were not included in any of the regressions we replicate.[12] Furthermore, in 1996, Zaire disintegrated politically and was reconstituted as the Democratic

[12] These are regressions 1) to 3) of Demirgüç-Kunt and Detragiache (1998) Table 2 (see Appendix 6). Sectoral data for these countries could not be adequately sourced for the sample period we investigate. The original authors also expressed a difficulty relating to these countries.

Republic of Congo. However this event resulted in several data anomalies which cannot be reconciled back with the original data, therefore the Democratic Republic of Congo is also omitted.[13] The countries are listed in alphabetical order with mean, min and max values per country for the key macroeconomic variables of interest. These include GDP growth-rate, real-interest rate, inflation, M2 money to foreign exchange reserves ratio and private-credit-to-GDP ratio. A financial sector variable, private-credit-growth-rate is also included as it formed part of Demirgüç-Kunt and Detragiache's (1998) analysis.

We present summary data for panel A in Table 1.1 below. Column 2 depicts the systemic crisis episodes by country and year as per Demirgüç-Kunt and Detragiache (1998). This data, based upon an earlier survey conducted by Caprio and Klingebiel (1996), underpins their logit model's dependent variable and we re-constitute it for result replication purposes. However their definition of what constitutes a *systemic* banking crisis has been criticised as being too subjective (see Eichler and Sobański (2012)). Demirgüç-Kunt and Detragiache (1998) define a *systemic* banking crisis as one that satisfies at least one of the following conditions; 1) the ratio of non-performing assets to total assets in the banking system exceeds 10%, 2) the cost of the rescue operation is at least 2% of GDP, 3) banking sector problems result in large scale nationalisation of banks and 4) extensive bank runs take place or emergency measures such as deposit freezes, prolonged bank holidays, or generalised deposit guarantees are enacted by the government in response to the crisis.

Eichler and Sobański (2012) point out several difficulties. They query how, under condition 2 for example, costs are measured and what costs exactly are included. What does "large scale

[13] We included this country as part of our robustness checks and noted that its inclusion does not materially impact our key findings.

nationalisation" mean in terms of condition 3 and what constitutes "extensive bank runs" under condition 4? The publication of a comprehensive systemic financial crisis database by Laeven and Valencia (2013), under the auspices of the IMF, helps to resolve these issues. This dataset establishes precisely when systemic crisis episodes occurred in country / year pairings based upon detailed specific criteria established by the IMF. Thus, a systemic banking crisis is defined more objectively as an event meeting only two conditions; 1) there are significant signs of financial distress in the banking system (as quantified by significant bank runs, threshold-exceeding losses in the banking system, and/or extent of bank liquidations) and 2) significant banking policy intervention measures in response to significant losses in the banking system are evident.

Both conditions are objective rather than subjective, therefore the dataset represents a benchmark for future research employing pooled logit techniques where the dependent variable is driven by consistent globally-applicable criteria.

We detail the systemic crisis episodes as per Laeven and Valencia's (2013) database in column 3. Having replicated the Demirgüç-Kunt and Detragiache (1998) results we rely exclusively upon this column for all subsequent panel A analysis. The summary statistics show that up to 29 systemic crisis episodes were identified in their 1998 paper, whereas Laeven and Valencia (2013) now identify 57 crises over the extended 1980-2010 period.

TABLE 1.1

	Demirgüç-Kunt & Detragiache (1998)	Laeven & Valencia (2013)	Deposit Insurance	GDP Growth Rate			Real Interest Rate			Inflation			M2 Money to Forex Reserves			Private Credit to GDP Ratio			Private Credit Growth Rate		
Country	**Crisis Year(s)**	**Crisis Year(s)**		**Avg**	**Min**	**Max**	**Avg**	**Min**	**Max**	**Avg**	**Min**	**Max**	**Avg**	**Min**	**Max**	**Avg**	**Min**	**Max**	**Avg**	**Min**	**Max**
Australia	-	-	-	3.32	-1.06	6.28	3.70	-0.95	10.23	4.72	0.36	12.09	19.64	7.71	51.94	65.59	24.36	123.97	12.40	0.00	37.81
Austria	-	2008-2010	1980	2.24	-3.81	5.46	2.66	-0.57	5.69	2.48	0.01	6.63	62.13	25.86	107.72	92.50	64.24	123.83	3.07	-100.00	10.92
Bahrain	-	-	1993	5.17	-2.75	12.88	2.03	-10.27	24.58	2.23	-17.38	14.35	3.09	0.78	5.36	53.38	28.05	133.37	-38.15	-1344.63	261.32
Belgium	-	2008-2010	1980	2.74	-2.75	27.18	4.02	-1.71	19.33	2.32	-16.61	7.57	55.01	42.92	68.21	58.95	25.78	136.85	5.75	-100.00	118.67
Burundi	-	1994-1998	-	2.16	-8.61	10.91	-1.32	-52.07	17.47	11.07	-6.17	59.99	3.49	0.99	13.10	14.86	6.57	28.68	17.48	-18.84	84.35
Canada	-	-	1980	2.58	-2.86	5.81	1.45	-2.24	5.16	3.47	-1.95	10.78	53.17	18.25	146.26	104.62	66.29	182.58	6.96	-100.00	81.52
Colombia	1982-1985	1982, 1998-2000	1986	3.51	-4.20	6.90	1.83	-0.46	2.39	18.48	3.41	52.34	3.61	1.86	9.15	28.12	20.86	40.39	16.19	-100.00	99.29
Congo, Rep.	-	1992-1994	2007	4.38	-6.88	23.57	3.90	-39.46	40.19	8.02	-29.19	46.46	2129.73	0.55	62234.97	11.46	2.04	31.72	-21.29	-1078.22	196.44
Cyprus	-	-	2000	4.73	-1.86	9.92	0.67	-6.29	3.75	4.96	0.09	13.99	10.21	4.42	18.84	149.74	59.98	272.92	15.18	0.00	59.31
Denmark	-	2008-2010	1988	1.56	-5.67	5.53	4.12	-3.44	10.83	3.90	0.66	11.78	7.70	3.79	12.66	70.24	22.06	208.14	12.71	-6.85	164.91
Ecuador	-	1982-1986,1998-2002	-	3.10	-5.98	10.49	22.01	-11.51	87.77	4.14	-31.52	24.70	4.69	1.60	14.44	23.10	12.93	40.67	10.25	-31.87	136.87
Egypt, Arab Rep.	-	1980	-	5.47	1.11	10.01	0.18	-8.44	8.13	10.09	0.87	18.84	17.96	3.00	63.94	37.66	17.82	60.41	16.08	-7.15	51.46
El Salvador	-	1989-1990	1999	2.58	-8.67	21.26	6.89	-0.94	18.11	8.10	-1.32	37.04	4.07	1.26	6.32	5.52	2.08	10.80	8.70	-45.13	40.01
Finland	1991-1994	1991-1994	1980	2.55	-8.54	6.67	3.58	-0.31	11.81	3.86	-0.69	10.91	9.21	0.97	42.82	65.26	42.04	93.28	9.38	-8.83	24.65
France	-	2008-2010	1980	1.91	-3.05	4.75	3.08	-1.30	8.51	3.61	-1.47	11.73	80.10	54.52	105.06	90.94	72.76	111.40	3.81	-100.00	16.13
Germany	-	2008-2010	1980	2.10	-5.07	13.22	2.49	-0.55	5.79	2.06	-0.67	5.89	113.86	84.38	131.13	99.52	75.32	117.54	5.21	-1.97	15.21
Greece	-	2008-2010	1993	1.78	-4.94	5.95	0.33	-11.96	7.70	11.65	0.90	27.21	706.17	24.71	2363.45	48.14	27.14	105.92	16.56	0.00	43.04
Guatemala	-	-	1999	2.88	-3.54	6.30	1.14	-32.46	14.66	10.57	-4.08	41.46	5.36	2.40	19.98	18.44	11.25	26.38	17.57	-20.65	76.37
Guyana	1993-1995	1993	-	1.24	-11.50	8.48	-9.81	-147.42	14.44	23.00	-0.63	162.61	22.61	1.27	129.08	37.76	16.68	60.58	-23.73	-579.49	192.95
Honduras	-	-	1999	3.30	-2.13	6.57	11.37	-3.27	21.17	11.18	2.83	30.82	9.10	2.10	83.55	33.24	22.79	52.47	17.48	-14.15	123.18
India	1991-1994	1993	1980	5.69	-5.25	9.57	1.06	-15.11	9.26	8.39	3.26	24.84	15.94	3.21	115.22	28.79	21.63	44.67	16.70	0.00	29.01
Indonesia	1992-1994	1997-2001	1998	5.13	-13.13	9.88	0.63	-16.28	21.61	14.11	5.12	75.27	4.47	2.21	7.51	27.72	9.05	53.53	30.02	-56.66	313.72
Ireland	-	2008-2010	-	4.57	-5.46	11.57	2.90	-2.43	12.30	4.89	-4.64	17.44	150.88	4.28	957.64	86.76	42.83	237.15	16.60	-7.03	87.47
Israel	1983-1984	-	-	4.69	-0.18	24.00	-0.75	-167.45	158.77	46.61	-0.58	384.75	5.55	1.30	11.35	64.54	41.35	96.76	127.14	-455.54	3554.18
Italy	1990-1994	2008-2010	1987	1.70	-5.50	5.53	2.28	-8.84	9.76	6.43	0.38	21.35	23.85	0.01	72.99	65.54	47.56	115.22	9.69	0.00	20.93
Jamaica	-	1996-1998	1998	1.12	-14.08	17.09	0.14	-52.45	18.98	19.39	-3.58	86.81	9.76	3.17	34.45	22.36	13.09	30.66	21.33	-15.65	118.79
Japan	1992-1994	1997-2001	1980	2.34	-5.53	7.26	1.60	-0.22	3.99	0.42	-2.16	5.77	56.09	9.34	117.11	175.71	121.88	228.03	3.73	-13.96	13.21
Jordan	1989-1990	1989-1991	2000	5.09	-10.73	20.80	0.54	-14.41	6.62	5.43	-0.41	19.35	7.24	2.24	67.78	67.06	41.58	84.98	12.66	-12.86	49.43
Kenya	1993	1985, 1992-1994	1985	5.66	-0.80	52.55	3.65	-18.86	30.01	8.98	-27.19	41.86	9.21	3.46	84.68	29.09	25.25	34.96	16.83	-22.45	84.87
Korea, Rep.	-	1987-1988	1996	6.18	-6.85	11.10	3.38	-4.74	8.63	6.52	-1.04	23.60	6.36	2.28	13.73	67.70	38.28	104.68	16.62	0.00	42.71

TABLE 1.1 (Continued)

	Demirgüç-Kunt & Detragiache (1998)	Laeven & Valencia (2013)	Deposit Insurance	GDP Growth Rate			Real Interest Rate			Inflation			M2 Money to Forex Reserves			Private Credit to GDP Ratio			Private Credit Growth Rate		
Country	**Crisis Year(s)**	**Crisis Year(s)**		**Avg**	**Min**	**Max**	**Avg**	**Min**	**Max**	**Avg**	**Min**	**Max**	**Avg**	**Min**	**Max**	**Avg**	**Min**	**Max**	**Avg**	**Min**	**Max**
Malaysia	1985-1988	1997-1999	2007	6.11	-7.36	10.00	0.59	-7.00	12.76	3.80	-8.64	12.06	4.66	2.40	9.99	95.72	36.38	155.17	13.78	-39.21	72.22
Mali	1987-1989	1987-1991	-	3.60	-7.23	15.16	4.17	-33.10	62.09	3.57	-57.14	38.05	20.90	1.44	233.96	15.20	4.30	29.27	6.94	-44.40	47.97
Mexico	1982, 1994	1981-1985, 1994-1996	1986	2.83	-6.17	9.16	-2.33	-43.25	18.47	30.75	4.01	140.98	9.18	2.82	69.77	17.80	8.69	33.32	-9.23	-885.95	542.13
Nepal	1988-1994	1988	-	4.17	-2.98	9.68	-3.39	-9.56	4.39	9.23	3.07	18.46	3.93	1.99	14.24	19.50	5.51	51.13	19.03	-6.77	48.65
Netherlands	-	2008-2010	1980	2.17	-3.66	4.70	3.18	-1.32	9.89	2.37	-0.26	6.50	56.04	3.88	166.26	105.96	58.17	209.45	4.02	-100.00	25.03
New Zealand	-	-	-	2.66	-3.28	8.47	4.29	-5.19	17.07	5.32	0.24	19.40	9.89	2.50	19.55	77.90	16.95	147.47	15.22	-3.43	152.84
Niger	-	1983-1985	-	1.97	-16.83	10.42	3.85	-12.37	21.68	4.77	-5.90	20.82	2.98	1.28	17.25	10.60	3.54	18.25	8.03	-15.93	118.57
Nigeria	1991-1994	1991-1995, 2009-2010	1988	3.68	-8.39	10.60	-7.11	-99.06	23.82	21.49	-6.29	111.56	5.92	0.65	27.29	14.30	8.38	35.39	48.84	-50.29	442.31
Norway	1987-1993	1991-1993	1980	2.69	-1.64	5.89	2.97	-8.93	14.82	4.93	-5.39	15.65	4.28	2.60	7.25	69.75	48.57	87.61	6.12	-100.00	29.67
Papua New Guinea	1989-1994	-	-	3.16	-6.34	18.21	4.74	-3.85	15.89	6.48	-4.27	28.94	3.67	1.48	17.17	19.31	10.52	29.43	12.04	-14.19	54.50
Paraguay	-	1995	2003	3.52	-3.84	15.05	-0.36	-15.09	10.16	15.85	-0.12	47.25	2.52	1.32	4.52	20.37	11.75	32.30	24.01	-30.83	123.55
Philippines	1981-1987	1983-1986, 1997-2001	1980	3.30	-7.32	7.63	2.82	-24.81	13.13	9.83	2.77	53.34	6.36	2.27	17.48	32.68	17.01	55.60	16.86	-43.46	136.26
Portugal	1986-1989	2008-2010	1992	2.38	-2.91	8.45	0.35	-9.14	7.73	9.16	0.91	26.17	106.85	19.84	337.82	95.25	47.99	186.46	14.95	0.00	39.37
Senegal	1983-1988	1988-1991	-	3.37	-4.00	15.35	1.74	-25.21	15.43	5.10	-6.71	30.76	91.47	2.00	794.38	23.96	14.52	36.44	7.31	-29.12	42.54
Seychelles	-	-	-	3.40	-6.64	14.96	5.15	-16.95	18.50	6.54	-4.89	34.62	10.48	2.64	25.30	18.06	8.51	30.11	13.50	-17.27	63.92
Singapore	-	-	2007	7.02	-1.62	14.76	-0.08	-6.40	4.11	2.29	-2.68	11.45	1.20	1.01	1.37	96.97	67.77	120.37	13.38	-17.22	100.49
South Africa	1985	-	-	2.48	-2.14	6.62	-0.02	-20.27	8.82	11.43	4.78	24.92	51.17	7.09	242.10	97.80	48.82	149.78	11.70	-100.00	49.92
Sri Lanka	1989-1993	1989-1990	1987	4.96	-1.55	8.02	2.30	-9.02	12.77	11.08	0.62	20.80	4.40	1.92	9.92	21.67	8.26	30.57	17.87	-14.99	69.63
Swaziland	-	1995-1999	-	4.18	-4.41	14.63	-0.91	-33.74	12.50	10.93	-1.00	44.87	1.42	0.88	2.36	17.54	10.92	24.57	29.00	-70.47	483.52
Sweden	1990-1993	1991-1995, 2008-2010	1996	2.28	-5.03	6.56	2.53	-9.59	11.86	4.46	0.31	16.39	11.57	4.19	24.29	94.69	67.54	124.47	11.01	-5.37	124.51
Switzerland	-	2008-2010	1984	1.80	-1.94	4.40	0.26	-12.92	5.63	2.45	-0.45	13.93	9.70	3.91	16.31	144.58	98.37	165.05	5.47	-0.48	18.72
Syrian Arab Republic	-	-	-	4.45	-8.96	13.47	-3.64	-17.82	7.78	10.33	-2.78	28.61	56.43	5.65	247.18	8.83	1.45	20.43	15.47	-19.31	46.05
Tanzania	1988-1994	1987-1988	1994	5.05	0.58	7.83	-0.97	-33.20	13.47	17.34	5.28	47.70	41.61	1.27	555.00	5.31	0.46	14.64	22.21	-9.66	78.57
Thailand	-	1983, 1997-2000	1997	5.60	-10.51	13.29	2.40	-5.73	11.63	4.24	-4.04	13.13	5.88	2.23	13.70	89.84	39.43	165.80	12.26	-10.65	28.11
Togo	-	1993-1994	-	2.25	-15.10	14.98	3.55	-29.74	12.35	5.33	-6.44	34.69	2.43	1.08	5.93	20.04	6.33	29.96	8.98	-28.22	99.18
Uganda	1990-1994	1994	1994	9.74	-13.62	60.22	-17.04	-193.01	37.32	36.29	-11.90	223.51	35.30	0.96	825.28	4.83	1.21	12.01	26.31	-166.64	157.81
United Kingdom	-	2007-2010	1982	2.25	-3.97	5.03	2.71	-6.54	6.92	4.72	0.67	19.54	42.48	7.24	111.93	108.28	23.01	213.66	13.71	0.00	71.98
United States	1981-1992	2007-2010	1980	2.66	-3.07	7.19	2.13	-1.44	5.82	3.23	0.87	9.37	216.41	81.37	471.34	139.85	90.49	202.75	6.89	-0.12	13.98
Uruguay	1981-1985	1981-1985, 2002-2005	-	2.53	-9.39	8.90	41.05	-9.85	144.55	37.37	0.68	107.05	8.99	1.62	51.09	31.21	19.99	60.65	-231.56	-8520.12	277.90
Venezuela, RB	1993-1994	1994-1998	1985	2.08	-8.86	18.29	-12.84	-98.82	23.96	30.54	1.44	115.52	3.18	1.25	13.56	18.74	8.13	30.66	27.65	-589.17	760.33
Zambia	-	1995-1998	-	2.49	-3.51	7.62	-0.87	-41.79	25.12	39.66	6.14	165.52	7.85	1.66	33.41	9.59	3.69	24.18	3.67	-372.00	401.09
Summary Statistics:																					
Average				3.48	-5.61	12.34	1.98	-24.28	20.13	10.52	-3.78	46.06	72.94	7.99	1172.09	53.94	29.84	90.48	9.48	-254.87	178.20
Std. Deviation				1.73	4.14	9.79	8.83	38.82	25.73	11.28	10.91	52.32	44.33	14.51	228.27	44.05	27.33	68.77	45.30	1525.51	182.21
Max Crises	29	57																			
Max Countries	61	61																			
Max Observations	854	1830																			

Panel 1 presents summary statistics of key variables used in the original Demirguc-Kunt and Detragiache (1998) study. The data driving the two alternatives for the dependant variable are shown in cols 2 and 3 with the Demirguc-Kunt and Detragiache (1998) crises listed in column 2 and the Laeven and Valencia (2013) crises shown in column 3. The variables shown became central to future research and invariably show up as being significantly associated with crisis likelihood. These include GDP growth rates, real interest rates, inflation and money to foreign exchange reserves. Demirguc-Kunt and Detragiache (1998) also included two sectoral variables, these are the ratio of total lending (credit extended) to GDP as well as total lending growth rates.

The overall summary statistics relate to the full 1980-2010 time frame. Countries experience positive GDP growth of 3.5% on average with average inflation of 10.5%. M2-money-to-foreign-exchange-reserves is used to assess the potential exposure of countries to sudden capital outflows (see Calvo (1998) and Bruno and Shin (2013)). Over the sample this averages at 60 times foreign reserves. Private-credit-to-GDP ratio has an average of 54%, however average credit growth of 9.5% is reported over this period, representing almost 3 times the corresponding GDP growth-rate. This increase in leverage is considered by many to be one of the major sources of systemic risk, especially when it outstrips the GDP growth rate over the same period (see Brunnermeier et al. (2009)). We also note that average real interest rates are a modest 1.98%, this being a signal that high rates are unlikely to feature as crisis determinants in our study. However there is considerable variation across the countries making up our sample and the standard deviation of inflation is just under 9%. Overall, panel A comprises 61 countries with up to 1830 observations depending upon the particular regression specification. In terms of the key variables outlined in Table 1.1 we focus upon those which, if subjected to a large shock, are theorised to adversely impact bank asset values.[14] Demirgüç-Kunt and Detragiache (1998) believe these to be inextricably linked to GDP growth-rate disturbances, the consequences of which are assumed to be:- 1) lack of investor confidence, 2) downturn in the business cycle leading to reduced investment activity, 3) higher unemployment levels and 4) increasing inability of borrowers to meet repayment obligations. As asset values decline investors are less inclined to meet payment obligations, therefore non-performing loan levels rise. Because banks often rely upon inter-bank deposits (wholesale funding) as a primary source of funding, an unexpected

[14] Under fair value accounting rule 157 (FAS 157) banks must mark asset values to market, therefore any asset valuation disturbances must immediately be reflected in their balance sheets. Brunnermeier et al. (2009) recommend a relaxation / suspension of FAS 157 to help prevent short-term liquidity issues spiralling into asset valuation / insolvency crises.

increase in real-interest rates reduces the repayment capacity of borrowers and increases bank operating costs via higher weighted-average cost of capital. Rates shocks can also make private-sector investment projects more difficult to justify via increased hurdle rates. The overall impact entails reduced asset values with mark-to-market accounting rules requiring immediate reflection of these lower values and that revenue streams be reappraised using higher discount factors. These circumstances in turn lead to increased loan default rates and lower or non-existent bank profits.

According to Fisher (1930) interest rates and inflation are indelibly linked, therefore inflationary measures are included as part of the analysis. M2 money to foreign exchange reserves level is included because it is a proxy variable for banks' exposure to unexpected capital outflows following an unexpected devaluation of the local currency. In turn, capital flows have been shown to be associated with past financial crises, where large outflows have been observed during periods when bank credit-worthiness issues emerged (see Calvo (1998), Lane and McQuade (2014) and Bruno and Shin (2013)). As short-term inter-bank funding weakens and/or becomes more expensive banks may be forced to de-leverage their balance sheets by selling off assets, often all of them acting in unison. Thus funding-liquidity shortages may drive asset de-leveraging spirals to such an extent that asset values fall (sometimes temporarily) below liabilities and banks become insolvent.

Private-credit-to-GDP and private-credit-growth-rates feature because, during business cycle upswings, the level of private credit in an economy drives bank revenues and, in turn, earnings. Private credit levels reflect current asset valuations and investment appetite. They also help fuel asset "bubbles" (see Schularick and Taylor (2012)). Theory suggests that where economies become increasingly leveraged relative to GDP, systemic risk is increasing.

Other factors included in panel A but which show weak crisis explanatory power are included for completeness and to replicate (and extend) the results of Demirgüç-Kunt and Detragiache (1998). Bank profitability can be adversely affected whenever there is an unexpected mismatch between expected return-on-assets and cost of capital. If banks raise finance in a foreign currency but lend predominantly locally, then an unexpected depreciation of a country's currency reduces the value of any assets held in the local currency whilst increasing debt service costs. Therefore a measure of currency depreciation is considered. A deposit-insurance dummy variable, taking the value of 1 if the deposits of a country's banking system are insured and 0 otherwise, is included to test Diamond and Dybvig's (1983) theory that deposit runs constitute a primary source of systemic risk. Budgetary-surplus-to-GDP ratios are included because theory suggests that stable economies, where inflation levels remain under control and where borrower credit-worthiness concerns are moderate, are less likely to experience systemic banking shocks. Finally terms-of-trade-deterioration is included as a result of its pre-1998 significance in earlier papers (see Caprio and Klingebiel (1996) and Gorton (1988)). All panel A variables included in our regressions are described in detail in appendix 1, including a reference to their source dataset. Our second panel, panel B, is similar in certain respects to the first in that many of the countries from panel A are retained, along with panel A's most significant explanatory variables. The purpose of the second panel is to examine the role played by sectoral variables as systemic crisis determinants. In doing so we make use of more comprehensive sectoral datasets made recently available, including the Financial Structures and Development database (see Cihák et al.(2013)) as well as an exhaustive financial crisis database spanning the GFC (see Laeven and Valencia (2013)). However, in contrast with panel A, those variables with poorly-demonstrated explanatory power are omitted, as are countries with sparsely-reported sectoral data. New countries are added in line with geo-political developments such as the collapse of the Soviet Bloc. Panel B is shallower than panel A in that it only spans the period 1998-2011. As stated, this is necessary because of a shortage of generally available bank-sector data, including important variables such as Tier-1 capital ratios, Bank Z-scores and risk-weighted assets prior to 1998 (this being the year they were introduced as part of the amended Basel I accord, Basel II).

The capital-to-asset ratio (CAR, sometimes called leverage ratio) is included because of its regulatory importance. The CAR measures levels of bank credit extended per unit of capital held. We have mentioned how sectoral shocks foreshadow increases in non-performing loan levels (NPL). If NPL levels increase banks may experience large trading losses, which in turn must be absorbed by bank capital or reserves. If losses become so severe that capital is fully depleted then the bank is insolvent and must be "resolved", a euphemistic term that can have several meanings such as "wound up", "nationalised", "re-capitalised" or some combination of the three. A bank's Z-score is a risk measure that can be calculated in several ways. One is as a distance-to-default measure which is based upon a variant of Merton's (1974) option pricing model. However, our measure being drawn from the Financial Structures and Development dataset means our Z-Score is in turn based upon the more general Altman (2000) Z-Score measure which makes use of book values of equity in its calculation.[15] The higher the Z-score the less likelihood there is that the bank will become insolvent therefore we anticipate a significantly negative coefficient in our regressions.

Notable by its absence in many of the studies described earlier is an examination of liquidity from a systemic risk perspective. Demirgüç-Kunt and Detragiache (1998) include a liquidity measure in their regressions, this being the ratio of liquid bank assets to total assets, but this ratio

[15] Calculated as $(ROA_{i,t} + CAR_{i,t})$ / StDev(ROA) where ROA is return on assets and CAR is the capital-to-assets ratio for country "i" in year "t".

is shown to be insignificant from a crisis perspective. We therefore consider two alternative liquidity measures, both of which include bank deposits based on the following rationale.

Duffie (2010) likens a situation whereby a bank cannot source "Repo" counterparties to the deposit-withdrawal stampede theorised by Diamond and Dybvig (1983). Repos are instruments used by banks to help with their funding requirements. In such an arrangement a bank sells securities (e.g. Government Bonds) to the buyer for an agreed period of time and commits to their re-purchase at an agreed price and time. Thus potentially low-yielding assets may be temporarily converted to cash and the proceeds invested in higher-yielding assets on a rolling basis. In essence Repos can be considered as similar to short-term collateralised borrowing arrangements.[16] However, as Repos reach maturity they need to be rolled-over in order for a bank to remain solvent, requiring counterparties to the Repos to be identified. When banks / banking sectors experience large shocks credit-ratings of the affected banks may be downgraded. Such downgrades make it both more difficult and expensive to enter into Repo contracts as margins are raised and interest spreads widen. If counterparties cannot be found then asset deleveraging is forced, which leads to lower asset prices and further rounds of deleveraging in stressed periods (see Brunnermeier et al. (2009)). This is a form of liquidity risk in the sense that deposit and Repo financing both represent important short-term financing options for banks. Banks turn to Repos for funding when deposits are insufficient to finance asset-growth targets, therefore deposit-based measures can act as a proxy for inter-bank liquidity.

The bank credit-to-deposit ratio (a.k.a. loans-to-deposits) is one such liquidity measure and is also an alternative (to CAR) leverage measure. Similar to the credit-to-GDP ratio described

[16] Definition comes from www.investopedia.com and www.icmagroup.org

above, the greater the leverage the higher the risk-exposure to sharp asset-value reductions and the greater the dependency upon debt (or Repos) as a finance instrument. In recent years, as central banks strived to maintain relatively low inflation and interest rate levels (see Table 1.1 summary information), debt financing has become more expensive than deposit financing, even taking debt tax shields into account, therefore higher leverage is associated with higher risk exposure. However, in circumstances where there is a tightening of liquidity and/or concerns over bank credit-worthiness, mark-to-market accounting rules and higher margin-posting requirements can cause liquidity shocks to eventually worsen to such an extent that inter-bank activity disappears entirely, i.e. the "credit crunch" phenomenon now synonymous with the GFC. Likewise, the deposits-to-total-assets ratio is another liquidity measure, but one which includes non-loan- related assets in the denominator. Examples of this class of assets are government bonds, subsidiary holdings and ownership positions taken in other firms or ventures. In theory this ratio's asset base represents more highly-diversified assets, thereby lowering the overall risk profile of banks.

We include non-performing-loan levels as it represents a sign of deteriorating macroeconomic conditions where borrowers' incomes become squeezed and loan repayments made more challenging.

This is especially true if borrowers are experiencing negative-equity concerns. Tier-1 capital is defined as high-quality capital plus disclosed reserves measured in proportion to a bank's risk-weighted assets. Its purpose is to absorb unexpected bank losses and to shield depositors and their insurance underwriters (usually the sovereign) from large shocks. Regulatory authorities place great emphasis on monitoring minimum standards for this measure and have ratcheted up minimum Tier-1 capital levels over the years.

TABLE 1.2

	Laeven & Valencia (2013)	CAR			Bank Z-Score			Credit to Deposits			Deposits to Total Assets			Non-performing Loan %			Tier 1 Capital Ratio			Net Interest Margin		
Country	Crisis Year(s)	Avg	Min	Max	Avg	Min	Max	Avg	Min	Max	Avg	Min	Max	Avg	Min	Max	Avg	Min	Max	Avg	Min	Max
Argentina	2001-2003	12.25	10.60	13.50	4.12	0.43	5.45	68.67	44.52	97.75	77.54	68.30	93.82	7.84	1.20	18.10	14.16	0.00	20.80	3.64	-0.73	8.81
Australia		5.88	5.00	7.60	11.18	4.45	14.68	133.07	124.72	144.23	97.00	94.37	98.50	0.90	0.20	2.20	10.54	9.60	11.90	2.02	0.59	4.30
Austria	2008-2011	5.67	4.70	7.50	24.44	17.97	40.86	116.19	0.00	130.01	99.28	98.90	99.56	2.51	1.70	3.00	13.61	11.80	15.80	1.61	0.81	2.18
Bahrain		-	-	-	18.92	14.84	25.99	79.54	64.36	98.65	96.92	94.41	99.24	-	-	-	13.51	11.55	16.54	1.86	1.58	2.35
Belgium	2008-2011	3.60	2.70	5.00	5.83	2.56	7.74	80.20	0.00	94.58	99.54	98.98	99.78	2.44	1.40	3.00	13.83	11.20	19.30	1.26	0.93	2.16
Brazil	1998	10.56	8.90	12.10	18.67	15.49	20.20	71.04	59.16	87.22	82.40	76.30	85.73	4.87	2.90	10.20	17.26	13.80	19.00	6.38	3.44	8.00
Bulgaria		11.26	7.30	15.30	19.14	14.16	28.11	62.49	0.00	129.21	83.54	63.50	99.85	7.49	2.00	26.70	22.82	13.80	41.80	4.91	3.97	5.77
Burundi	1998	-	-	-	18.27	13.78	21.48	102.36	66.85	143.95	63.00	51.43	70.09	-	-	-	-	-	-	8.83	4.50	13.78
Canada		4.53	3.50	5.60	20.60	14.63	25.60	74.69	0.00	113.95	97.37	96.41	98.28	1.00	0.40	1.60	13.36	10.60	15.90	2.08	1.12	3.87
Colombia	1998-2000	12.32	9.40	14.30	7.05	4.50	8.58	153.64	92.70	200.95	97.64	94.70	99.50	6.12	2.50	13.60	14.43	10.30	17.30	5.13	3.70	6.49
Congo, Rep.		-	-	-	0.00	0.00	0.00	55.06	21.07	152.63	55.82	33.18	96.18	-	-	-	-	-	-	2.72	1.45	3.49
Croatia	1998-1999	12.05	8.60	18.30	38.22	30.32	46.74	97.53	71.55	110.08	99.92	99.58	99.99	8.23	4.80	12.30	17.00	12.70	21.30	3.80	3.20	4.42
Cyprus		6.15	4.90	6.90	3.89	-0.74	7.81	101.21	92.63	121.57	94.68	92.36	97.52	5.23	3.60	7.20	10.73	5.40	12.84	2.83	-0.23	5.67
Czech Republic	1998-2000	5.75	5.20	6.50	7.98	4.21	9.77	55.84	0.00	108.39	97.26	95.12	99.65	9.34	2.70	29.30	13.56	11.40	17.40	3.04	2.52	3.88
Denmark	2008-2011	5.55	4.20	6.30	15.52	10.34	18.80	203.46	0.00	313.33	98.98	96.52	99.90	1.52	0.20	4.10	12.78	9.27	17.00	1.41	1.08	1.89
Ecuador	1998-2002	9.80	8.10	14.50	-1.40	-6.68	2.90	114.52	89.57	237.35	89.15	76.76	99.60	9.19	3.20	31.00	14.47	8.14	19.80	3.60	-6.45	7.08
Egypt, Arab Rep.		5.39	4.80	6.20	35.76	30.96	40.32	63.98	48.06	81.94	73.95	62.72	82.14	17.94	11.00	26.50	12.50	7.55	16.40	1.72	1.23	2.43
El Salvador		10.97	6.90	13.90	21.61	14.85	31.04	99.35	88.86	109.16	90.38	88.26	92.07	2.98	1.90	4.30	14.08	11.50	17.50	5.87	2.47	10.38
Estonia		10.77	8.20	16.20	7.68	3.77	10.24	163.01	125.64	206.01	99.90	99.75	99.98	1.74	0.20	5.40	15.83	11.50	22.30	3.19	2.05	5.25
Finland		7.06	4.40	10.90	17.86	10.05	29.84	137.11	107.42	158.39	99.74	99.10	99.99	0.55	0.20	1.20	14.23	10.50	19.10	1.16	0.28	2.00
France	2008-2011	5.32	3.70	6.80	16.75	9.71	21.45	127.54	0.00	149.70	99.49	98.39	99.77	4.19	2.70	6.30	12.02	10.20	15.81	0.87	0.41	1.17
Germany	2008-2011	4.26	4.00	4.80	12.23	7.18	16.67	115.29	90.04	178.87	99.84	99.58	99.87	4.12	2.70	5.20	13.04	11.40	16.40	1.05	0.78	1.34
Guatemala		9.23	8.20	10.50	16.23	9.81	20.95	83.61	59.62	134.07	78.60	68.88	87.01	4.05	1.60	8.10	11.47	0.00	15.90	6.83	5.53	7.73
Guyana		-	-	-	16.38	14.09	19.68	59.74	48.35	80.16	68.58	51.37	83.43	-	-	-	3.14	0.00	12.12	4.79	4.11	5.94
Honduras		10.24	8.80	11.20	29.83	27.75	33.49	99.06	90.21	111.24	89.69	84.84	96.99	6.19	2.90	11.20	8.39	0.00	15.30	7.63	6.34	10.02
Hungary	2008-2011	9.09	8.20	10.00	14.91	11.27	18.00	80.32	0.00	143.02	87.41	55.43	99.18	4.50	1.80	13.30	13.10	10.40	16.50	4.22	3.31	5.20
India		6.32	5.30	7.30	31.58	24.46	37.70	68.40	59.93	76.42	92.18	80.37	97.47	7.19	2.30	14.70	12.45	11.10	14.20	3.26	2.72	3.72
Indonesia	1998-2001	9.57	6.00	11.40	0.60	-7.31	1.88	62.68	38.64	95.86	78.99	67.24	93.69	15.16	2.20	48.60	19.08	16.10	22.30	4.16	-3.86	6.64
Ireland	2008-2011	5.56	4.40	7.30	3.13	0.45	7.34	169.10	120.29	222.69	99.81	99.31	100.00	3.14	0.70	14.70	12.43	10.60	19.20	0.71	0.18	1.26
Israel		5.99	4.90	7.30	24.29	20.78	27.34	100.69	93.76	107.88	98.03	96.76	99.50	3.66	1.40	9.90	10.95	9.20	14.30	2.30	1.40	3.02
Italy	2008-2011	7.44	6.40	9.40	12.53	8.15	28.14	149.79	134.42	167.44	95.35	91.20	97.06	7.88	5.30	11.80	11.03	10.10	12.80	1.94	1.35	3.45
Jamaica	1998	-	-	-	3.46	0.00	11.62	59.00	30.73	76.57	77.65	68.17	84.77	11.00	11.00	11.00	10.62	0.00	26.63	8.35	6.31	11.78
Japan	1998-2001	4.21	2.40	5.30	10.26	5.99	13.42	59.46	47.29	89.59	91.53	88.77	95.70	3.80	1.40	8.40	11.87	9.40	13.80	1.24	1.01	1.49
Jordan		8.76	6.20	11.30	36.69	23.26	52.90	78.18	68.33	88.26	91.61	86.97	95.80	10.62	4.10	19.30	19.03	15.90	21.70	2.99	2.10	3.47
Kenya		11.99	8.90	13.20	12.11	8.74	16.38	78.60	72.60	88.16	91.46	86.21	96.13	19.05	4.40	34.90	14.46	0.00	20.80	7.71	5.50	10.49
Korea, Rep.		6.39	2.80	9.30	5.37	1.29	9.24	137.01	115.69	168.46	98.56	95.81	99.39	3.09	0.70	8.90	12.07	8.20	14.60	2.35	0.51	4.98
Kuwait		11.66	10.30	13.00	16.66	12.44	19.42	88.09	66.62	112.61	99.80	99.51	100.00	8.58	3.80	19.20	19.82	15.60	23.70	2.80	2.24	3.60
Latvia	2008-2011	7.21	2.00	9.10	3.35	0.32	4.08	128.29	0.00	278.41	95.66	89.38	98.52	5.89	0.50	19.00	13.42	10.10	17.40	3.36	1.26	6.49
Lithuania		9.62	7.60	13.90	6.23	1.46	8.97	89.79	0.00	197.41	99.58	96.25	99.98	8.39	0.60	19.70	14.45	10.30	23.80	3.42	1.45	6.28
Mali		-	-	-	18.33	10.97	29.37	102.70	86.52	119.73	84.71	71.41	97.28	-	-	-	-	-	-	5.65	2.13	6.88
Mexico		9.69	8.00	11.40	25.87	18.67	33.79	69.82	56.99	81.26	-	-	-	4.00	1.50	11.30	15.21	13.80	16.90	5.78	2.04	13.19

TABLE 1.2 (Continued)

	Laeven & Valencia (2013)	CAR			Bank Z-Score			Credit to Deposits			Deposits to Total Assets			Non-performing Loan %			Tier 1 Capital Ratio			Net Interest Margin		
Country	**Crisis Year(s)**	**Avg**	**Min**	**Max**	**Avg**	**Min**	**Max**	**Avg**	**Min**	**Max**	**Avg**	**Min**	**Max**	**Avg**	**Min**	**Max**	**Avg**	**Min**	**Max**	**Avg**	**Min**	**Max**
Nepal		-	-	-	3.65	-6.17	10.22	75.68	64.51	88.69	90.95	81.95	95.81	-	-	-	5.67	-1.40	10.27	3.90	3.18	4.82
Netherlands	2008-2011	4.22	3.00	5.10	9.31	2.36	26.25	138.48	0.00	159.38	99.86	99.66	99.95	2.34	1.50	3.20	12.35	10.70	14.90	0.98	0.26	1.73
New Zealand		-	-	-	17.80	6.35	26.25	137.36	0.00	162.03	97.80	96.84	98.26	-	-	-	4.33	0.00	10.23	2.00	1.46	2.80
Niger		-	-	-	18.05	12.50	21.94	92.33	76.49	119.36	62.09	45.60	83.14	-	-	-	6.54	0.00	14.70	4.83	2.53	7.14
Nigeria	2009-2011	10.70	3.20	18.50	3.10	-4.51	5.18	90.03	69.53	104.66	77.83	48.13	96.52	18.82	7.20	36.10	14.27	0.00	23.40	7.55	4.92	10.47
Norway		6.66	5.90	7.60	23.91	18.70	27.36	93.88	0.00	160.37	99.13	98.18	99.98	1.21	0.50	2.00	12.32	11.20	14.20	1.82	1.28	2.49
Papua New Guinea		-	-	-	5.52	0.00	9.66	54.27	44.77	64.41	91.31	67.54	97.42	-	-	-	-	-	-	6.64	3.74	9.25
Paraguay		10.74	8.50	14.90	12.34	8.98	15.01	113.49	84.94	150.36	80.13	69.74	93.38	7.83	1.10	20.60	15.33	0.00	20.90	8.86	7.68	10.55
Peru		9.38	8.30	10.20	12.08	9.83	13.72	87.42	75.59	105.51	99.64	98.78	100.00	6.13	2.20	14.80	12.69	11.20	14.00	6.44	4.97	9.76
Philippines	1998-2001	12.53	10.60	14.50	29.89	19.53	47.49	61.96	49.93	87.20	91.23	86.53	95.18	11.64	3.30	27.70	16.88	15.50	18.40	4.00	1.00	5.92
Portugal	2008-2011	6.06	5.50	6.60	16.43	11.51	26.05	151.13	112.75	169.77	99.80	99.38	99.95	3.20	1.50	6.90	10.36	9.20	12.50	1.76	1.01	2.51
Romania		10.29	8.60	12.90	4.91	-1.96	7.86	81.56	36.17	130.63	94.84	79.51	100.00	6.54	1.40	14.10	19.10	13.40	28.80	7.37	3.76	13.58
Russian Federation	2008-2011	12.77	7.30	15.70	8.14	2.00	12.76	105.48	85.56	134.56	89.04	57.53	98.82	6.72	2.40	17.30	17.21	11.50	20.90	4.22	0.06	7.94
Senegal		8.91	7.60	10.30	37.20	33.63	41.50	89.35	78.65	101.07	81.24	65.37	93.38	16.72	11.90	20.20	14.85	11.10	20.60	5.96	3.63	7.27
Seychelles		8.35	6.60	9.90	5.82	0.00	15.85	30.75	17.77	49.86	79.94	73.80	82.98	4.35	2.00	8.10	8.16	0.00	24.20	3.74	2.29	5.83
Singapore		9.76	8.30	11.00	21.78	8.29	26.88	91.95	77.93	109.47	97.60	97.05	98.54	3.93	1.20	8.00	17.06	13.50	20.60	1.76	0.14	3.73
Slovak Republic	1998-2001	8.51	4.60	11.10	7.35	-0.75	9.51	80.02	56.22	100.77	99.55	97.24	99.97	9.01	2.50	31.60	14.62	6.60	22.40	3.09	1.27	4.34
South Africa		7.84	5.60	9.30	16.93	8.13	65.36	123.39	110.12	140.07	98.04	93.21	99.52	3.37	1.10	5.90	12.91	10.10	14.90	4.11	1.92	11.67
Spain	1998,2008-2011	6.84	5.90	8.50	22.92	18.07	27.44	133.76	119.11	143.87	98.53	96.98	99.26	2.01	0.70	5.30	11.99	11.00	12.90	1.89	0.87	2.58
Sri Lanka		-	-	-	9.95	5.54	14.67	86.21	73.57	94.69	89.89	81.98	95.44	-	-	-	0.76	0.00	10.61	4.63	3.50	5.37
Swaziland	1998-1999	14.92	11.70	17.60	11.64	3.02	16.66	82.65	55.30	107.43	97.97	92.23	99.83	7.16	2.00	9.30	14.11	0.00	33.80	6.67	4.78	7.54
Sweden	2008-2011	5.11	4.70	6.50	19.47	16.66	23.03	133.63	0.00	241.00	97.40	96.75	98.22	1.42	0.60	2.60	10.18	7.00	12.70	1.37	0.90	2.00
Switzerland	2008-2011	5.17	4.30	6.00	7.46	3.73	9.23	121.20	111.05	135.92	99.30	98.67	99.84	1.85	0.30	5.20	13.34	11.30	17.90	0.91	0.51	1.35
Syrian Arab Republic		-	-	-	4.09	0.00	12.72	26.31	0.00	42.11	62.87	50.97	80.48	-	-	-	-	-	-	2.20	0.06	4.37
Tanzania		5.15	3.8	6.5	9.81	7.49	17.17	47.02	30.85	64.82	80.60	67.82	88.70	24.05	22.90	25.20	8.11	0.00	19.52	7.68	5.78	10.10
Thailand	1998-2000	8.41	5.90	11.30	3.02	0.08	4.45	103.38	90.13	148.18	97.74	97.05	98.62	13.96	2.90	42.90	13.48	10.90	16.00	2.51	0.73	3.56
Togo		-	-	-	3.96	-1.43	8.91	82.91	61.30	125.56	80.85	68.78	95.74	-	-	-	11.30	0.00	22.30	4.80	2.15	9.76
Turkey	2000-2001	11.04286	5.2	15	6.22	-0.43	26.43	61.37	35.89	99.56	93.12	74.40	98.85	8.11	2.70	29.30	20.22	8.20	30.90	6.73	1.58	12.40
Uganda		11.6	7.000	15.800	15.02	10.85	19.91	61.09	46.33	83.81	53.59	29.84	66.74	5.77	2.10	20.20	18.85	11.00	23.10	10.59	6.72	13.39
United Kingdom	2007-2011	6.585714	4.4	9.9	11.04	4.62	18.72	99.60	99.33	99.95	99.60	99.33	99.95	2.44	0.90	4.00	13.56	12.60	15.90	1.37	0.91	2.25
United States	2007-2011	9.764286	8.4	11.2	22.82	19.87	25.65	77.21	69.55	83.22	89.75	79.21	95.50	2.00	0.70	5.40	13.24	12.20	15.30	3.70	3.07	5.45
Uruguay	2002-2004	9.791667	7.2	15.3	1.84	-3.78	3.17	82.77	55.76	125.90	72.90	56.57	86.57	7.41	1.00	33.90	16.51	10.20	22.70	5.04	-3.35	8.11
Venezuela, RB		11.84286	8.6	15.9	12.39	7.45	21.32	68.76	45.96	83.34	92.27	76.85	99.22	4.26	1.10	9.20	16.26	12.90	25.10	11.60	3.40	25.49
Zambia	1998	-	-	-	11.78	10.36	14.04	49.59	33.11	73.00	47.89	12.42	83.82	-	-	-	16.20	0.00	27.94	7.05	3.07	11.23
Summary Statistics:																						
Average		8.44	6.33	10.66	13.86	8.53	20.01	94.08	57.94	126.64	89.15	80.98	95.30	6.56	2.73	14.58	13.28	8.33	18.70	4.08	2.06	6.25
Std. Deviation		2.73	2.29	3.74	9.46	9.10	12.70	33.67	38.58	50.12	12.49	19.59	6.99	5.02	3.57	11.12	3.87	5.18	5.63	2.50	2.30	4.16
Max Crises	36																					
Max Countries	75																					
Max Observations	1050																					

Panel B comprises data on 75 countries over the period 1998 to 2011 as shown. Our dependent variable is driven by the Laeven and Valencia (2013) database with crisis years listed in column 2. For each of our key variables of interest we itemise Average, Minimum and Maximum values and provide overall sample statistics at the bottom of the Table.

Opinion is divided on this macro-prudential measure. Regulatory authorities such as the Basel Committee for Banking Supervision (BCBS) believe higher Tier-1 capital helps to stabilise banking systems (see Wellink (2009) and Bank for International Settlements (2011a)). Others believe that by increasing minimum capital, meeting return-on-equity (ROE) analyst expectations requires a corresponding increase in earnings, causing bank managers to adopt more risky loan and investment portfolios (see Brunnermeier et al. (2009) and Chapter 2). Net-interest-margins are included as they are proxy variables for earnings generally whilst simultaneously capturing an aspect of interest rate risk. The sample average of 4%, coupled with a small standard deviation of 2.5% illustrates how difficult it is for banks to generate significant earnings from their traditional lending activities, especially in the context of low GDP growth levels (see Table 1.1 summary).

We also examine other sectoral variables not summarised in Table 1.2. Bank deposits-to-GDP ratios are included as a (wealth-controlled) liquidity measure which also acts as a proxy variable for investment activity. Bank concentration is included because the literature has, on occasion, shown this variable to be significant, although opinion is divided about the sign of the regression coefficient. Beck et al. (2006) first theorise (and subsequently demonstrate) that low concentration is associated with crises (i.e. a negative coefficient) on the basis that higher asset concentration will result in monopoly-like profits being enjoyed by the main sectoral participants and therefore more highly-concentrated banking sectors ought to demonstrate relatively greater stability. Alternatively, Schaeck et al. (2009) find that more competitive banking sectors are less likely to experience a systemic crisis (see also Allen and Gale (2003)).

We also analyse the proportion of lending activity in an economy undertaken by non-resident banks. This variable is an alternative capital-flow disturbance proxy variable. We anticipate non-resident banks as being more likely to wind up their operations during cyclical or shock-related downturns than local banks would be, therefore we anticipate a positive regression coefficient.

Finally, a house price index is included because financial crises often develop in the wake of real-estate "bubbles" where property has become overvalued and borrowers over-extended. According to Minsky (1986) there is a "euphoric" phase inherent in such bubbles where caution is thrown to the wind and long-standing bank lending rules are either relaxed or ignored. All panel B variables are described in detail in Appendix 2, including their source dataset.

1.5. Approach

One of our main goals is to analyse the explanatory power of previously known systemic crisis determinants over a long period. This requires us to first replicate and then extend the results of Demirgüç-Kunt and Detragiache (1998) by employing the same econometric technique. In this way our results can be meaningfully compared and contrasted with their earlier findings. Though criticised in the past the pooled logit methodology is tractable and theoretically intuitive in that the model yields predicted systemic crisis probabilities and identifies those factors most closely associated with such events (see Davis and Karim (2008)). As per Demirgüç-Kunt and Detragiache (1998), once a country has experienced its first systemic crisis all subsequent rows relating to that country are excluded from the logit regressions. Doing so mitigates a modelling criticism that dependent variable and explanatory variables become jointly-determined (endogenous) once a systemic crisis has emerged. We show in section 1.6 that this concern is immaterial to the primary results obtained.

We commence by attempting to replicate several key findings of the original Demirgüç-Kunt and Detragiache (1998) paper. Specifically we set out to replicate the first 3 regressions of their Table results, a copy of which is presented in Appendix 6 for comparison purposes.[17] We consider the same countries, time period (1980-1994) and econometric model. We then extend the time-span under consideration beyond 1994 up to 2010 such that the relevance of the original findings over a longer time-frame, up to and including the GFC, may be assessed. From this point onwards our binary dependent variable is driven by data drawn from Laeven and Valencia (2013). We next introduce several new explanatory variables. Some of Demirgüç-Kunt and Detragiache's (1998) ex-ante theorised factors are shown, ex-post, to have poor explanatory power therefore they do not feature in the subsequent analysis. Instead these are replaced by other sectoral variables following the motivation described in the introduction and as per the theory described in section 1.4.

Demirgüç-Kunt and Detragiache (1998) describe their method for predicting in-sample crises as follows: A sample threshold crisis probability is established, this being the ratio of crises to total observations (approx. 5%).[18] For each regression the corresponding predicted (fitted) crisis probabilities are determined.[19] If the predicted probability exceeds the sample threshold probability the model is assumed to "*predict*" a crisis. As a result, correct as well as incorrect predictions can be quantified. A good model should predict a high proportion of actual in-

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[17] We do not replicate regression 4 from this table as data for the law and order index reported in this regression could not be reliably sourced. In general we attempt to recreate their original dataset as faithfully as possible, though this is not always possible due to data modifications which have taken place in the intervening years.

[18] Schularick and Taylor (2009) in their long-term study of crisis estimate that systemic crises occur slightly in excess of 4% of the time.

[19] We make use of the Stata analytical package for this purpose. Predictions are made via the "*Predict*" command.

sample crises without over-predicting them.[20] They should do so by also simultaneously correctly predicting a high proportion of no-crisis outcomes.

1.6. Results

Table 1.3 highlights the results achieved via the first set of regressions using panel A and should be contrasted with the results reported by Demirgüç-Kunt and Detragiache (1998) which are shown as the shaded regressions (see also Appendix 6). The sample size is comparable to the original 1998 sample (656 in our initial regression compared with 546 in the corresponding original) and the number of crisis episodes identical. The finding that low GDP growth-rates are significantly associated with systemic bank crises is reconfirmed. The importance of real-interest rate levels to the well-being of banks is also validated in that high real-interest rates are significantly associated with bank crises in two out of three regressions. We also successfully replicate their findings that the presence of explicit deposit-insurance is associated with sectoral instability as are high levels of private-credit to GDP ratios. Also reconfirmed are the findings that depreciation of a country's currency, cash (liquid assets) to bank asset ratio and budget-deficit-to-GDP ratio do not feature as systemic crisis determinants.

Where Table 1.3 differs from the original paper is in relation to inflation, terms of trade and reversals of capital flows. Demirgüç-Kunt and Detragiache (1998) find that high inflation is positively associated with systemic banking crises at a 1% level of significance, a result which we

[20] This is characterised as the model consistently returning predicted crisis probabilities that are higher than the threshold probability coupled with low no-crisis prediction accuracy.

TABLE 1.3

	(1)	(2)	(3)	(1)	(2)	(3)
GDP Growth Rate	-0.093*	-0.120**	-0.223***	-.067***	-.136***	-.252***
	(0.048)	(0.051)	(0.075)	(.025)	(.039)	(.063)
Terms of Trade Change	-0.013	-0.001	-0.015	-.030*	-.025	-.043*
	(0.015)	(0.016)	(0.023)	(.019)	(.020)	(.027)
Depreciation of Currency	0.011	0.011	0.011	.002	-.001	-.002
	(0.009)	(0.010)	(0.014)	(.006)	(.007)	(.008
Real Interest Rate	0.036**	0.030*	0.048	.088***	.086***	.131***
	(0.016)	(0.017)	(0.031)	(.024)	(.025)	(.039)
Inflation	0.004	0.010	0.019	.040***	.044***	.053***
	(0.012)	(0.017)	(0.026)	(.016)	(.018)	(.023)
Surplus Govt. Budget to GDP %	0.018	0.000	0.028	.012	.024	.016
	(0.035)	(0.036)	(0.071)	(.034)	(.036)	(.053)
M2 Money to Forex Reserves %		-0.000	0.007		.012**	.014**
		(0.000)	(0.009)		(.005)	(.007)
Private Credit to GDP %		0.021**	0.034*		.019*	.033**
		(0.010)	(0.018)		(.012)	(.015)
Ratio of bank liquid reserves to bank assets		-0.018	-0.006		.009	.018
		(0.022)	(0.033)		(.016)	(.023)
Private Credit Growth rate, lagged 2 years		-0.001	0.000		.007	.022**
		(0.003)	(0.004)		(.012)	(.010)
Real GDP Per Capita	-0.000	-0.000	-0.000**	-.034	-.090*	-.158**
	(0.000)	(0.000)	(0.000)	(.033)	(.055)	(.079)
Deposit Insurance Dummy Variable			2.266***			1.415**
			(0.788)			(.738)
Constant	-3.268***	-3.529***	-4.777***		Not Reported	
	(0.415)	(0.647)	(1.083)			
Summary Results:						
No. Observations	656	451	333	546	493	395
No. Systemic Crisis Episodes	28	26	20	28	26	20
Akaike Information Criterion (AIC Score)	196	151	101	204	187	131
Model Chi2	14.29	32.28	68.08	31.88	40.36	53.79
Total Correct In-Sample Predictions %	66.67	46.11	47.48	74	77	79
Correct Crisis Predictions %	67.86	70.37	80.95	61	58	55
Correct No-Crisis Predictions %	66.62	45.13	46.11	75	78	81
Degrees of Freedom	7	11	12	n/a	n/a	n/a
Model Significance - P Value	0.05	0.00	0.00	n/a	n/a	n/a
Log Likelihood	-94.00	-69.36	-43.81	n/a	n/a	n/a

This table replicates the first 3 regressions Demirguc-Kunt & Detragiache (1998) Table 2 regressions. Their corresponding results are reported in the shaded columns. The dependent variable takes the value of "1" if a country experienced a systemic banking crisis in a year. The time frame covered by these regressions is 1980 to 1994 as per the original paper. The country composition is also the same as in 1998. The definition of what constitutes a systemic crisis comes from the definition supplied by the authors in 1998 plus a table of crisis events described in the paper. All rows for a country are removed after the first crisis is recorded due to endogeneity concerns post crisis. Statistical significance is denoted by ***, **, * for the 1%, 5%, 10% levels respectively.

do not confirm. Similar outcomes for reversals of capital flow (M2-to-foreign-exchange-reserves) and deteriorating terms-of-trade are observed.[21]

In neither case do we find these variables to be significant, at least as far as our panel A analysis is concerned. We fully confirm the results relating to 8 out of 12 variables considered while we find only partial support / discrepancies relating to 4 out of 12. As we narrow this gap further (see for example the result for capital flows in Table 1.4) and also when we rely upon our Panel B data we therefore believe the replication results to be satisfactory overall.

Next model-fit, measured via the AIC scores, are considered (see section 1.3 above). Those reported in our Table 1.3 regressions are similar to the original paper, though it must be pointed out that the number of observations, i.e. sample sizes, are not identical due to data replication discrepancies. In general however, the lower the AIC score the better the model-fit. In 1998 the AIC scores ranged from 204 to 131 whereas we report AIC scores in the range 196 to 101.

As far as comparative crisis-prediction outcomes are concerned our results are mixed. The original 1998-reported total correct predictions (i.e. correct crisis as well as correct no-crisis predictions) are higher than we achieve (reported as 74%, 77% and 79% accuracy rates compared with our corresponding rates of 67%, 46% and 47%). One explanation for this difference could be the significant inflation, terms of trade and capital flow coefficients as are reported in 1998, but which we do not reproduce. However, in terms of correctly predicting actual sample crises, some improvement is achieved. We correctly predict crises 68%, 70% and 81% of the time depending upon the specification. These compare favourably with the original paper's 61%, 58% and 55% crisis-accuracy levels.

[21] Terms of trade are only weakly significant at the 10% level and only in two regressions.

Table 1.4 illustrates the results obtained by extending panel A's coverage to 2010. Identical explanatory variables to Table 1.3 are again assessed, this time with the dependent variable determined by Laeven and Valencia's (2013) dataset. Several interesting results emerge. Low GDP growth remains statistically significant as invariably found in the literature as does the presence of deposit insurance, both of which are still associated with increased crisis likelihood.

However whereas the real-interest rate which was reported as being significant at up to the 5% level in Table 1.3, this result does not hold in the long run. In regression three, controlling for the presence of deposit-insurance, we now find support for the significance of capital flow reversals, private-credit-to-GDP and low real-GDP-per-capita as systemic crisis determinants (see Lane and McQuade (2014), Calvo (1998) and Bruno and Shin (2013) regarding capital flows and Beck et al. (2006) regarding deposit-insurance).

Overall, these results are very similar to Demirgüç-Kunt and Detragiache's (1998) findings, albeit being driven by an alternative dependent variable. However, as the summary section of Table 1.4 demonstrates, when measured over a thirty year time span these variables lose efficacy as *predictors* of in-sample crisis events compared with their predictive power over the shorter 1980-1994 period. This suggests that other variables might do a better job at helping us to classify systemic crisis likelihoods.

TABLE 1.4			
	(1)	(2)	(3)
GDP Growth Rate	-0.116***	-0.119***	-0.132**
	(0.039)	(0.044)	(0.057)
Terms of Trade Change	0.004	-0.005	-0.023
	(0.013)	(0.014)	(0.019)
Depreciation of Currency	-0.000	0.009	0.014
	(0.010)	(0.010)	(0.011)
Real Interest Rate	0.014	0.012	0.020
	(0.010)	(0.013)	(0.014)
Inflation	0.001	-0.010	-0.013
	(0.012)	(0.015)	(0.017)
Surplus Govt. Budget to GDP %	-0.011	-0.004	0.036
	(0.024)	(0.026)	(0.043)
M2 Money to Forex Reserves %		-0.000	0.003**
		(0.000)	(0.001)
Private Credit to GDP %		0.007*	0.015**
		(0.004)	(0.006)
Ratio of bank liquid reserves to bank assets		-0.007	0.013
		(0.015)	(0.018)
Private Credit Growth rate, lagged 2 years		-0.002	-0.001
		(0.002)	(0.005)
Real GDP Per Capita	-0.000	-0.000	-0.000**
	(0.000)	(0.000)	(0.000)
Deposit Insurance Dummy Variable			0.976**
			(0.467)
Constant	-2.768***	-2.664***	-3.529***
	(0.301)	(0.436)	(0.645)
Summary Results:			
No. Observations	1,080	785	608
No. Systemic Crisis Episodes	48	46	37
Akaike Information Criterion (AIC Score)	382.9	314.6	236.3
Model Chi2	13.59	16.03	86.21
Total Correct In-Sample Predictions %	55.24	38.33	40
Correct Crisis Predictions %	60.42	78.26	75.68
Correct No-Crisis Predictions %	55.01	36.54	38.39
Degrees of Freedom	7	11	12
Model Significance - P Value	0.06	0.14	0.00
Log Likelihood	-187.5	-151.3	-111.7

This table extends the results of Table 1.1 for a time span that now runs from 1980 - 2010. Refer to Table 1.1 for details. The dependent variable takes the value of "1" if a country experienced a systemic banking crisis in a year but comes from the Laeven and Valencia (2013 Updated) database. The country composition is also the same as in 1998. All rows for a country are removed after the first crisis is recorded due to endogeneity concerns post crisis. Statistical significance is denoted by ***, **, * for the 1%, 5%, 10% levels respectively.

Overall, how are we to interpret the results thus far? It is possible that the factors most closely associated with systemic banking crises have changed relative to the period 1980-1994. Monetary policy, e.g. achieving low EU inflation, might partially explain the loss of real-interest rate significance. Schularick and Taylor (2012) also find that inflation and real interest rates have weak explanatory power in their long-run model. They theorise this result could imply that these variables have more relevance to emerging economies than to developed ones, given the findings in the literature and the fact that their dataset comprises only 12 developed economies.

It is also possible that bank operational diversification plays a role. We know banks compete with each other in terms of return-on-equity (ROE), this being a key performance indicator assessed by investors and analysts. However, with more stringent capital-adequacy requirements demanding banks hold more capital, achieving ROE growth is rendered increasingly difficult. Higher returns must be generated just to maintain ROE levels at historical levels in circumstances where minimum equity levels are ratcheted upwards by regulators. Yet Table 1.1 shows real-interest rates in leading economies such as the USA, the UK and Germany averaged at less than 3%, thus applying pressure on bank earnings derived via net-interest-margin (NIM) channels. Banks responded by diversifying their business activities so as to focus less upon NIM returns but more on complex securities-trading activities. The search for higher (or at the very least maintenance of) ROE requires asset and leverage growth, thus changing the risk profile of banks (see Brunnermeier et al. (2009) and Chapter 3).

We believe the business-cycle phase plays a fundamental determinants-establishing role in pooled logit models, especially whenever panels are shallow and do not span a full cycle. We provide evidence for this via Table 1.5. Here our sample is broken into three time-frames (termed triads), 1980-1990, 1991-2000 and 2001-2010.[22] First we consider regressions 1) to 3) wherein all country observations are discounted after the first recorded systemic crisis, as per the usual approach. Several variables, reported as determinants in 1998, are re-assessed over each discrete triad with the results showing the choice of time-frame to be highly relevant. For example GDP growth-rates are not significant in the period 1980-1999 but are significant during the subsequent twenty years. The terms of trade variable measured over the time frame 2001-2010 is found to be significantly negative, as per Demirgüç-Kunt and Detragiache (1998), but this result is also triad dependent. A similar finding relates to capital flows. Note also that this is not a consequence of having our sample observations concentrated in the first triad, as regressions 4) to 6) demonstrate. Here we have retained *all* observations and do not discard those subsequent to the first recorded crisis per country. Naturally this results in greatly increased crisis counts. However, once again we see broadly the same patterns of coefficient variation as was observed in regressions 1) to 3). Regressions 4) to 6) also show that explanatory variable endogeneity concerns post-crisis-onset are immaterial to the primary results because, with the sole exception of the real interest rate in regression 4), we observe the same significant variables as before and with the same coefficient sign in all other cases. We also note that significantly different degrees of model fit are reported depending upon the triad involved and nature of the model specification.

Whatever the underlying reasons might be, Tables 1.4 and 1.5 indicate that some macroeconomic variables either have no crisis-related explanatory power or that they lose

[22] Note that because all entries for a country subsequent to the first observed systemic crisis are removed from the panel there are considerably more observations covering the earlier years of the overall panel than there are for the latter years. However this approach is necessary due to crisis-onset endogeneity concerns as described above.

TABLE 1.5

	(1) (1980-1990)	(2) (1991-2000)	(3) (2001-2010)	(4) (1980-1990)	(5) (1991-2000)	(6) (2001-2010)
GDP Growth Rate	0.041	-0.212***	-0.490***	-0.082**	-0.198***	-0.274***
	(0.057)	(0.061)	(0.153)	(0.036)	(0.034)	(0.047)
Real Interest Rate	0.019	-0.006	-0.070	0.018***	-0.010	0.016
	(0.012)	(0.024)	(0.082)	(0.006)	(0.008)	(0.021)
Terms of Trade Change	0.004	0.018	-0.167**	-0.010	-0.002	-0.018
	(0.017)	(0.025)	(0.077)	(0.012)	(0.010)	(0.019)
M2 Money to Forex Reserves %	-0.000	-0.002	0.004**	-0.001	-0.000	0.005***
	(0.001)	(0.008)	(0.002)	(0.004)	(0.001)	(0.001)
Constant	-3.544***	-2.068***	-2.356***	-2.344***	-1.126***	-2.011***
	(0.353)	(0.319)	(0.421)	(0.206)	(0.149)	(0.188)
Summary Results:						
No. Observations	470	262	223	537	525	588
No. Systemic Crisis Episodes	17	18	13	44	84	55
Akaike Information Criterion (AIC Score)	141.7	120.9	77.89	284.7	413.0	292.8
Model Chi2	5.000	16.73	42.97	17.37	43.52	72.40
Total Correct In-Sample Predictions %	22.74	43.77	71.12	36.36	50.33	72.91
Correct Crisis Predictions %	88.24	55.56	92.31	77.27	61.90	72.73
Correct No-Crisis Predictions %	20.77	43.09	69.86	33.49	48.48	72.92
Degrees of Freedom	4	4	4	4	4	4
Model Significance - P Value	0.29	0.00	0.00	0.00	0.00	0.00
Log Likelihood	-68.37	-57.95	-36.44	-139.8	-204.0	-143.9

This table should be considred in conjunction with Table 1.4. We take the significant factors from Table 1.4 and subject them to a timeframe analysis, showing the importance of the analysis time-frame. Regression 1) covers the years 1980-1990, regression 2) covers 1991-2000 and regression 3 covers the 2000 - 2010 timeframe. In regressions 4), 5) and 6) we repeat the same regressions but this time leave all crisis years in the panel. Whether or not a variable is a significant crisis determinant appears to be time (or business cycle) dependent. Statistical significance is denoted by ***, **, * for the 1%, 5%, 10% levels respectively.

efficacy as systemic banking crisis determinants measured over the medium to long-term. Also the choice of time-frame is fundamental in terms of results reported. In line with our introductory motivation we next consider whether the replacement of potentially redundant macroeconomic variables with financial-services sector alternatives might offset some of this absence of explanatory power. With this in mind such variables as terms-of-trade, currency depreciation, inflation and fiscal deficit are no longer considered, primarily because they demonstrate either weak or else inconsistent systemic crisis explanatory power. They are replaced with sectoral variables not yet considered and include the capital-to-asset ratio (CAR) and a house price index.

The results are presented in Table 1.6 and should be contrasted with those of Table 1.4. As before the GDP growth rate, private-credit-to-GDP rate, real-interest rate and exposure to capital flow reversals remain among the most significant variables. However neither the leverage ratio nor the deposit-insurance variable is significant in these models. Real-estate price increases are significantly negatively associated with crises, contrary to expectations. This may illustrate that real-estate price growth is more reflective of the benefits of increased economic activity rather than as a signal of possible property bubbles and/or troubled banking sectors.

The regressions deliver an improvement in terms of total correct crisis (as well as no-crisis) predictions relative to Table 1.4. These range from 73% to 81% in terms of overall correct predictions, representing a marked improvement upon the 38% to 55% achieved in Table 1.4. We conclude that more appropriately constituted samples, combining macroeconomic and sectoral variables, are better suited for predicting in-

TABLE 1.6					
	(1)	(2)	(3)	(4)	(5)
Capital to Assets (Leverage) Ratio %	-0.107	-0.080	0.055	0.079	-0.176
	(0.086)	(0.089)	(0.099)	(0.101)	(0.236)
GDP Growth Rate	-0.337***	-0.356***	-0.352***	-0.361***	-0.313
	(0.074)	(0.076)	(0.083)	(0.085)	(0.200)
Real Interest Rate	0.066**	0.067**	0.083**	0.091**	0.026
	(0.029)	(0.030)	(0.037)	(0.039)	(0.290)
M2 Money to Forex Reserves %		0.003**	0.002**	0.002**	0.002
		(0.001)	(0.001)	(0.001)	(0.002)
Private Credit to GDP %			0.017***	0.017***	0.028**
			(0.005)	(0.005)	(0.013)
Deposit Insurance Dummy Variable				0.696	0.028
				(0.672)	(1.377)
House Price Index Growth Rate					-0.320**
					(0.137)
Constant	-1.575**	-1.911***	-4.618***	-5.298***	-4.379*
	(0.623)	(0.679)	(1.117)	(1.309)	(2.405)
Summary Results:					
No. Observations	417	400	398	387	162
No. Systemic Crisis Episodes	24	24	24	24	13
Akaike Information Criterion (AIC Score)	151.0	142.2	133.1	132.2	58.66
Model Chi2	29.56	53.68	34.20	36.12	45.97
Total Correct In-Sample Predictions %	73.47	75.55	75.18	75.51	80.86
Correct Crisis Predictions %	70.83	75	79.17	79.17	84.62
Correct No-Crisis Predictions %	73.63	75.58	74.93	75.27	80.54
Degrees of Freedom	3	4	5	6	7
Model Significance - P Value	0.00	0.00	0.00	0.00	0.00
Log Likelihood	-73.48	-68.62	-63.55	-62.60	-25.33

This table introduces some modifications to Tables 1.3 and 1.4. Non significant variables from Tables 1.3 and 1.4 are omitted and some new sectoral specific variables are introduced including leverage ratio (capital to asset ratio) and house price index. The panel is panel A data (with time frame 1980 - 2010) and using the same countries as per Tables 1.3 and 1.4. The definition of what constitutes a systemic crisis is based upon Laeven & Valencia (2013) as per Table 1.1. All rows for a country are removed after the first crisis is recorded due to endogeneity concerns post crisis. Statistical significance is denoted by ***, **, * for the 1%, 5%, 10% levels respectively.

sample crises. However the findings need to be set in a proper context. The number of observations and crisis episodes in Table 1.6 is significantly smaller than in Table 1.4 due to the dearth of capital-to-asset adequacy ratio and house price index data. This motivates the creation of our second panel, i.e. panel B, and so we now turn to analysing sectoral data in more detail.

The data comprising panel B data has been extracted (almost) exclusively from bank balance sheets, enabling us to analyse sectoral-centric models in the absence of any macroeconomic controls. In turn we contrast the performance of such sector-centric models with their macroeconomic-centric counterparts, over the period 1998-2011. Several new explanatory variables are introduced, the rationale for which was described in section 1.4 above.

The results are presented in Table 1.7. Bank Z-score is significantly negative in all regressions as expected, highlighting the importance of earnings and capital / reserves to bank stability. Private-credit-to-GDP rates are also significant, showing that the level of indebtedness of a country relative to its income contributes strongly to the likelihood of a systemic banking crisis. The bank-credit-to-deposit ratio also takes on the expected sign, i.e. the more multiples of deposit units invested the higher the risk exposure of banks, however this is only significant at the 5% level in one out of five regressions. This result, coupled with the more-significant non-performing-loan coefficient, exposes the importance of loan quality from a systemic stability perspective.

Neither the deposits-to-total-assets variable nor the net-interest-margin is significant. So far all of our asset-dependent ratios, including the capital-to-assets ratio of Table 1.4, have invariably been reported as insignificant from a systemic crisis perspective. This is surprising, given our knowledge of the GFC being associated with a downwards liquidity spiral which in turn reflected institutional investors'/depositors' concerns over rapidly-declining asset values and associated

TABLE 1.7

	(1)	(2)	(3)	(4)	(5)	(6)
Bank Z-Score	-0.086**	-0.106***	-0.104**	-0.105**	-0.090**	-0.113**
	(0.036)	(0.040)	(0.043)	(0.042)	(0.045)	(0.050)
Private Credit to GDP %	0.015***	0.011**	0.011**	0.009*	0.009*	0.018**
	(0.004)	(0.004)	(0.005)	(0.005)	(0.006)	(0.009)
Private Credit Growth Rate lagged 2 years	0.008	-0.002	0.003	0.004	-0.002	0.002
	(0.013)	(0.015)	(0.015)	(0.016)	(0.023)	(0.021)
Bank Concentration	-0.007	-0.008	-0.010	-0.011	-0.015	-0.012
	(0.009)	(0.009)	(0.009)	(0.009)	(0.011)	(0.012)
Bank Credit to Deposit Ratio		0.011**	0.007	0.005	0.003	0.000
		(0.004)	(0.005)	(0.006)	(0.007)	(0.007)
Bank Deposits to Total Assets Ratio			0.020	-0.003	0.066	0.047
			(0.035)	(0.038)	(0.080)	(0.081)
Net Interest Margin				-0.196	-0.148	-0.156
				(0.151)	(0.216)	(0.226)
Non-performing Loans to Total Loans %					0.137**	0.131**
					(0.061)	(0.062)
Non-resident Loans to Total Loans %						-0.008
						(0.006)
Constant	-3.139***	-3.798***	-5.171*	-1.937	-6.595	-4.790
	(0.634)	(0.704)	(3.003)	(3.411)	(7.782)	(7.964)
Summary Results:						
No. Observations	541	541	499	480	347	347
No. Systemic Crisis Episodes	35	35	35	35	35	35
Akaike Information Criterion (AIC Score)	143.3	138.9	129.4	127.1	112.3	111.5
Model Chi2	14.49	50.54	47.24	41.64	26.02	20.23
Total Correct In-Sample Predictions %	62.84	63.66	57.51	52.73	37.02	37.02
Correct Crisis Predictions %	80	88.57	88.57	85.71	85.71	88.57
Correct No-Crisis Predictions %	61.98	62.41	55.95	51.08	34.58	34.43
Degrees of Freedom	4	5	6	7	9	10
Model Significance - P Value	0.01	0.00	0.00	0.00	0.00	0.03
Log Likelihood	-69.16	-66.43	-61.18	-59.55	-50.64	-49.73

This table reports the results of regressing bank Balance Sheet data against a binary dependent variable that takes the value of "1" if a country experiences a systemic banking crisis in a panel with one row per country / year combination and "0" otherwise. The panel is Panel B as described in Appendix 1 below, covering the period 1998 to 2011. The dependent variable data comes from Laeven & Valencia (2013 Updated) database of systemic banking crises. Bank Z Score data comes from the Financial Structures and development database (Demirguc-Kunt, Beck & Levine (2013). All rows for a country are removed from the panel after the first occurrence of a systemic banking crisis is recorded to mitigate feedback from dependent variable to control variables. Statistical significance is denoted by ***, **, * for the 1%, 5% and 10% levels respectively.

credit risk increases (see Brunnermeier (2008)). The GFC patently demonstrates the extent to which banks were exposed to a large asset-valuation shock, however if those assets are not comprehensively reported on bank balance sheets the fact that the GFC was not signalled well in advance is perhaps not so surprising after all. Our findings show the importance of maintaining all assets "on" rather than "off" balance sheet, or at least that all assets must be subjected to the same degree of regulatory control and are not germane only to the "on" balance sheet items. Our concern is reinforced when one considers that one of the most important macro-prudential measures, i.e. Tier-1 Capital, has risk-weighted assets as its denominator yet this measure also does not show up as being a significant systemic crisis determinant (see Chapter 2).

Whereas Table 1.6 demonstrates how sudden capital flow reversals may be associated with bank instability, this result is not driven by the departure of non-resident banks in troubled times, as the Table 1.7 coefficient for non-resident-bank-loans-to-GDP variable illustrates. Bruno and Shin (2013) argue that it was a capital flow disturbance, resulting from a lending maturity mismatch where banks borrowed internationally but lent domestically, which was a major GFC contributory factor. Our result provides further evidence of that. We also note that bank concentration is not significant in any sectoral-centric regression, contrary to Beck et al.'s (2006) findings which are based primarily on macroeconomic variables (see also Eichler and Sobański (2012)).

As far as in-sample predictive power is concerned the results are mixed. In Table 1.7 the total correct prediction rate ranges from 37%-63% whereas in Table 1.3 the range is 46%-67%. Accurate crisis predictions range from 80%-89% versus 68%-81% in Table 1.3, representing a significant improvement. This is offset by the relative deterioration of correct no-crisis predictions, especially when we control for non-performing loans and non-resident-loans-to-total-loans, where Table 1.3 performs considerably better. One might argue that logit regressions involving exclusively balance sheet data over-predict crises, however one could also argue that the higher crisis likelihoods reported using sectoral-centric variables represent a better alignment between systemic banking crises and their underlying sectoral variables than is the case when macroeconomic variables are employed.

Our final objective is to develop a cluster of control variables for use in future research and for assessing the appropriateness of different systemic risk index measures currently under development (see Acharya et al. (2010) and Adrian and Brunnermeier (2011)). We present these results in Table 1.8. The first specification contains only sectoral variables, all of which are significant, including Bank Z-Score, bank-credit-to-deposit ratio, non-performing loan levels and net-interest-margins. These four factors jointly capture several aspects of systemic bank risk exposure. The second column details those traditional macroeconomic factors invariably reported in the literature as systemic crisis determinants. These include GDP growth-rate, real-interest rate and inflation. As before, when considered in isolation, all the coefficients are significant.

Combining both sets of variables, as per regression 3), we find that only Bank Z-Score and NPL levels are the variables to lose a degree of significance. The lower AIC score of regression 3 relative to regression 1, suggests that a combination of sectoral and proven macroeconomic variables yields better models. They are relatively more successful at predicting crises although this is at the expense of predicting crises in years when none in fact were recorded. As always regulatory authorities must weigh the cost associated with overlooking a crisis versus the cost of taking remedial action when none in fact is warranted.

TABLE 1.8			
	(1)	(2)	(3)
Bank Z-Score	-0.069***		-0.053*
	(0.025)		(0.027)
Bank Credit to Deposit Ratio	0.009**		0.009**
	(0.004)		(0.004)
Non-performing Loans to Total Loans %	0.094***		0.068**
	(0.027)		(0.031)
Net Interest Margin	-0.211**		-0.231**
	(0.097)		(0.108)
GDP Growth Rate		-0.235***	-0.142**
		(0.046)	(0.057)
Real Interest Rate		0.030**	0.040*
		(0.014)	(0.021)
Inflation		0.017	0.028
		(0.012)	(0.017)
Constant	-2.969***	-2.783***	-2.908***
	(0.814)	(0.258)	(0.883)
Summary Results:			
No. Observations	511	732	511
No. Systemic Crisis Episodes	35	35	35
Akaike Information Criterion (AIC Score)	196.5	245.7	186.4
Model Chi2	32.63	42.94	36.13
Total Correct In-Sample Predictions %	41.53	76.64	47.81
Correct Crisis Predictions %	74.29	65.71	77.14
Correct No-Crisis Predictions %	39.89	77.19	46.34
Degrees of Freedom	4	3	7
Model Significance - P Value	0.00	0.00	0.00
Log Likelihood	-95.76	-120.8	-89.19

This table presents the control cluster results using Panel B data. The model is logistic with a binary systemic crisis dependent variable as driven by the Laeven & Valencia (2013) database. Regression 1 shows only sectoral variables all of which are significant. Regression 2 shows only macroeconomic variables which past research have shown to be consistently significant, as repeated here. Regression shows both sets of variables combined. Statistical significance is denoted by ***, **, * for the 1%, 5% and 10% levels respectively.

1.7. Robustness Checks

The results relating to the various pooled logit regressions are presented in Tables 1.3 thru 1.8, with detailed panel A and B descriptions described in the appendices. We present alternatives to pooled logit specifications in Table 1.9 for comparison purposes. Whereas pooled logit has been the most common method used to identify determinants in the past the technique has been criticised for its inherent assumption that all countries have the same relationship between systemic crises and the vector of explanatory variables over the panel's time-period. A fixed-effects (FE) model (see Table 1.9 regression 2) can be adopted to capture inter-country differences via the intercept coefficient (the regression constant). However the use of fixed-effects estimation vis-à-vis systemic crisis determinants is not preferred because no time-invariant factors can be included. Therefore countries without any crisis during our sample period must be omitted due to model collinearity between the dependent variable (all zeroes for a non-crisis country) and the dummy variable identifying the country (all ones for that country). This restriction results in greatly reduced sample sizes (from 387 to 154) and leaves the analysis absent any non-crisis country controls, which is also not preferred as it leaves the model open to sample selection bias criticism. Interestingly the fixed effects specification identifies the same determinants with the same signs as the pooled logit specification, thus increasing our confidence in the pooled logit alternative. We conclude that little is gained as a result of adopting fixed effects specifications which have the considerable disadvantages of yielding reduced sample sizes as well resulting in over-predicting models (the FE specification only correctly anticipates 1% of non-crisis outcomes).

Another alternative is to use a random-effects (RE) specification (see Table 1.9 regression 3), whereby an assumption is made that the individual specific differences across countries are not

TABLE 1.9			
	(1)	(2)	(3)
Capital to Assets (Leverage) Ratio %	0.079	0.131	0.079
	(0.101)	(0.434)	(0.101)
GDP Growth Rate	-0.361***	-0.517***	-0.361***
	(0.085)	(0.189)	(0.085)
Real Interest Rate	0.091**	0.083	0.091**
	(0.039)	(0.187)	(0.039)
M2 Money to Forex Reserves %	0.002**	0.029	0.002**
	(0.001)	(0.028)	(0.001)
Private Credit to GDP %	0.017***	0.227***	0.017***
	(0.005)	(0.081)	(0.005)
Deposit Insurance Dummy Variable	0.696	-0.595	0.697
	(0.672)	(11.927)	(0.672)
Constant	-5.298***		-5.299***
	(1.309)		(1.309)
Summary Results:			
No. Observations	387	154	387
No. Systemic Crisis Episodes	24	24	24
Akaike Information Criterion (AIC Score)	132.2	24.63	133.2
Model Chi2	36.12	53.12	31.33
Total Correct In-Sample Predictions %	75.51	7.071	75.51
Correct Crisis Predictions %	79.17	100	79.17
Correct No-crisis Predictions %	75.27	1.075	75.27
Model Degrees of Freedom	6	6	6
Model Significance - P Value	0.00	0.00	0.00
Log Likelihood	-62.60	-9.314	-62.60

This table illustrates a model robustness check. Compare the results with regression 4 of Table 1.6. In (1) the same values are reported where the model is estimated with pooled logit coefficients. In (2) the same variables are estimated using a Fixed Effects specification. In (3) a random effects specification is employed. (1) and (3) match closely with no tangible gain from the strong assumption of random effects models that individual effects are not correlated with the explanatory variables. The fixed effects model results in a large loss of observations and over-predicts crisis. Pooled logit is preferred (see Davis & Karim (2008))

TABLE 1.10						
	Country Removed					
	Benchmark	UK	USA	Germany	Sweden	Russia
Bank Z-Score	-0.090**	-0.088*	-0.120**	-0.081*	-0.090**	-0.086*
	(0.045)	(0.046)	(0.054)	(0.044)	(0.045)	(0.047)
Private Credit to GDP %	0.009*	0.008	0.008	0.010*	0.009*	0.010*
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Private Credit Growth Rate lagged 2 years	-0.002	-0.003	-0.008	-0.000	-0.002	-0.007
	(0.023)	(0.023)	(0.027)	(0.021)	(0.023)	(0.027)
Bank Concentration	-0.015	-0.016	-0.012	-0.016	-0.015	-0.012
	(0.011)	(0.012)	(0.012)	(0.012)	(0.011)	(0.012)
Bank Credit to Deposit Ratio	0.003	0.005	0.006	0.004	0.003	0.003
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Bank Deposits to Total Assets Ratio	0.066	0.065	0.087	0.071	0.066	0.074
	(0.080)	(0.079)	(0.104)	(0.082)	(0.080)	(0.087)
Net Interest Margin	-0.148	-0.166	-0.175	-0.125	-0.148	-0.221
	(0.216)	(0.217)	(0.252)	(0.220)	(0.216)	(0.233)
Non-performing Loans to Total Loans %	0.137**	0.143**	0.163**	0.142**	0.137**	0.169**
	(0.061)	(0.061)	(0.069)	(0.062)	(0.061)	(0.070)
Constant	-6.595	-6.527	-8.536	-7.258	-6.595	-6.895
	(7.782)	(7.688)	(10.042)	(7.940)	(7.782)	(8.251)
Summary Results:						
No. Observations	347	340	340	339	347	339
No. Systemic Crisis Episodes	35	34	34	34	34	34
Akaike Information Criterion (AIC Score)	112.3	105.9	101.1	104.9	111.3	103.8
Model Chi2	26.02	26.35	28.10	28.60	26.02	21.17
Total Correct In-Sample Predictions %	37.02	37.40	37.26	37.45	37.31	37.73
Correct Crisis Predictions %	85.71	85.29	88.24	85.29	85.29	88.24
Correct No-crisis Predictions %	34.58	35.03	34.74	35.08	34.93	35.23
Model Degrees of Freedom	9	9	9	9	9	9
Model Significance - P Value	0.00	0.00	0.00	0.00	0.00	0.01
Log Likelihood	-50.64	-47.95	-45.57	-47.45	-50.64	-46.88

This table illustrates the effect of removing crisis episodes from the panel on a country by country basis. The benchmark regression is regression 5 of Table 1.7. Then all observations for the UK are removed and the regression re-run. Having reinstated the UK observations, those for the United States are removed and the process repeated for each of Germany, Sweden and Russia. Standard errors are reported in parentheses below the coefficients. Significance levels are denoted by ***, ** and * at the 1%, 5% and 10% significance levels respectively. Results are robust to country of origin effects.

correlated with the explanatory variables. This overcomes the difficulty of greatly reduced sample sizes but it is a strong assumption to make. We see that the random-effects estimates are essentially identical to their pooled counterparts, increasing confidence in the earlier estimates, i.e. those achieved without having to make the strong assumption described.

Using an estimation enhancement (see Conniffe and O'Neill (2009)) we repeat our analysis whereby missing values are inferred from the distribution parameters of the available data. Doing so does not materially alter the primary results thus reducing any concerns that missing values, as are occasionally reported in Table 1.2, may be yielding inaccurate outcomes. Another robustness check involves the removal of crisis episodes via the elimination of countries from the panel. The purpose of this check is to ensure that our results are not driven by factors peculiar to any individual country. Starting with regression 5 of Table 1.7 as the benchmark, the data for the United Kingdom, United States, Germany, Sweden and Russia are removed one at a time (non-cumulatively) and the model re-estimated each time. Every country removed will have experienced at least one systemic crisis. The results are reported in Table 1.10. It can be seen that in all cases the most significant variables retain their sign and significance, with only small differences reported in coefficient estimates, statistical significance and crisis prediction statistics.

A final robustness check is included where we control specifically for the year 2008 by way of a dummy variable. Although Laeven and Valencia (2013) do not discriminate one systemic crisis from another we demonstrate that the primary results are robust to this control Table 1.11 applies the control to the results reported in Table 1.4. We see that GDP growth remains significant as does real GDP per capita. Unlike Table 1.4 real interest rates are significant in regression one, however only at the 10% level of significance, thus the central finding that this variable loses explanatory power over longer sample time-frames remains valid. We also see that the reversal of international capital flows (see Adrian and Shin (2008)) as a determinant of the

GFC is valid as this variable loses all its explanatory power to the 2008 dummy when that year is controlled for. Table 1.12 (listed in Appendix 7) shows the effect of the inclusion of a 2008 dummy variable upon the results reported in Table 1.4. The same variables are reported as being significant and with the same sign.

TABLE 1.11

	(1)	(2)	(3)
GDP Growth Rate	-0.111***	-0.106**	-0.102*
	(0.041)	(0.047)	(0.060)
Terms of Trade Change	0.003	-0.006	-0.025
	(0.014)	(0.015)	(0.019)
Depreciation of Currency	-0.002	0.009	0.014
	(0.011)	(0.011)	(0.012)
Real Interest Rate	0.018*	0.018	0.023
	(0.011)	(0.013)	(0.015)
Inflation	0.003	-0.012	-0.013
	(0.013)	(0.016)	(0.018)
Surplus Govt. Budget to GDP %	0.001	0.010	0.071
	(0.024)	(0.027)	(0.046)
M2 Money to Forex Reserves %		-0.000	0.002
		(0.000)	(0.002)
Private Credit to GDP %		0.003	0.009
		(0.005)	(0.007)
Ratio of bank liquid reserves to bank assets		-0.012	0.013
		(0.016)	(0.020)
Private Credit Growth rate, lagged 2 years		-0.002	-0.001
		(0.002)	(0.005)
Real GDP Per Capita	-0.000*	-0.000*	-0.000**
	(0.000)	(0.000)	(0.000)
Deposit Insurance Dummy Variable			0.921*
			(0.493)
Year 2008 Dummy Variable	3.385***	3.389***	3.603***
	(0.479)	(0.523)	(0.606)
Constant	-2.788***	-2.495***	-3.375***
	(0.305)	(0.463)	(0.710)
Summary Results:			
No. Observations	1,080	785	608
No. Systemic Crisis Episodes	48	46	37
Akaike Information Criterion (AIC Score)	382.9	314.6	236.3
Model Chi2	13.59	16.03	86.21
Total Correct In-Sample Predictions %	55.24	38.33	40
Correct Crisis Predictions %	60.42	78.26	75.68
Correct No-Crisis Predictions %	55.01	36.54	38.39
Degrees of Freedom	7	11	12
Model Significance - P Value	0.06	0.14	0.00
Log Likelihood	-187.5	-151.3	-111.7

This table is a duplicate of table 1.4, however we include a dummy variable to control for the effects of 2008, the year of the Global Financial Crisis when a significant number of countries reported a systemic banking crisis. Statistical significance is denoted by ***, **, * for the 1%, 5%, 10% levels respectively.

1.8. Conclusions

This paper utilises several newly-released data sources and examines the determinants of systemic banking crises in circumstances where the explanatory data has been drawn primarily from financial-services (aggregate bank balance sheet) datasets over a time-frame that spans the Global Financial Crisis. The results are compared and contrasted with those attained in earlier papers where explanatory variables are drawn principally from well-known sources such as the IMF / World Bank. Having replicated the results of the first paper to examine systemic bank crisis determinants (see Demirgüç-Kunt and Detragiache (1998)) we go on to show how these determinants behave when considered over a full business cycle. Tables 1.3, 1.4 and 1.5 show that whereas macroeconomic variables perform well as crisis determinants over a short period (up to 15 years) they lose explanatory power when measured over a longer time span (30 years). If only shallow panels are available, researchers must take the current business cycle phase into account when reporting results (see Table 1.5).

We show that short-run models encompassing such sectoral variables as leverage ratio, deposit-insurance and property prices perform at least equally as well in terms of crisis-prediction as their earlier macroeconomic-centric counterparts. In fact we show that models containing explanatory variables drawn exclusively from bank balance sheet data (see Table 1.7) over the period 1998-2011 are equally as informative as were macroeconomic variables in terms of explaining systemic crises over the period 1980-1994. However several important sectoral variables such as Bank Z-scores and non-performing loan levels are not generally available pre-1998, therefore a long-run comparison of macroeconomic versus sectoral models must wait until deeper sectoral panels become available. Nevertheless, given the importance of asset-values to each of these measures it is important that all bank assets (i.e. "off" as well as "on" balance sheet) should be subject to regulatory control.

Finally, we present a control cluster of key sectoral and macroeconomic variables which may be used in future systemic banking crisis research, particularly in matters of bank stress-testing, systemic risk model calibration and in the assessment of regulatory effectiveness.

Chapter 2

The Determinants of Systemic Banking Crises:

A Regulatory Perspective

Abstract

Using a sample of 75 developed and emerging economies covering the period 1998-2011 we show that the enhanced Basel III Accord variables Tier-1 capital and the new liquidity measure known as the Net Stable Funding Ratio (NSFR), when measured in levels, do not feature as systemic banking crisis determinants. However the compound annual growth-rate of Tier-1 capital is shown to be more significantly associated with overall financial-sector stability. Certain aspects of the regulatory environment are also shown to contribute positively towards systemic risk mitigation whereas others do not. For example by restricting the breadth of trading activities permitted to banks, banking sectors are made stable. However regimes where capital-adequacy standards are rigorously enforced are no more robust than their less strictly-enforced counterparts. We provide a model specification that performs optimally in terms of in-sample crisis versus no-crisis prediction, based upon CAMELS ratings but one which reinforces the view that modern banking crises are strongly linked with credit booms.

2.1 Introduction

At a cost in wealth terms of up to $22 trillion the 2008 Global Financial Crisis (GFC) is unprecedented in the modern era (see Weise (2012) and Melendez (2013)). Various theories regarding the cause of the crisis have been proposed. Examples include but are not limited to: 1) the flow of vast sums of cheap international capital, 2) financial liberalisation, 3) the creation of derivative instruments (e.g. Asset-Backed-Securities), 4) large-scale sub-prime lending to individuals who were likely to default, 5) too complicated / interwoven financial technologies and 6) the growth of organisations which became too-big-to-fail (see Brunnermeier (2008), Connor et al. (2010), Bruno and Shin (2013) and Lane and McQuade (2014)). Failure to properly regulate the banking system is regularly cited as one of the key ingredients enabling risk to build up in a systematically sustained manner over several years (see Brunnermeier et. al (2009), Claessens et al. (2010) and Crotty (2009)). The sudden collapse of important financial institutions such as Lehman Brothers, Citigroup, AIG and Merrill Lynch merely revealed the extent to which risk levels had accumulated but had not been fully comprehended.

As the crisis deepened those regulatory authorities with responsibility for macro-prudential standards, such as the Basel Committee for Banking Supervision (BCBS) and the Financial Stability Board (FSB), moved to underpin the financial system via the introduction of new or newly-strengthened regulations governing bank operations. These regulations are more commonly known as the Basel III Accord (see Bank for International Settlements (2011a) and Wellink (2009)).[23] Minimum Tier-1 Capital levels, that is high-quality unencumbered shareholder

[23] Under the Basel Committee for Banking Supervision (BCBS), a unit within the Bank for International Settlements (BIS), these amendments to the existing set of bank regulations became known as the Basel III Accord and are sometimes simply referred to as Basel III.

equity plus disclosed reserves, were raised to 8.5% (of total risk-weighted assets).[24] New liquidity measures were established to ensure banks could meet all of their known payment obligations within specific time-frames and that their funding positions are more resilient. For example a liquidity standard entailing a 12 month outlook, called the Net Stable Funding Ratio (NSFR), has been introduced. The stated purpose of these measures is to bolster the resilience of banks to large economic shocks, the crucial assumption being that if each bank in its own right demonstrates fortitude in the face of significant market disturbances then the banking sector as a whole must be more robust.[25]

The purpose of this paper is to empirically examine the effectiveness of the systemic risk-reduction measures proposed as part of Basel III. Our objective is to test the design / proposed revamp of the regulatory architecture in terms of its potential to reduce risk. There are several issues worth considering. Have regulatory authorities exhaustively targeted all key systemic risk factors falling within their remit? How effective are these new regulatory standards in terms of reducing the probability of systemic crisis events emerging? We question the utility of these new measures in crisis-prediction terms if they are to be incorporated into early-warning systems. If not we ask what factors should be considered instead?

Given the destructive power of banking crises it is natural to assume the enhanced regulatory standards will resolve whatever regulatory deficiencies/lacunae existed prior to 2008 and will help prevent their reoccurrence in future (see Bank for International Settlements (2011a) and Wellink (2009)). However these enhancements have not been universally welcomed. Flannery

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[24] This includes the mandatory 2.5% capital conservation buffer.

[25] This assumption is sometimes described as follows: aggregate micro-prudential stability equals macro-prudential stability (see Brunnermeier et al. (2009) and Chapter 3).

(2009) highlights how several failed institutions were well-capitalised according to the amended Basel III standards. Haldane (2010) criticises the cost and complexity of Basel III compliance and shows how in many disciplines simple heuristics and rule-of-thumb guidelines yield better risk-reward outcomes. Acharya and Richardson (2009) demonstrate how banks move assets off balance sheet, thereby circumventing regulatory inspection and in the process rendering such controls redundant. Finally, Duttweiler (2010) highlights deficiencies in the new liquidity standards and warns of the dangers of banks potentially becoming periodically illiquid. This risk is highest in circumstances where large corporations / banks avail of previously-agreed, contractually-binding credit facilities in the wake of an economic downturn. In extreme cases, i.e. during systemic crises, short-term funding for bank assets becomes increasingly difficult to source leading in turn to fire-sales of assets and extremely low money-market trading volumes (see Brunnermeier et al. (2009) and Bisias et al. (2012)).

We bring all of these strands together by focusing on three specific key questions. 1) Are the newly-strengthened capital and liquidity reserves positively (i.e. they increase the likelihood) or negatively (i.e. they reduce the likelihood) associated with systemic crises? 2) Do they make systemic crises easier to predict? Finally 3) What effect does the choice of regulatory framework have in terms of systemic stability?[26]

To answer these questions we form a sample panel, termed panel C, comprising 75 emerging and developed economies covering the period 1998-2011 (see Tables 2.1 and 2.2). Panel C's depth and breadth spans 36 systemic banking crisis episodes (see Laeven and Valencia (2013)). We utilise a logit methodology (see Demirgüç-Kunt and Detragiache (1998), Davis and Karim

[26] Throughout the paper a reference to a crisis or bank crisis is intended to mean a *systemic* bank crisis. The shorter form is used for readability purposes. The definition of what constitutes a systemic bank crisis is described in the first entry of Table 7 of the Appendices.

(2008), Schaeck et al. (2009) and Eichler and Sobański (2012)) and rely on several new banking-sector databases (see Laeven and Valencia (2013), Cihák et al. (2013) and Barth et al. (2013)).

By taking this approach we make several contributions to the literature. We provide empirical evidence in favour of enhanced standards by showing how the growth of Tier-1 capital may significantly reduce the odds of systemic banking crises. Next we find that more stringent bank-license and trading restrictions represent macro-prudential stability enhancement measures. However we also provide empirical evidence of Basel III deficiencies. In particular we demonstrate how Tier-1 capital (measured in levels), the under-provisioning of Tier-1 capital, stricter enforcement of capital-adequacy standards and the NSFR ratio are all insignificant systemic-crisis determinants. In fact, we find that their inclusion in early warning systems may actually make such crises more difficult to predict.

Other contributions include the following. This paper is one of relatively few papers to provide a macro-prudential effectiveness examination of Tier-1 capital and one of the first to consider the role of the NSFR in systemic stability terms. By conducting a multi-faceted structural examination of the regulatory environment on a per-country basis we identify the systemic crisis-related focal points for future policy makers. Finally we identify a regression model which synthesises all of our Chapter 1 and 2 findings in such a way that it performs optimally as an in-sample systemic crisis prediction tool. Taken together our results have important post-GFC ramifications for those involved in the maintenance and enhancement of future early warning systems.

The paper proceeds as follows. Section 2.2 presents a review of the most important and relevant prior literature. In section 2.3 we describe the econometric model employed before presenting an overview of our data in section 2.4. The order in which the research was conducted together with the associated rationale is outlined in section 2.5. The results are presented in detail in section 2.6. A description of our robustness checks is provided in section 2.7 and section 2.8 concludes.

2.2. Literature Review

A systemic banking crisis is an event meeting two conditions: 1) there are significant signs of financial distress in the banking system (as indicated by significant bank runs, losses in the banking system, and/or bank liquidations) and 2) significant banking policy intervention measures in response to significant losses in the banking system appear (see Laeven and Valencia (2013)). Such crises have occurred many times historically, however as we are primarily concerned with recent crises and with the GFC in particular we restrict the literature review to papers published since the beginning of the high-tech era.

The seminal theoretical paper by Diamond and Dybvig (1983) shows how a run on a single bank's deposits can lead to the collapse of multiple banks as panic spreads and deposits are systematically depleted. The creation of institutions such as the Federal Deposit-insurance Corporation helped to mitigate this, but new risks emerged as financial liberalisation came to prominence during the 1990s. As banks became increasingly de-regulated their products and operations increased in breadth and complexity. Aided and abetted by enormous technological advances financial systems became increasingly interconnected and inter-dependent. Towards the turn of the millennium there were clearly multiple new sources of systemic bank risk as evidenced by the wave of crises in the mid-to-late 1990s (see Table 2.1).

These risk-related factors were first identified by Demirgüç-Kunt and Detragiache (1998). Using a pooled logit model they find that systemic crises are associated with low GDP growth-rates, high real-interest and inflation rates and that they occur in countries where there are explicit deposit-insurance schemes. In a more recent paper they reconfirm these findings and also highlight the importance of capital flow disturbances as well as the level of credit extended to the private sector (see also Demirgüç-Kunt and Detragiache (2002)).[27] Barth et al. (2004) examine the durability of banks in the context of various regulatory controls. They find that the imposition of bank trading restrictions and higher capital levels has a stabilising effect. However their dataset is limited to the period 1990-1997 and does not include any of the major recent crises or consider the corresponding regulatory changes.

Beck et al. (2006), in an identical framework, examine sectoral stability from a variety of perspectives including the degree of bank concentration, the regulatory environment and the level of development of the intra-country legal system. They find that crises are less likely in countries with more concentrated banking systems and where there are restrictions on bank competition and trading activities. Using minor methodological variations other researchers reiterate the destabilising influence of deposit-insurance schemes (see Hoggarth et al. (2005a)), low economic growth-rates and high inflation (see Von Hagen and Ho (2007) and Davis and Karim (2008)), and weakening terms-of-trade (see Davis and Karim (2008)).[28]

A useful exposition of the various studies and econometric techniques deployed is contained in Eichler and Sobański (2012). They use high-frequency data in an adapted Merton (1974) model and re-assert the vulnerability of banks on a micro-prudential level to low GDP growth-rates and high real-interest rates. Appendix 1 of their paper makes clear that past studies share a common shortcoming in that none of the sample datasets adequately cover the period up to and including the GFC. It is also apparent that relatively few papers examine either regulatory or liquidity

[27] In their paper the ratio of broad money to foreign-exchange reserves is considered a proxy for capital flows.
[28] Sometimes probit models are used instead of logit but the basic approach yields similar results.

concerns, both of which are now inextricably linked with the GFC-synonymous term "credit crunch".

Barrell et al. (2010) examine factors such as capital-adequacy, liquidity and property prices as potential crisis determinants, all of which they find to be significant. While similar in ethos to this paper there are considerable differences. The authors do not consider any of the proposed GFC regulatory-response measures. Their panel only contains data on 14 OECD countries and, most importantly, their logit model's dependent variable is triggered for both systemic as well as non-systemic banking crises. Therefore their model generates predicted probabilities of crises generally which are likely to be higher than the corresponding probabilities of systemic banking crises and their determinants cannot be said to be specifically related to systemic events.

Other important contributions include Kaminsky and Reinhart (1999) and Davis and Karim (2008). Using signals approach models they show that, in addition to low GDP growth-rates, appreciation of real exchange rates, low export growth-rates and rapid financial liberalisation are significant factors signalling the onset of a financial and/or currency crisis. Finally, Honohan (1999) demonstrates how banking crises can arise as a result of risky lending activities carried out by managers taking advantage of "informational externalities", i.e. the asymmetric information they possess relating to the risk-level incorporated into their loan books, and the put-option inherent in explicit state-backed deposit-insurance schemes.

2.3. Methodology

To test whether a regulatory measure represents a systemic banking crisis determinant we make use of a pooled logit model (see Chapter 1, section 1.3 for a full description). Note, once again the dependent variable, P(i,t) is a dummy variable with a value of 1 if country "i" experiences a systemic banking crisis in year "t" and 0 otherwise. The coefficients are determined by maximising the following log likelihood function:

$$\text{Argmax}(\beta): \quad LnL = \sum_{t=1}^{T} \sum_{i=1}^{N} \mathrm{P}(i,t)\ln[F(W^{'}_{i,t}\beta)] + (1-P(i,t))\ln[1-F((W^{'}_{i;t}\beta)] \qquad \textbf{(2.1)}$$

Here $W^{'}_{i,t}$ is a row vector comprising two sub-vectors $X^{'}_{i,t}$ and $Z^{'}_{i,t}$ arranged alongside each other, i.e. W'=[X':Z']. The latter represents the various regulatory variables we wish to analyse whereas $X^{'}_{i,t}$ represents a control cluster of ex-ante known significant systemic crisis determinants (see Chapter 1 and section 2.4 below for details). As such (2.1) is identical in form to equation (1.9) with the exception that we have separated our explanatory variables into two groupings for the sake of clarity.

2.4. Data

A panel of data, panel C, covering 75 developed / developing countries and spanning the period 1998-2011 has been compiled. One of the key variables is the logit model's binary dependent variable. This is sourced via Laeven and Valencia's (2013) database where details such as the country involved, start and end-dates as well as crisis descriptions are provided.[29] The most important explanatory variables we test include Tier-1 capital, Net Stable Funding Ratio, and distance to minimum Basel III Tier-1 capital standards, which we set at 8.5% of risk-weighted assets.[30] Data for these variables is sourced via the Financial Development and Structures dataset (see Cihák et al. (2013)). The other important explanatory variables we wish to examine relate to

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[29] The panel start date of 1998 is driven by data availability considerations for many countries in the pre-Basel Accord era.

[30] Another Basel III liquidity metric, the Liquidity Coverage Ratio, has also been proposed. However it has a 30-day operational window and to-date annual report data relating to this variable is unavailable. As the unit of time measures are years no suitable proxy for the LCR has been determined.

the intra-country regulatory framework, data for which is sourced via the Barth et al. (2013) regulatory survey dataset. This repository contains a summary of up to 180 central-banks' responses to survey questions first posed in 1999 and repeated in each of 2003, 2007 and 2011.[31]

Tier-1 capital is a measure that has received significant regulatory attention since the introduction of the first Basel Accord in 1998. It represents the ratio of high-quality capital to risk-weighted assets. Thus Tier-1 capital is unencumbered capital such as shareholder equity plus disclosed reserves which are always available for loss-assimilation purposes. The denominator applies risk-weights to bank assets with the more risky assets assigned higher weightings thereby making it more onerous to achieve the minimum standards. Under Basel III the Tier-1 threshold is set at 8.5%. Given its regulatory pre-eminence, we anticipate significantly negative Tier-1 capital coefficients in our logit regressions, meaning the higher the ratio of capital to risk-weighted assets the lower the odds of a systemic crisis. We also envisage the actual to minimum Tier-1 gap will be reported with significantly positive coefficients for the same reason.

The Net Stable Funding Ratio (NSFR) is a new liquidity-based regulatory standard. It is defined as follows (see Bank for International Settlements (2010));

$$\frac{\text{Available Amount of Stable Funding}}{\text{Required Amount of Stable Funding}} > 100\%$$

The measure will come into full force by the end of 2018, but in the interim banks are required to progressively move towards this position and to report their progress via their annual reports. As this is a new standard historical data is not directly available. We are required to make use of a

[31] Prior to 1999, regulatory framework data for banking systems was not maintained or reported in any globally-consistent manner.

proxy variable, one readily available in relevant datasets and which represents as close a match as possible to NSFR. We opt for the ratio of liquid assets to deposits plus short term funding for several reasons. First this variable is a liquidity metric readily available in the Financial Structures and Development database (see Cihák et al (2013)). As such it yields us with relevant liquidity data spanning the full depth and breadth of our panel. Secondly, we recognise that a second Basel III liquidity measure, the Liquidity Coverage Ratio (LCR) was also introduced as a complementary measure to NSFR. This is defined as follows:

$$\frac{\text{Stock of high-quality liquid assets}}{\text{Total net cash outflows over the next 30 calendar days}} > 100\%$$

The LCR is intended to ensure that banks have enough working capital in the coming 30 days to meet payment obligations as and when they fall due without having to resort to short-term borrowing. In the LCR denominator provision is made for a potential run-off of retail deposits in the coming 30 days (see Bank for International Settlements (2010). Prior research by the author (H.Dip. and Master Theses) have shown that the ratio of liquid assets to deposits plus short-term funds comprises the majority of the information content of the LCR for Irish banks. Therefore our choice of proxy variable is strongly related to LCR except that ours is measured at the annual level via the relevant Financial Structures dataset. Thus our proxy is, essentially, a 12-month measure of the LCR which in turn is related to the scope and purpose of the NSFR. For these reasons our proxy variable is justified as being as close a match to NSFR as is possible given the data limitations surrounding NSFR generally.

The Tier-1 delta variable measures, in absolute terms, how far the Tier-1 capital of a country's banking system is from the minimum Basel III threshold. Our primary objective is to understand whether the under-provisioning of a banking system's Tier-1 capital relative to the threshold increases the likelihood of systemic crises. For this purpose we make use of a dummy variable in the regressions which is set to the value 1 if Tier-1 capital levels are below the threshold. Theory suggests that under-capitalised banks are susceptible to insolvency in circumstances involving only moderate trading losses. By contrast, over-capitalisation of banks may have the effect of dampening investment activity, due to banks withholding finance, possibly damaging GDP growth-rates and which earlier literature has shown to be significantly associated with systemic crises (see Bank for International Settlements (2011b) and Chapter 1).

The capital regulation index measures how stringent the capital-adequacy requirements are and the extent to which they are enforced locally, with higher values representing more tightly-regulated sectors. The index range is from 0-10. If we assume stricter enforcement yields more robust banking sectors, we anticipate significantly negative logit coefficients. The securities-trading restrictions index measures the extent to which aspects of banks' trading-desk operations are permitted. The index has a range from 1 (i.e. no securities-trading restrictions exist) to 4 (i.e. securities-trading activities are completely prohibited). Connor et al. (2010) highlight the role played by banks accumulating enormous positions in asset-backed financial instruments in the run-up to the GFC, therefore this index is also anticipated as being significantly negatively associated with systemic crises. In several regressions we include the banking-entrants restrictions index. This variable captures the level of difficulty associated with securing a bank license, in that the higher the value the more difficult it is to secure the license. Allen and Gale (2000, 2003) using a theoretical model find that concentrated banking sectors are more prone to financial instability whereas Beck et al. (2006) report the opposite based upon empirical findings.

The overall trading restrictions index (which ranges from 3-12) is a measure of the extent to which banks are curtailed from diversifying operations across multiple service lines. For example retail banks may be restricted in terms of certain investment-banking service offerings or from offering insurance-underwriting services. No ex-ante assumption is made about this variable.

Banks may become more stable and less prone to shocks if earnings are derived from diversified service offerings. On the other hand expertise and resources may become thinly spread where banks try to compete along too many service lines.

Summary statistics for these key variables are shown in Tables 2.1 and 2.2 below. Table 2.1 lists countries that experienced a systemic crisis at some stage during the 1998-2011 period whereas Table 2.2 lists those countries that never experienced a systemic crisis throughout these years. For each of the key variables the average, minimum and maximum values are provided for each sub-sample. Some interesting statistics emerge. The average Tier-1 capital is 14% in countries that experienced a systemic crisis but only 12.5% in countries that never experienced a crisis, a result supporting Flannery's (2009) contention as outlined above. However, it is also the case that crisis countries are farther on average from the Tier-1 minimum Basel III standard than non-crisis countries (5.6% versus 4% respectively). The average Net Stable Funding Ratio for both categories is almost identical, suggesting that this variable may not play a significant role as a crisis determinant in our regressions.

The no-crisis bloc of countries is, on average, more strictly regulated in terms of overall and securities trading activities. However these countries appear to experience slightly less-strictly-enforced capital-adequacy environments than their crisis-bloc counterparts (average 6.2 versus 6.7 respectively). These findings appear counter-intuitive, especially as far as Tier-1 capital standards are concerned. Under the various Basel accords there has been a persistent upward trend in terms of minimum capital-adequacy thresholds. Therefore a reasonable expectation is that higher minimum levels ought to be associated with greater stability, with tighter adherence / enforcement of those standards reinforcing such stability. However the data suggests otherwise and may represent a case-in-point of Goodhart's (1975) Law, i.e. "when a measure becomes a target it ceases to be a good measure".

We examine this issue further in Table 2.3 below. Here, summary statistics by key variables are decomposed into full sample, crisis and no-crisis sub-categories. So, for instance, the sample average Tier-1 capital is 13.22% but when crisis years only are measured the average Tier-1 capital is actually slightly higher at 13.45% during those years, which appears contrary to what regulators would expect given the expectation that high levels of unencumbered capital (Tier-1) ought to be associated with more resilient banking systems.

The corresponding average Tier-1 capital, measured across the no-crisis years, is 13.19%. As before average Tier-1 capital is higher during crisis years than in no-crisis years, but once again average distance from the minimum 8.5% Basel III threshold is also higher at 4.95% than it is during the no-crisis years (i.e. 4.69%). Another surprising and possibly counter-intuitive statistic is shown in that the Net Stable Funding Ratio proxy is higher on average in crisis years (38.72%) than it is in the no-crisis years (37.07%).

In relation to the regulatory framework data the average capital regulation index value does not vary across crisis versus no-crisis groupings but remains a consistent 6.19 on average. However both the securities trading restrictions index and the overall trading restrictions index are higher on average in no-crisis years than they are during crisis years. Overall Tables 2.1-2.3 are suggestive of some of the key findings we report in the results section.

The variables listed in Table 2.3 represent the Z vector of key regulatory factors as described in section 2.3 above.

TABLE 2.1

		Tier 1 Capital			NSFR			Tier 1 Delta			Overall Capital Regulation Index			Securities Trading Restrictions Index			Overall Trading Restrictions Index		
Country	**Crisis Year(s)**	**Avg**	**Min**	**Max**	**Avg**	**Min**	**Max**	**Avg**	**Min**	**Max**	**Avg**	**Min**	**Max**	**Avg**	**Min**	**Max**	**Avg**	**Min**	**Max**
Argentina	2001 - 2003	14.16	0.00	20.80	23.75	12.41	38.10	5.66	-8.50	12.30	7	5	9	2	1	2	5	3	7
Austria	2008 - 2013	13.61	11.80	15.80	39.06	27.09	55.23	5.11	3.30	7.30	4	4	4	1	1	1	5	3	6
Belgium	2008 - 2013	13.83	11.20	19.30	30.29	22.65	35.17	5.33	2.70	10.80	7	3	9	1	1	2	5	4	6
Brazil	1994 - 1998	17.26	13.80	19.00	57.19	48.09	65.30	8.76	5.30	10.50	5	5	5	2	1	2	5	3	7
Burundi	1994 - 1998	N/A	N/A	N/A	34.69	10.22	52.93	N/A	N/A	N/A	6	5	6	2	1	3	9	8	9
Colombia	1998 - 2000	14.43	10.30	17.30	24.66	18.81	31.81	5.93	1.80	8.80	6	6	7	2	2	3	10	7	12
Croatia	1998 - 1999	17.00	12.70	21.30	42.62	21.21	59.19	8.50	4.20	12.80	5	4	8	2	1	2	5	4	7
Czech Republic	1996 - 2000	13.56	11.40	17.40	45.39	24.72	68.94	5.06	2.90	8.90	4	4	4	1	1	2	7	6	7
Denmark	2008 - 2013	12.78	9.27	17.00	39.40	29.46	59.00	4.28	0.77	8.50	N/A	N/A	N/A	1	1	2	7	6	7
Ecuador	1998 - 2002	14.47	8.14	19.80	29.89	17.02	36.38	5.97	-0.36	11.30	9	9	9	4	2	4	8	8	8
France	2008 - 2013	12.02	10.20	15.81	51.93	45.84	56.67	3.52	1.70	7.31	8	8	8	1	1	1	5	4	6
Germany	2008 - 2013	13.04	11.40	16.40	39.83	26.45	133.78	4.54	2.90	7.90	6	6	8	1	1	1	5	4	6
Hungary	2008 - 2013	13.10	10.40	16.50	38.72	25.83	63.10	4.60	1.90	8.00	9	4	10	2	1	2	7	5	7
Indonesia	1997 - 2001	19.08	16.10	22.30	32.80	27.84	39.33	10.58	7.60	13.80	7	5	10	3	2	4	8	8	10
Ireland	2008 - 2013	12.43	10.60	19.20	33.05	23.45	48.50	3.93	2.10	10.70	6	3	8	1	1	1	6	5	6
Italy	2008 - 2013	11.03	10.10	12.80	45.46	29.08	56.77	2.53	1.60	4.30	5	5	6	1	1	2	7	7	8
Jamaica	1996 - 1998	10.62	0.00	26.63	26.07	17.01	50.19	2.12	-8.50	18.13	9	8	10	3	2	3	7	5	10
Japan	1997 - 2001	11.87	9.40	13.80	10.79	9.68	11.94	3.37	0.90	5.30	N/A	N/A	N/A	2	2	3	7	7	8
Latvia	2008 - 2013	13.42	10.10	17.40	37.23	23.56	46.38	4.92	1.60	8.90	7	6	9	2	1	2	5	4	6
Netherlands	2008 - 2013	12.35	10.70	14.90	43.80	22.96	84.91	3.85	2.20	6.40	6	6	8	1	1	2	5	4	5
Nigeria	2009 - 2013	14.27	0.00	23.40	70.08	34.47	86.78	5.77	-8.50	14.90	6	6	6	2	2	3	6	5	7
Philippines	1997 - 2001	16.88	15.50	18.40	25.18	11.88	36.01	8.38	7.00	9.90	8	8	8	1	1	1	8	8	8
Portugal	2008 - 2013	10.36	9.20	12.50	35.69	24.96	46.58	1.86	0.70	4.00	8	4	9	1	1	2	6	5	7
Russian Federation	2008 - 2013	17.21	11.50	20.90	41.45	26.78	51.99	8.71	3.00	12.40	7	7	7	2	1	2	5	4	6
Slovak Republic	1998 - 2002	14.62	6.60	22.40	34.77	9.51	57.18	6.12	-1.90	13.90	6	4	8	1	1	1	7	6	8
Spain	2008 - 2013	11.99	11.00	12.90	31.75	19.88	47.66	3.49	2.50	4.40	9	8	9	1	1	1	5	4	6
Swaziland	1995 - 1999	14.11	0.00	33.80	34.23	16.04	46.76	5.61	-8.50	25.30	N/A	N/A	N/A	2	2	4	10	8	10
Sweden	2008 - 2013	10.18	7.00	12.70	43.78	33.26	61.36	1.68	-1.50	4.20	4	3	4	1	1	2	5	5	6
Switzerland	2008 - 2013	13.34	11.30	17.90	59.68	55.19	65.45	4.84	2.80	9.40	7	7	7	1	1	1	4	4	5
Thailand	1997 - 2000	13.48	10.90	16.00	16.92	10.25	21.65	4.98	2.40	7.50	9	9	9	3	2	4	9	9	9
Turkey	2000 - 2001	20.22	8.20	30.90	31.34	14.34	73.29	11.72	-0.30	22.40	10	10	10	3	2	3	6	5	6
United Kingdom	2007 - 2013	13.56	12.60	15.90	50.50	36.71	61.13	5.06	4.10	7.40	7	3	8	1	1	1	4	3	5
United States	2007 - 2013	13.24	12.20	15.30	19.76	17.56	27.16	4.74	3.70	6.80	7	7	8	2	2	3	8	7	10
Uruguay	2002 - 2005	16.51	10.20	22.70	49.45	37.96	61.21	8.01	1.70	14.20	7	7	8	1	1	1	8	8	8
Venezuela, RB	1994 - 1998	16.26	12.90	25.10	27.83	16.31	38.95	7.76	4.40	16.60	4	3	9	2	2	3	8	7	9
Zambia	1995 - 1998	16.20	0.00	27.94	50.34	37.42	65.24	7.70	-8.50	19.44	N/A	N/A	N/A	1	1	1	10	10	10
Summary Statistics:																			
Average		14.07	9.33	19.21	37.48	24.61	53.95	5.57	0.83	10.71	6.7	5.7	7.8	1.7	1.3	2.1	6.6	5.6	7.4
Std. Deviation		2.37	4.33	5.10	12.33	11.13	21.15	2.37	4.33	5.10	1.63	2.01	1.74	0.72	0.47	0.99	1.67	1.91	1.71
No. of Countries		36																	
No. Observations		504																	

This table gives an overview of several key sample variables for countries that experienced a systemic crisis during the sample time-frame (1998-2011). Included are statistics relating to Tier 1 Regulatory Capital, the Net Stable Funding Ratio (NSFR), distance to default (Bank Z-Score) and the ratio of private credit to GDP. Sub-sample summary statistics are also presented. Tier 1 capital is the ratio of high-quality unencumbered capital or reserves to risk-weighted assets. NSFR is proxied by measuring the ratio of liquid assets to deposits plus short term funds. Bank Z-score measures distance to default, the higher the score the less likely a banking system is to becoming insolvent. Private credit to GDP measures the levels of credit extended to the private sector as a proportion of GDP. The crisis year is drawn from the Laeven and Valencia (2013 updated) database.

TABLE 2.2

	Tier 1 Capital %			NSFR			Tier 1 Delta			Overall Capital Regulation Index			Securities Trading Restrictions Index			Overall Trading Restrictions Index		
Country	**Avg**	**Min**	**Max**	**Avg**	**Min**	**Max**	**Avg**	**Min**	**Max**	**Avg**	**Min**	**Max**	**Avg**	**Min**	**Max**	**Avg**	**Min**	**Max**
Australia	10.54	9.60	11.90	31.79	11.60	88.18	2.04	1.10	3.40	7	7	9	2	1	2	7	6	8
Bahrain	13.51	11.55	16.54	32.03	27.38	36.85	5.01	3.05	8.04	8	8	8	1	1	1	6	5	7
Bulgaria	22.82	13.80	41.80	54.33	21.98	102.55	14.32	5.30	33.30	7	5	9	2	1	3	6	5	7
Canada	13.36	10.60	15.90	15.34	7.76	34.52	4.86	2.10	7.40	4	4	6	2	1	2	8	8	9
Congo, Rep.	N/A	N/A	N/A	68.23	41.52	93.10	N/A	N/A	N/A	1	1	1	1	1	1	6	4	7
Cyprus	10.73	5.40	12.84	35.59	19.21	49.35	2.23	-3.10	4.34	7	6	9	2	1	2	8	7	9
Egypt, Arab Rep.	12.50	7.55	16.40	35.14	25.22	51.10	4.00	-0.95	7.90	5	5	10	2	2	2	7	7	7
El Salvador	14.08	11.50	17.50	24.86	17.32	44.99	5.58	3.00	9.00	4	2	7	3	1	4	10	7	11
Estonia	15.83	11.50	22.30	28.65	16.31	48.35	7.33	3.00	13.80	8	8	8	2	1	2	6	5	8
Finland	14.23	10.50	19.10	59.29	27.02	82.59	5.73	2.00	10.60	6	6	6	2	1	2	5	4	6
Guatemala	11.47	0.00	15.90	23.30	19.07	33.15	2.97	-8.50	7.40	6	5	8	3	2	3	7	6	8
Guyana	3.14	0.00	12.12	31.13	15.85	54.84	-5.36	-8.50	3.62	5	5	9	3	1	4	7	6	7
Honduras	8.39	0.00	15.30	19.61	12.10	31.53	-0.11	-8.50	6.80	6	5	7	2	2	2	9	7	10
India	12.45	11.10	14.20	12.10	6.68	21.02	3.95	2.60	5.70	9	9	9	2	1	3	8	7	10
Israel	10.95	9.20	14.30	25.42	19.10	29.12	2.45	0.70	5.80	6	5	8	2	2	3	9	8	10
Jordan	19.03	15.90	21.70	47.05	31.84	57.44	10.53	7.40	13.20	8	7	9	1	1	3	6	5	7
Kenya	14.46	0.00	20.80	33.19	18.59	39.79	5.96	-8.50	12.30	8	8	8	2	2	3	8	6	10
Korea, Rep.	12.07	8.20	14.60	11.39	4.97	23.20	3.57	-0.30	6.10	6	4	9	2	2	3	8	7	10
Kuwait	19.82	15.60	23.70	44.36	19.62	67.20	11.32	7.10	15.20	9	9	9	1	1	1	7	5	8
Lithuania	14.45	10.30	23.80	37.68	17.26	58.13	5.95	1.80	15.30	4	3	7	2	1	2	7	6	8
Mali	N/A	N/A	N/A	30.18	21.19	38.17	N/A	N/A	N/A	7	7	7	2	2	3	7	7	9
Mexico	15.21	13.80	16.90	68.86	14.99	129.43	6.71	5.30	8.40	3	3	3	2	1	3	6	3	9
Nepal	5.67	-1.40	10.27	31.87	23.13	53.19	-2.83	-9.90	1.77	6	6	6	1	1	2	N/A	N/A	N/A
New Zealand	4.33	0.00	10.23	7.71	1.28	16.01	-4.17	-8.50	1.73	2	2	2	1	1	1	3	3	7
Niger	6.54	0.00	14.70	32.70	21.19	41.30	-1.96	-8.50	6.20	7	7	7	2	2	3	7	7	9
Norway	12.32	11.20	14.20	20.71	11.76	32.23	3.82	2.70	5.70	7	7	7	2	1	2	8	7	10
Papua New Guinea	N/A	N/A	N/A	35.37	7.95	54.62	N/A	N/A	N/A	7	7	7	4	4	4	9	8	9
Paraguay	15.33	0.00	20.90	43.20	34.27	55.92	6.83	-8.50	12.40	5	5	5	3	1	3	9	9	9
Peru	12.69	11.20	14.00	27.36	21.87	38.33	4.19	2.70	5.50	8	8	8	2	2	3	6	5	6
Romania	19.10	13.40	28.80	46.49	23.04	66.90	10.60	4.90	20.30	5	4	8	2	1	2	6	5	7
Senegal	14.85	11.10	20.60	23.09	18.53	29.77	6.35	2.60	12.10	7	7	7	2	2	3	7	7	9
Seychelles	8.16	0.00	24.20	60.04	48.69	73.31	-0.34	-8.50	15.70	6	4	8	2	1	4	7	5	8
Singapore	17.06	13.50	20.60	37.90	19.38	80.67	8.56	5.00	12.10	8	7	8	1	1	1	7	6	8
South Africa	12.91	10.10	14.90	15.09	5.45	22.12	4.41	1.60	6.40	5	5	5	2	2	2	6	5	9
Sri Lanka	0.76	0.00	10.61	38.66	19.32	52.95	-7.74	-8.50	2.11	5	5	5	1	1	2	8	4	9
Syrian Arab Republic	N/A	N/A	N/A	93.67	45.56	130.45	N/A	N/A	N/A	8	8	8	1	1	1	9	9	9
Tanzania	8.11	0.00	19.52	85.53	36.61	144.47	-0.39	-8.50	11.02	7	7	7	1	1	2	8	8	10
Togo	11.30	0.00	22.30	43.26	28.27	70.32	2.80	-8.50	13.80	7	7	7	2	2	3	7	7	9
Uganda	18.85	11.00	23.10	44.58	22.09	68.91	10.35	2.50	14.60	9	9	9	3	3	4	8	8	8
Summary Statistics:																		
Average	12.49	7.32	18.19	37.35	20.64	57.59	3.99	-1.18	9.69	6.2	5.8	7.2	1.9	1.4	2.5	7.1	6.2	8.4
Std. Deviation	4.77	5.71	6.05	18.91	10.52	30.31	4.77	5.71	6.05	1.81	2.00	1.93	0.67	0.67	0.90	1.35	1.51	1.23
No. of Countries	39																	
No. Observations	546																	

This table gives an overview of several key sample variables for countries that did not experience a systemic crisis during the sample time-frame (1998-2011). Included are statistics relating to Tier 1 Regulatory Capital, the Net Stable Funding Ratio (NSFR), distance to default (Bank Z-Score) and the ratio of private credit to GDP. Sub-sample summary statistics are also presented. Tier 1 capital is the ratio of high-quality unencumbered capital or reserves to risk-weighted assets. NSFR is proxied by measuring the ratio of liquid assets to deposits plus short term funds. Bank Z-score measures distance to default, the higher the score the less likely a banking system is to becoming insolvent. Private credit to GDP measures the levels of credit extended to the private sector as a proportion of GDP.

TABLE 2.3									
	Full Sample			Crisis Years			No-Crisis Years		
Variable	Avg	Min	Max	Avg	Min	Max	Avg	Min	Max
Tier 1 Regulatory Capital %	13.22	-1.40	41.80	13.45	0.00	22.70	13.19	-1.40	41.80
Net Stable Funding Ratio	37.26	1.28	144.47	38.72	10.12	133.78	37.07	1.28	144.47
Tier 1 Delta	4.72	-9.90	33.30	4.95	-8.50	14.20	4.69	-9.90	33.30
Capital Regulation Index	6.19	1.00	10.00	6.19	3.00	10.00	6.19	1.00	10.00
Securities Trading Restrictions Index	1.72	1.00	4.00	1.49	1.00	3.00	1.75	1.00	4.00
O verall Trading Restrictions Index	6.60	3.00	12.00	6.27	3.00	10.00	6.65	3.00	12.00

This table presents further summary statistics of the key variables examined in this paper. The statistics are drawn from the full panel C spanning 75 countries over the period 1998-2011 and can be compared with tables 1 and 2 where the data has been separated into crisis / no-crisis sub-samples. In addition to full sample statistics we provide sub-sample statistics for yeas in which our dependent variable is triggered to "1", i.e. a crisis year and the corresponding statistics for when the dependent variable was "0", meaning no-crisis was recorded.

It should be noted that there is quite a spread in the distribution of Tier-1 regulatory capital which has a range of -1.4% (Nepal in 2007) to 41.8% (Bulgaria in 1999). Hence the average value reported in Table 2.3 can mask wide variation. However over 80% of observations fall within the range of 7% to 19.5%. The full sample standard deviation for Tier-1 capital is 5.7%.

We now consider the variables comprising vector X, termed the "control cluster", and the rationale for each variable's inclusion. Without exception a variable is included in the control cluster on the basis that in earlier studies of systemic banking crises it has been consistently identified as a significant systemic crisis factor (see Chapter 1). Therefore if any of our key Z variables are shown to be significant whilst controlling for the cluster variables we know that they are capturing important aspects of systemic banking risk from a regulatory perspective.

A common feature shared by the cluster variables is their potential to impact either bank asset values or earnings. Theory states that a company becomes insolvent whenever its asset values decline below that of its liabilities.[32] Generally this requires a winding-up process or a forced sale

[32] An organisation can also be considered insolvent if it is unable to meet its payment obligations. However we are concerned with the definition of insolvency from an accounting point of view. Investopedia defines a firm as being

of assets (or of the company entirely) to occur. Therefore an economic shock with the potential to materially affect either asset values or profits has enterprise-stability implications. A failing bank may be so systemically important that its failure causes difficulties for the remaining banks in a banking system.[33] This is how systemic crises often unfold (see Brunnermeier et al. (2009)). To understand these implications in the context of the banking system a brief overview of banks raison d'etre together with a description of what we have learned from the earlier studies is necessary.

Probably the single most important function fulfilled by banks is to take *short-term* deposits and use the monies raised to extend *long-term* loans to borrowers. The full extent of the credit facilities extended by an individual bank is termed its "loan book". For decades the loan book constituted the bulk of a bank's asset base and its deposits, sourced either via individual investors or other banks, its primary liabilities. This "maturity" intermediation can, in certain circumstances, expose banks to significant risks. Such risks may become manifest as a result of large disturbances affecting the economy, the financial-services sector, or both. Therefore a range of potential shock sources has been examined in earlier studies – the results of which drive the selection of several of our X variables.

The literature shows that banking sectors are vulnerable when assets (i.e. the portfolio of loans and investments), are subjected to large valuation shocks. Demirgüç-Kunt and Detragiache (1998) demonstrate how GDP growth-rate disturbances can impact asset valuations, the consequences of which are: 1) lack of investor and borrower confidence, 2) downturn in the business cycle leading to reduced investment activity, 3) higher unemployment levels and 4)

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insolvent, from an accounting perspective, when liabilities of the organisation exceed assets. Our analysis relates to this latter definition.

[33] These difficulties may range from moderate to extreme and are termed "externalities" in the literature.

increasing inability of borrowers to meet repayment obligations. Each of the above has a negative impact upon asset values and often leads to increases in non-performing loans. Therefore GDP growth-rates form part of our control cluster.

Net-interest-margins represent an important source of bank income, these being the difference between what banks charge borrowers and pay to lenders / depositors, many of whom are other banks. From a bank's perspective there are both positive and negative outcomes relating to an interest rate shock (for the purposes of this discussion we assume an interest rate increase). On the one hand bank earnings have the potential to increase because borrowers who are subject to variable rate agreements are required to systematically pay more interest to banks. Note banks have sole discretion over what variable rates of interest are applicable as and when they see fit thus allowing them to pass whatever interest rate increases they wish to a large tranche of borrowers. Modest increases are often accompanied by an uplift in the market capitalisation of the banks as investors recognise their higher earnings potential and price the banks' securities accordingly which in turn yields a potential capital gain for shareholders. Thus a modest increase in interest rates can be valuable to banks.

However an interest rate increase (especially a large increase) has potentially negative consequences. The banks' own cost of funding will be higher and the associated increase cannot be passed on to fixed-rate borrowers (e.g. those on "Tracker" mortgages or fixed-rate agreements). This requires the banks to either pass on all of their increased costs to variable-rate borrowers or to allow their earnings to be negatively impacted. If the full extent of the rate increased is passed on then, inevitably, some borrowers will no longer be able to meet their loan repayment commitments. This results in higher levels of non-performing loans and write-off ratios which must be reflected in higher bad debt provisions. Also, fixed-income securities held as assets by the banks tend to have an inverse relationship with interest rates so a rate increase is often associated with a decline in the values of such assets. Thus the combined effect of an interest rate shock can outweigh the benefits accruing as the literature on systemic banking crises has regularly shown. Higher interest rates also make private-sector investment projects more difficult to justify via increased hurdle rates and reduce asset values as a result of higher discount factors being applied to future revenue streams. Due to its pervasive influence on bank health, interest rates have almost always featured in past analyses of crisis-related factors and are consistently shown to be systemic crisis determinants.

There are several other factors affecting bank earnings, shocks to which may result in a retrenchment of capital and/or retained earnings as losses are absorbed. In addition such shocks have the potential to affect credit-default levels, which in turn have downstream profitability and insolvency implications. Private-credit-growth-rates and private-credit-to-GDP ratios are included because in good times the level of private credit in an economy drives bank revenues. However in circumstances where borrowers have become over-extended or cannot repay loans, bank profits decline, asset values fall and shareholder equity / reserves are required to absorb whatever losses may arise. The money-supply-to-foreign-exchange-reserves level is included on the assumption that it acts as a proxy variable for the level of exposure of the banking sector to unexpected outflows of international capital, especially in the wake of an un-envisaged devaluation of the local currency (see Lane and McQuade (2014), Calvo (1998) and Bruno and Shin (2013)). If local assets are valued using local currency then there is a direct linkage between asset values and exchange rates.

Diamond and Dybvig (1983) theorise that the existence of explicit deposit-insurance in economies significantly reduces the likelihood of a systemic crisis following a deposit run. In fact empirical results show the opposite to be true. Deposit-insurance schemes appear to distort management incentives and result in high-risk loan books (see Demirgüç-Kunt and Detragiache

(1998) (2002); Barth et al. (2004) and Hoggarth et al. (2005a)). Given its proven significance a dummy variable for deposit-insurance is therefore included.

Our final X variable is the loans-to-deposits ratio. Its inclusion serves two purposes. Firstly it indicates the extent to which the bank is leveraged, i.e. how many times it has lent each unit of deposits. Secondly it is an important system-liquidity measure in that the higher the ratio the more that banking sector is reliant upon (usually more expensive) borrowed funds. Too-high a ratio also suggests banks might not have sufficient liquidity to absorb deposit shocks whereas too-low a ratio may signal that the sector is not earning as much revenue as may be optimal.

A comprehensive overview of all panel C variables, including source, description and rationale for inclusion is provided in Appendix 3 below. In addition we itemise the countries included in each regression for every table presented. This information is available in Appendices 5a and 5b.

2.5. Approach

Given the requisite data we can set about answering the key questions posed in the introduction. To reiterate: 1) are the newly-strengthened capital and liquidity reserves positively or negatively associated with systemic crises, 2) do they make systemic crises easier to predict, and 3) what impact does the choice of regulatory framework have in terms of systemic stability?

The first is answered by considering the sign (and statistical significance) of the logit-based regression coefficient for each of the Z vector variables. A positive coefficient means that the variable contributes towards the probability of sectoral instability whereas a negative coefficient means the opposite.[34]

To answer the second we proceed as first described by Demirgüç-Kunt and Detragiache (1998). A sample threshold crisis probability is established, this being the ratio of actual sample crises to total observations (approx. 5%). For each regression the corresponding predicted crisis probabilities are determined. If the predicted probability exceeds the sample threshold probability the model is assumed to "*predict*" a crisis. As a result the extent of correct and incorrect predictions can be quantified. A good econometric model should yield a high proportion of correct in-sample crisis predictions for country-year observations in which actual crises were observed. Likewise the model should also *simultaneously* correctly predict a high proportion of no-crisis outcomes when in fact no crisis was observed. By assessing the effect of a Z vector variable in a regression versus, ceteris paribus, its exclusion from the same regression we can objectively measure a specific variable's contribution towards accurate in-sample crisis predictions. Note the choice of crisis threshold at 5% is in keeping with the literature. Schularick and Taylor (2012) report financial crises as occurring in 4% of the years (1870-2008) of their observations. Demirgüç-Kunt and Detragiache (1998) report 31 crises in 546 observations (i.e. a systemic crisis rate of approx. 5.7%). The authors note that this is similar to crisis rates reported in Caprio and Klingebiel (1996). Finally Schaeck et al. (2009), using the exact same approach as adopted here report a systemic crisis rate of 4% in their models. Our threshold rate falls within this range.

[34] In this paper any reference to "significant" variables should be taken to mean statistical significance rather than financial or economic significance.

The third question is addressed by assessing the impact of the various regulatory index variables within the same logistic framework.

The final objective of the paper is to identify a particular specification combining the most significant sectoral and macroeconomic data in such a way as to maximise in-sample crisis prediction accuracy, over-and-above levels achieved in previous studies. We adopt a structured approach towards reaching this objective. Given its USA-based risk assessment pre-eminence we leverage the rationale underpinning the CAMELS methodology. Each letter of the term CAMELS corresponds to a risk metric. For instance "C" refers to bank capital-adequacy and, in this paper, the straightforward leverage ratio is considered, "A" relates to asset quality, measured as the ratio of non-performing loans to total assets. Management efficiency, "M" is evaluated using a proxy of total overhead costs to total assets ratio. Earnings, "E" are appraised using return on average assets and liquidity risk "L" is judged using the simple loan-to-deposit ratio. Finally, the letter "S" represents sensitivity to market risk and in particular interest rate risk.

Although individual banks' CAMELS scores are strictly confidential researchers are familiar with the broad parameters by which these scores are determined and, by extension, which balance sheet data elements / ratios must be considered (see Avery et al. (1988) and Krishnan et al. (2005) for details). Though widely criticised in the wake of the GFC due to its failure to flag the impending systemic collapse, the methodology still serves a useful purpose in the present context.

Commencing with the CAMELS variables the model is tweaked via the introduction of our established Z and X-vector determinants until the optimal specification is identified. The full set of explanatory variables used in the various regressions is comprehensively described in Appendices 1-3.

2.6. Results

In Table 2.4 we consider our first key variable, Tier-1 capital, and assess its role as a potential systemic crisis determinant. The regressions should be considered in pairs with the first regression including a coefficient for Tier-1 capital and the second omitting it. The remaining variables constitute our control cluster X. Thus regression 1 is paired with regression 2, 3 with 4 and so on. The first thing to note is that Tier-1 capital, measured in levels, is not a significant determinant of past crises. In none of the regressions in which Tier-1 capital is included do we report statistically significant coefficients from which we conclude that higher levels of Tier-1 capital, per se, are not associated with greater sectoral stability. This result was hinted at in our summary data Tables 2.1- 2.3 and is now confirmed.

In the "Summary Results" section of Table 2.4 we address the second key question. For each regression pair the one that includes Tier-1 capital has a slightly higher AIC score. The specifications where Tier-1 capital is included are worse-fitting than models where it is omitted. Also, examining the paired regressions once more one can see that in each case the overall percentage of correct in-sample predictions improves marginally whenever Tier-1 capital is omitted, from which we conclude that the presence of Tier-1 capital in early-warning models of this form increases uncertainty and actually makes crises more difficult to predict.

We believe these results are due to the inconsistent manner by which the Basel Accord risk-weighting guidelines have been implemented by various central banks. Given the considerable complexity surrounding risk-weighted assets calculations it would appear that Tier-1 capital has no role as a systemic crisis determinant, at least when it is measured in levels. To test this theory further we calculate the growth-rate of Tier-1 capital, per-country, compounded over a three year period. The purpose of this test is to eliminate the distortion arising from the various methods by which Tier-1 capital is calculated in different countries, each of whom is free to adopt their own risk-weighting methodologies under the auspices of the Basel Accord.

Table 2.5 presents the corresponding results. Now Tier-1 capital is significant in half of the regressions where it is included and also has the negative sign theory suggests. It appears that aggregating high quality capital over an extended period may yield significantly lower systemic banking crisis probabilities. This result provides support for Goodhart's (2008) recommendation that future capital-adequacy standards amendments should focus upon Tier-1 capital *growth* rather than simply moving the threshold to an arbitrarily higher level. However, a word of caution on this is necessary. The Lucas critique makes it clear that we must recognise how the optimal behaviour of agents changes as a result of policy changes, therefore we must not simply rely upon past data to argue for the introduction of a policy measure that may simply result in systemic risk being transferred elsewhere as agents respond to the new policy requirements (see Lucas (1976)). However we should also stress that the Lucas critique is unlikely to have had much relevance in terms of our results as the enhanced Tier-1 capital requirements were, in general, not economically binding as the summary data of Tables 2.1 and 2.2 show.

Further comparison between Tables 2.4 and 2.5 shows that compounded Tier-1 capital growth results in much better fitting models than Tier-1 capital measured in levels. For example the AIC scores for the Table 2.4 regressions is usually lower when Tier-1 capital is omitted whereas the opposite is true in Table 2.5 when the growth variable is include. However the Tier-1 growth measure also results in much lower in-sample crisis prediction accuracy than before. This is most notable in the sharp reduction of accurate no-crisis predictions which we interpret as the model over-predicting crises to an extent. However this outcome may be a result of reduced sample sizes associated with the compounding calculation.[35]

Next, deviations from the minimum required Tier-1 capital ratio of 8.5% are considered, the results of which are presented in Table 2.6. Note as the Tier-1 Delta variable is simply the value of Tier-1 capital subtracted from 8.5%, we know ex-ante that this measure will report insignificant coefficients on the basis of our Table 2.4 results.[36] However the direction of the deviation may matter, especially if the 8.5% threshold is binding. As per Table 2.4, Table 2.6 shows that deviations from Tier-1 capital, measured in either direction, are not significantly associated with systemic crises.

The reported coefficient relating to the under-provisioning dummy variable is not statistically significant (albeit with the positive sign we anticipate), suggesting that systemic crises are not necessarily more likely simply because a banking system is under-capitalised according to the Basel III Tier-1 capital threshold.

This outcome is compatible with Flannery (2009) and with the BIS Macroeconomic Assessment Group's report that meeting the minimum Base III capital reserves has quite a limited impact upon GDP growth (they estimate a GDP reduction of approx. 0.22% over several years) compared with the older Basel II standards (see Bank for International Settlements (2011b)). Once again these findings are compatible with our summary data conclusions (see Tables 2.1-2.3).

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[35] If compounding takes place over N years then N-1 observations per country are removed from the sample. Thus two observations per country are lost as a result of compounding over 3 years as described.

[36] Thus a positive Tier-1 Delta is associated with an under-capitalised banking sector meaning that Tier-1 Capital growth in that jurisdiction is binding.

TABLE 2.4												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Tier 1 Capital - Level	-0.042		0.007		-0.012		-0.001		-0.003		-0.056	
	(0.036)		(0.054)		(0.057)		(0.062)		(0.065)		(0.140)	
GDP Growth Rate	-0.208***	-0.210***	-0.179**	-0.180**	-0.183**	-0.182**	-0.167**	-0.166**	-0.141*	-0.141*	-0.190*	-0.178*
	(0.054)	(0.054)	(0.072)	(0.071)	(0.072)	(0.071)	(0.074)	(0.074)	(0.078)	(0.078)	(0.113)	(0.107)
Real Interest Rate	0.073***	0.072***	0.041	0.041	0.050	0.050	0.074*	0.074*	0.087**	0.087**	-0.024	-0.035
	(0.021)	(0.021)	(0.040)	(0.040)	(0.041)	(0.041)	(0.042)	(0.042)	(0.044)	(0.044)	(0.134)	(0.132)
Inflation	0.074***	0.071***	0.054*	0.054*	0.063**	0.062**	0.079**	0.078**	0.091***	0.091***	0.224*	0.209*
	(0.021)	(0.021)	(0.029)	(0.030)	(0.030)	(0.030)	(0.031)	(0.031)	(0.034)	(0.033)	(0.122)	(0.115)
Private Credit to GDP %	0.016***	0.015***	0.016***	0.016***	0.016***	0.016***	0.015***	0.015***	0.014**	0.014**	0.010	0.011
	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
Private Credit Growth Rate			-0.015**	-0.015**	-0.017**	-0.017**	-0.029***	-0.029***	-0.026***	-0.026***	-0.019**	-0.019**
			(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)
No Deposit Insurance Dummy					-0.776	-0.747	-1.389*	-1.386**	-1.722**	-1.717**	-1.769*	-1.708
					(0.594)	(0.576)	(0.714)	(0.704)	(0.819)	(0.812)	(1.057)	(1.049)
M2 Money to Forex Reserves %							0.004***	0.004***	0.004***	0.004***	0.005***	0.005***
							(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Bank Credit to Bank Deposit %									0.008	0.008	-0.000	0.000
									(0.006)	(0.006)	(0.008)	(0.008)
House Price Index											-0.069	-0.063
											(0.060)	(0.057)
Constant	-4.076***	-4.507***	-4.929***	-4.847***	-4.481***	-4.649***	-4.936***	-4.956***	-5.847***	-5.882***	-3.516	-4.273**
	(0.651)	(0.565)	(1.036)	(0.777)	(1.101)	(0.789)	(1.205)	(0.865)	(1.485)	(1.212)	(2.563)	(1.746)
Summary Results:												
No. Observations	664	664	597	597	578	578	558	558	558	558	264	264
No. Systemic Crisis Episodes	35	35	20	20	20	20	20	20	20	20	20	20
Akaike Information Criterion (AIC Score)	213.2	213.5	144.9	143.9	143.0	142.0	130.3	129.3	130.6	129.6	97.32	96.53
Model Chi2	41.17	39.94	26.32	22.97	23.94	21.36	62.10	54.64	69.57	66.13	60.77	63.61
Total Correct In-Sample Predictions %	68.85	76.78	68.35	75.84	64.68	71.10	65.75	71.25	64.53	70.18	26.15	27.37
Correct Crisis Predictions %	77.14	74.29	85	85	85	85	90	90	85	85	100	100
Correct No-Crisis Predictions %	68.44	76.90	67.82	75.55	64.04	70.66	64.98	70.66	63.88	69.72	23.82	25.08
Degrees of Freedom	5	4	6	5	7	6	8	7	9	8	10	9
Model Significance - P Value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Log Likelihood	-103.6	-104.3	-68.96	-68.97	-67.48	-67.50	-60.67	-60.67	-60.32	-60.32	-43.16	-43.27

This table reports the results of regressing Tier - 1 capital levels against a binary dependent variable that takes the value of "1" if a country experiences a systemic banking crises in a panel with one row per country year combination and "0" otherwise. The panel C data is described in the appendices and covers the time-frame 1998 to 2011. The explanatory variables are included for control purposes and are known to have been significant determinants of systemic banking crises as a result of earlier research. The dependent variable data comes from Laeven & Valencia (2013 Updated) database of systemic banking crises. Tier 1 data comes from the Financial Development and Structures database (see Čihák et al. (2013)). All rows for a country are removed from the panel after the first occurrence of a systemic banking crisis is recorded to mitigate feedback from dependent variable to control variables. Statistical significance is denoted by ***, **, * for the 1%, 5% and 10% levels respectively.

TABLE 2.5												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
3 Year CAGR of Tier 1 Capital %	-0.029**		-0.031**		-0.030**		-0.023		-0.023		-0.036	
	(0.014)		(0.014)		(0.015)		(0.016)		(0.016)		(0.067)	
GDP Growth Rate	-0.300***	-0.273***	-0.276***	-0.251***	-0.270***	-0.247***	-0.249***	-0.234***	-0.228***	-0.211**	-0.172	-0.165
	(0.079)	(0.077)	(0.081)	(0.079)	(0.080)	(0.079)	(0.082)	(0.080)	(0.086)	(0.085)	(0.108)	(0.108)
Real Interest Rate	-0.052	-0.006	-0.054	-0.001	-0.054	0.013	-0.004	0.052	0.010	0.066	-0.021	-0.030
	(0.069)	(0.063)	(0.070)	(0.062)	(0.076)	(0.065)	(0.079)	(0.063)	(0.082)	(0.067)	(0.134)	(0.134)
Inflation	0.042	0.065	0.021	0.050	0.031	0.062	0.069	0.091	0.078	0.098	0.219*	0.211*
	(0.066)	(0.060)	(0.075)	(0.066)	(0.073)	(0.064)	(0.067)	(0.062)	(0.068)	(0.063)	(0.116)	(0.115)
Private Credit to GDP %	0.014***	0.014***	0.013**	0.013**	0.013**	0.013**	0.013**	0.013**	0.012*	0.012*	0.011	0.010
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)
Private Credit Growth Rate			-0.013*	-0.012	-0.014*	-0.013*	-0.025***	-0.026***	-0.023***	-0.024***	-0.017**	-0.018**
			(0.008)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)
No Deposit Insurance Dummy					-0.638	-0.665	-1.347	-1.438*	-1.691*	-1.789*	-1.701	-1.736*
					(0.651)	(0.638)	(0.831)	(0.830)	(0.995)	(0.989)	(1.041)	(1.029)
M2 Money to Forex Reserves %							0.004**	0.004***	0.004**	0.004***	0.004**	0.004***
							(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Bank Credit to Bank Deposit %									0.006	0.006	0.000	0.000
									(0.007)	(0.007)	(0.008)	(0.008)
House Price Index											-0.073	-0.062
											(0.061)	(0.056)
Constant	-3.897***	-4.082***	-3.827***	-4.066***	-3.693***	-3.989***	-4.175***	-4.434***	-4.877***	-5.183***	-4.073**	-4.033**
	(0.914)	(0.896)	(0.948)	(0.924)	(0.956)	(0.938)	(1.029)	(1.022)	(1.399)	(1.398)	(1.718)	(1.709)
Summary Results:												
No. Observations	412	412	407	407	395	395	377	377	377	377	210	210
No. Systemic Crisis Episodes	35	35	20	20	20	20	20	20	20	20	20	20
Akaike Information Criterion (AIC Score)	116.6	119.2	114.8	117.8	114.3	116.9	104.8	105.6	105.6	106.3	93.87	93.15
Model Chi2	23.84	17.83	29.18	22.78	26.66	19.70	62.31	52.87	62.77	53.12	55.97	55.65
Total Correct In-Sample Predictions %	46.72	81.28	42.81	69.11	41.28	66.21	42.20	67.58	41.59	67.43	18.50	23.70
Correct Crisis Predictions %	88.57	68.57	85	85	85	85	95	90	95	90	100	100
Correct No-Crisis Predictions %	44.62	81.92	41.48	68.61	39.91	65.62	40.54	66.88	39.91	66.72	15.93	21.29
Degrees of Freedom	5	4	6	5	7	6	8	7	9	8	10	9
Model Significance - P Value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Log Likelihood	-55.31	-57.12	-53.91	-55.90	-53.17	-54.93	-47.88	-48.78	-47.80	-48.67	-41.43	-41.58

This table reports the results of regressing the compound annual growth rate (3 years) of Tier - 1 capital against a binary dependent variable that takes the value of "1" if a country experiences a systemic banking crisis in a panel with one row per country year combination and "0" otherwise. The panel C data is described in the appendices and covers the time-frame 1998 to 2011. The explanatory variables are included for control purposes and are known to have been significant determinants of systemic banking crises as a result of earlier research. The dependent variable data comes from Laeven & Valencia (2013 updated) database of systemic banking crises. Tier 1 data comes from the Financial Development and Structures database (see Čihák et al. (2013)). All rows for a country are removed from the panel after the first occurrence of a systemic banking crisis is recorded to mitigate feedback from dependent variable to control variables during crises. Statistical significance is denoted by ***, **,* for the 1%, 5% and 10% levels respectively.

TABLE 2.6

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Tier-1 Capital - Delta from 8.5% minimum	-0.066		-0.002		-0.008		0.036		0.047		-0.087	
	(0.064)		(0.078)		(0.079)		(0.077)		(0.077)		(0.163)	
Tier-1 Delta Positive Dummy	0.752		0.973		0.777		-0.123		-0.434			
	(0.973)		(1.503)		(1.544)		(1.595)		(1.590)			
GDP Growth Rate	-0.208***	-0.201***	-0.168**	-0.159**	-0.170**	-0.163**	-0.146**	-0.149**	-0.122	-0.129*	-0.195*	-0.178*
	(0.055)	(0.053)	(0.071)	(0.069)	(0.071)	(0.069)	(0.073)	(0.072)	(0.077)	(0.075)	(0.114)	(0.107)
Real Interest Rate	0.076***	0.075***	0.062**	0.062**	0.073**	0.072**	0.088**	0.089***	0.097***	0.098***	-0.017	-0.035
	(0.020)	(0.020)	(0.031)	(0.031)	(0.032)	(0.032)	(0.034)	(0.034)	(0.036)	(0.036)	(0.133)	(0.132)
Inflation	0.082***	0.077***	0.072***	0.068***	0.079***	0.077***	0.086***	0.090***	0.094***	0.098***	0.229*	0.209*
	(0.020)	(0.020)	(0.025)	(0.024)	(0.026)	(0.025)	(0.028)	(0.027)	(0.030)	(0.029)	(0.123)	(0.115)
Private Credit to GDP %	0.015***	0.015***	0.016***	0.016***	0.016***	0.016***	0.015***	0.015***	0.014**	0.014**	0.010	0.011
	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.006)	(0.006)	(0.007)	(0.007)
Private Credit Growth Rate			-0.016**	-0.017**	-0.017**	-0.018***	-0.030***	-0.030***	-0.028***	-0.028***	-0.018**	-0.019**
			(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)
No Deposit Insurance Dummy					-0.704	-0.777	-1.357**	-1.402**	-1.613**	-1.625**	-1.662	-1.708
					(0.566)	(0.553)	(0.685)	(0.673)	(0.767)	(0.748)	(1.059)	(1.049)
M2 Money to Forex Reserves %							0.004***	0.004***	0.004***	0.004***	0.005***	0.005***
							(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Bank Credit to Bank Deposit %									0.006	0.006	-0.000	0.000
									(0.006)	(0.006)	(0.008)	(0.008)
House Price Index											-0.072	-0.063
											(0.061)	(0.057)
Constant	-4.905***	-4.513***	-5.851***	-5.018***	-5.479***	-4.813***	-5.101***	-5.044***	-5.616***	-5.743***	-3.809**	-4.273**
	(0.803)	(0.549)	(1.353)	(0.717)	(1.404)	(0.724)	(1.444)	(0.791)	(1.534)	(1.120)	(1.936)	(1.746)
Summary Results:												
No. Observations	666	666	599	599	580	580	560	560	560	560	253	264
No. Systemic Crisis Episodes	34	34	21	21	21	21	21	21	21	21	21	21
Akaike Information Criterion (AIC Score)	223.4	222.6	155.7	154.6	153.6	152.0	140.2	138.6	140.8	139.2	97.92	96.53
Model Chi2	53.34	49.70	39.18	33.73	38.49	32.17	69.43	63.47	71.85	68.51	56.43	63.61
Total Correct In-Sample Predictions %	75.53	75.68	75.13	75.46	73.29	73.62	73.62	72.95	72.62	72.79	28.21	31.22
Correct Crisis Predictions %	73.53	70.59	76.19	71.43	80.95	80.95	90.48	85.71	90.48	85.71	100	100
Correct No-Crisis Predictions %	75.63	75.95	75.09	75.61	73.01	73.36	73.01	72.49	71.97	72.32	25.61	28.72
Degrees of Freedom	6	4	7	5	8	6	9	7	10	8	10	9
Model Significance - P Value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Log Likelihood	-108.2	-108.8	-73.84	-74.31	-72.31	-72.52	-65.12	-65.28	-64.92	-65.09	-42.96	-43.27

This table reports the results of regressing distance from the minimum Tier-1 capital levels allowed under Base III (8.5%) with a binary dependent variable that takes the value "1" if a country experiences a systemic banking crisis in a panel with one row per country / year combination and "0" otherwise. The panel C data is described in the appendices and covers the time-frame 1998 to 2011. The explanatory variables are included for control purposes and are known from the literature to have been significant determinants of systemic banking crises in the past. Also included is a dummy variable that takes the value "1" if the Tier -1 delta is positive, meaning that Tier -1 levels exceed the minimum regulatory level. The dependent variable data comes from Laeven & Valencia (2013 updated) database of systemic banking crises. Tier 1 data comes from the Financial Development and Structures database (see Čihák et al. (2013)). All rows for a country are removed from the panel after the first occurrence of a systemic crisis is recorded to mitigate feedback from dependent variables to control variables during crisis episodes. Statistical significance is denoted by ***, **, * for the 1%, 5% and 10% levels respectively.

In Table 2.7 we examine the role of the NSFR as a potential crisis determinant, using the proxy variable described above. As before the regressions should be considered in pairs. Table 2.7 shows that whenever banks hold higher levels of liquid assets as a proportion of deposits and short-term funding they tend to be more susceptible to systemic crises but not to any statistically significant degree, the exception being when a house price index is included as a control.

However this latter result must be interpreted with caution as the number of observations drops off sharply whenever house price information is included.[37] Furthermore, this specification is clearly over-predicting crises as evidenced by the 90% and 100% crisis prediction success rates associated with the final pair of regressions coupled with the simultaneous large reduction in accurate no-crisis predictions.

As was the case with Tier-1 capital (see Table 2.4), the inclusion of the NSFR proxy variable makes systemic crises marginally more difficult to predict as can be seen via the slightly lower percentage of total correct in-sample predictions. However the classification of crises via the inclusion of NSFR is considerably better than is the case when Tier-1 capital is considered (e.g. comparing the accuracy of Table 2.4 regression 1 with Table 2.7 regression 1)

Also, although it represents an improvement over Tier-1 capital, the NSFR proxy variable is not as effective at improving prediction success rates as the Tier-1 capital growth measure. For example compare regression 1 of Table 2.5 with regression 1 of Table 2.7.

[37] House price data is difficult to source for many emerging countries, therefore its inclusion tends to result in much smaller sample sizes. This could be interpreted as meaning that enhance liquidity matters more for developed economies, for which house price data is available than it does for emerging economies though we cannot be definitive about this until we have more detailed house price data for emerging economies than we currently do.

TABLE 2.7												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Liquid Assets to Deposits + Short Term Funds	0.005		0.013		0.012		0.013		0.013		0.028**	
	(0.009)		(0.011)		(0.012)		(0.013)		(0.013)		(0.014)	
GDP Growth Rate	-0.210***	-0.210***	-0.174**	-0.176**	-0.176**	-0.178**	-0.161**	-0.161**	-0.134*	-0.134*	-0.145	-0.178*
	(0.049)	(0.050)	(0.071)	(0.072)	(0.071)	(0.072)	(0.074)	(0.075)	(0.078)	(0.079)	(0.105)	(0.107)
Real Interest Rate	0.049***	0.049***	0.041	0.041	0.046*	0.046*	0.061*	0.060*	0.070**	0.070*	0.010	-0.035
	(0.017)	(0.017)	(0.026)	(0.026)	(0.027)	(0.027)	(0.032)	(0.032)	(0.036)	(0.036)	(0.140)	(0.132)
Inflation	0.033***	0.033***	0.048*	0.049*	0.050*	0.053**	0.055*	0.060**	0.065**	0.071**	0.248**	0.209*
	(0.013)	(0.013)	(0.026)	(0.026)	(0.027)	(0.026)	(0.029)	(0.028)	(0.031)	(0.030)	(0.121)	(0.115)
Private Credit to GDP %	0.013***	0.013***	0.017***	0.017***	0.016***	0.016***	0.015***	0.015***	0.013**	0.013**	0.014*	0.011
	(0.003)	(0.003)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.007)	(0.007)
Private Credit Growth Rate			-0.017**	-0.016**	-0.018**	-0.017**	-0.030***	-0.028***	-0.027***	-0.025***	-0.022**	-0.019**
			(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)
No Deposit Insurance Dummy					-0.664	-0.730	-1.277*	-1.297*	-1.589**	-1.622**	-1.836	-1.708
					(0.569)	(0.563)	(0.682)	(0.671)	(0.779)	(0.770)	(1.178)	(1.049)
M2 Money to Forex Reserves %							0.004***	0.004***	0.004***	0.004***	0.005***	0.005***
							(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Bank Credit to Bank Deposit %									0.008	0.008	0.001	0.000
									(0.006)	(0.006)	(0.009)	(0.008)
House Price Index											-0.081	-0.063
											(0.061)	(0.057)
Constant	-4.145***	-3.943***	-5.492***	-4.948***	-5.155***	-4.635***	-5.283***	-4.783***	-6.165***	-5.668***	-6.098***	-4.273**
	(0.595)	(0.454)	(0.863)	(0.683)	(0.877)	(0.699)	(0.943)	(0.770)	(1.238)	(1.097)	(2.146)	(1.746)
Summary Results:												
No. Observations	724	724	647	647	613	613	593	593	593	593	264	264
No. Systemic Crisis Episodes	35	35	20	20	20	20	20	20	20	20	20	20
Akaike Information Criterion (AIC Score)	233.6	232.9	146.0	146.2	143.9	143.9	131.8	131.8	132.0	131.9	93.99	96.53
Model Chi2	38.89	38.23	40.34	35.82	36.56	30.21	57.70	56.79	75.53	76.34	63.53	63.61
Total Correct In-Sample Predictions %	73.77	74.73	75.99	76.30	72.02	71.25	71.10	71.25	69.88	70.03	27.83	27.37
Correct Crisis Predictions %	74.29	74.29	75	80	80	80	85	85	85	85	100	100
Correct No-Crisis Predictions %	73.74	74.75	76.03	76.18	71.77	70.98	70.66	70.82	69.40	69.56	25.55	25.08
Degrees of Freedom	5	4	6	5	7	6	8	7	9	8	10	9
Model Significance - P Value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Log Likelihood	-113.8	-113.9	-69.50	-70.08	-67.94	-68.47	-61.42	-61.89	-60.98	-61.47	-41.50	-43.27

This table reports the results of regressing Liquid Assets to Deposits plus Short Term Funds (NSFR proxy %) where a binary dependent variable takes the value of "1" if a country experiences a systemic banking crises in a panel with one row per country year combination and "0" otherwise. The panel C data is described in the appendices and covers the time-frame 1998 to 2011. The explanatory variables are included for control purposes and are known to have been significant determinants of systemic banking crises as a result of earlier research. The dependent variable data comes from Laeven & Valencia (2013 updated) database of systemic banking crises. Liquid Assets to Deposits plus short term funds data comes from the Financial Development and Structures database (see Čihák et al. (2013)). All rows for a country are removed from the panel after the first occurrence of a systemic banking crisis is recorded to mitigate feedback from dependent variable to control variables. Statistical significance is denoted by ***, **, * for the 1%, 5% and 10% levels respectively.

Unlike Tier-1 capital, which banks are actively required to benchmark and grow wherever minimum standards have not been achieved, the NSFR merely represents a snapshot of the banking-sector's ability to pay its way in the coming year. This is driven in-part by operational factors beyond management control (e.g. the decision by a large client to draw down committed facilities or to avail of contractually-binding alternative repayment schedules) therefore we do not consider a similar NSFR growth measure as being appropriate for estimation purposes.

We now examine the architecture of the regulatory system itself via the inclusion of several regulatory indices drawn from the Barth, Caprio and Levine (2013) regulatory survey database. These are described in section 2.4 and comprise the remainder of the Z-vector of key variables. The results are presented in Table 2.8.

The securities trading restrictions index is reported with significantly negative coefficients in 4 out of 7 regressions where it is included, thus confirming the difference in sub-sample averages reported in Tables 2.1 and 2.2 to be significant. Whenever banks face greater restrictions in terms of securities trading those banking sectors are less susceptible to systemic crises. However whenever the securities trading index is included with a capital-adequacy measure such as Tier-1 capital / leverage ratio it loses significance. This weakens the case for increasing securities trading restrictions as a crisis-avoidance policy weapon due to the capital-adequacy enhancements already envisaged under the Basel III framework. Similar results are reported for the overall trading restrictions index which also reports significant coefficients in all regressions where it is included. Once again, when regulators make it more difficult for banks to diversify their service offerings those banking sectors are generally more robust.

Due to lack of response data relating to capital-adequacy rule enforcement the overall capital regulation index features in only 2 of the Table 2.8 regressions.

TABLE 2.8								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
3 Year CAGR of Tier-1 Capital %	-0.019	-0.019	-0.038					
	(0.012)	(0.012)	(0.027)					
Liquid Assets to Deposits plus Short Term Funds	0.009	0.008	-0.015	0.007	0.009	0.008	0.001	-0.015
	(0.011)	(0.011)	(0.022)	(0.010)	(0.011)	(0.011)	(0.012)	(0.022)
No Deposit Insurance Dummy	-0.460	-0.446	-0.381	-0.543	-0.460	-0.446	-0.480	-0.381
	(0.590)	(0.591)	(0.750)	(0.584)	(0.590)	(0.591)	(0.600)	(0.750)
Securities Trading Restriction Index	-0.729*	-0.761*	-0.527		-0.729*	-0.761*	-0.567	-0.527
	(0.440)	(0.438)	(0.604)		(0.440)	(0.438)	(0.468)	(0.604)
New Banking Entrants Restriction Index		0.280	0.224			0.280	0.314	0.224
		(0.315)	(0.420)			(0.315)	(0.325)	(0.420)
Overall Trading Restrictions Index			-0.357*				-0.220	-0.357*
			(0.227)				(0.169)	(0.227)
Overall Capital Regulation Index			-0.060					-0.060
			(0.188)					(0.188)
3 Year CAGR of of Leverage Ratio (CAR) %				-0.009	-0.019	-0.019	-0.024*	-0.038
				(0.012)	(0.012)	(0.012)	(0.014)	(0.027)
Constant	-2.292***	-4.304*	-0.554	-3.304***	-2.292***	-4.304*	-3.182	-0.554
	(0.841)	(2.532)	(3.991)	(0.503)	(0.841)	(2.532)	(2.707)	(3.991)
Summary Results:								
No. Observations	420	415	205	431	420	415	401	205
No. Systemic Crisis Episodes	36	36	36	36	36	36	36	36
Akaike Information Criterion (AIC Score)	140.5	139.9	83.08	144.9	140.5	139.9	137.6	84.08
Model Chi2	9.939	15.42	20.02	3.756	9.939	15.42	20.47	20.02
Total Correct In-Sample Predictions %	37.37	37.89	20	48.16	37.37	37.89	37.89	20
Correct Crisis Predictions %	77.78	80.56	91.67	69.44	77.78	80.56	77.78	91.67
Correct No-Crisis Predictions %	35.36	35.77	16.44	47.10	35.36	35.77	35.91	16.44
Degrees of Freedom	4	5	7	3	4	5	6	7
Model Significance - P Value	0.04	0.01	0.01	0.29	0.04	0.01	0.00	0.01
Log Likelihood	-67.77	-66.96	-37.54	-70.47	-67.77	-66.96	-65.32	-37.54

This table shows the results of regression analysis, using a logit model on a binary dependent variable, of several regulatory framework index variables. Regressions 1 through 4 also control for 3 year compound annual growth rate of Tier 1 capital, whereas the remaining regressions control for the 3 year compounded growth rate of the leverage ratio with the same controls. The dependent variable takes the value of "1" if a country experienced a systemic banking crisis in a year and "0" otherwise. This data is driven by the Laeven & Valencia (2013) database of systemic banking crises with regulatory structure variables sourced via Barth et al.'s, (2013) regulatory survey database. Statistical significance is denoted by ***, **, * at the 1%, 5%, 10% levels respectively. Standard Errors reported in parentheses below the coefficients.

Nevertheless the findings re-confirm the results of Tables 2.1-2.4 and show that more stringent capital standards enforcement does not result in more resilient banking sectors.

Before discussing these results further it is appropriate to frame the purpose of regressions 4-8 of Table 2.8. Critics of Basel III (see Haldane (2012)) argue that the complexity of the rules governing the determination of risk-weightings by asset class, coupled with the freedom afforded to banks to stipulate their own risk-weighting guidelines, have weakened the value of Tier-1 capital as a risk-mitigation weapon and have also damaged investor confidence. We have presented evidence supporting this contention in Tables 2.1 – 2.4. Bruno and Shin (2013) illustrate the growth in assets (lending) which occurred in the run-up to the GFC but also claim that banks reported only marginally-increased risk levels over the same period. The implication is that by allowing banks to determine their own risk-weightings, as per the Basel II Accord (2001), manipulation of compliance standards has resulted. In addition to moving risky assets off balance sheet, banks have engaged in credit-risk / interest-rate arbitrage by interpreting risk-weighting guidelines according to temporal considerations. As a result they have taken advantage of sometimes contradictory Basel Accord protocols.

The result of all this has been a distortion of the regulatory-compliance landscape emanating from the banks' asymmetric risk-related knowledge and associated compliance reports. Blundell-Wignall et al. (2014) and Haldane (2012) make the case for simpler measures to serve as a backdrop against which investors and regulators may assess risk levels more transparently. Therefore in regressions 4-8 a simpler 3-year compound annual growth-rate of the leverage ratio (capital-to-assets) is considered in lieu of Tier-1 capital growth. Then the set of regressions is re-estimated whilst controlling for the regulatory indices as before.

In contrast with Tier-1 capital, the simpler capital-to-assets ratio is significant in regression 7, a result which provides (albeit limited) evidence that simpler regulations can be as effective as their more complicated counterparts.

Note that the use of regulatory framework variables exclusively results in low levels of in-sample crisis prediction accuracy. No regression achieves a total in-sample successful prediction rate higher than 49% with performance levels deteriorating as variables are added. The coefficients on the regulatory indices are generally negative suggesting that more stringent regulatory regimes are weakly more stable. However the coefficient on the entry restrictions index is positive, suggesting that more restrictive entry for new banks is associated with greater instability of the banking sector. This finding appears to contradict the findings of Beck et al. (2006) whereby greater bank concentration levels are associated with improved sectoral stability. However we must separate the issue of bank concentration from that of license acquisition. Our measure simply says that if it is more difficult to gain a banking license then the associated country tends to be more susceptible to systemic crises, regardless of the distribution of banking assets among existing market participants.

We now turn our attention towards finding the best-predicting model based upon our results thus far, the results of which are reported in Table 2.9. It is very difficult to develop a model of an economy or banking sector that can predict out-of-sample future crises with any high level of certainty, due to the complexity and dynamics of the systems involved. Nevertheless, as a rudimentary early warning system it is useful to establish the econometric specification yielding the best *in-sample* prediction results based upon a synthesis of our results thus far as well as those who have examined systemic crises in the past.

The desired characteristics of this "best" model are as follows. On the one hand it should correctly predict crises when they actually occur. It must also correctly predict a "no crisis" outcome when in fact none occurs. Therefore our goal is to simultaneously minimise two forms of error, the first whereby the model fails to predict a crisis when in fact one occurred and secondly to avoid predicting a crisis when none in fact occurred.[38] When the results of different regressions are contrasted those specifications which increase crisis-prediction success rates, without adversely affecting the corresponding "no-crisis" accuracy levels (i.e. over-predicting crises), are preferred.

We prefer a formal approach to an ad-hoc one. A micro-prudential risk-assessment structure is imposed from the outset, in that we commence our search for the best-predicting model by considering the well–known CAMELS methodology. A bank's CAMELS score is a multi-dimensional risk metric, calculated by the FDIC, with higher scores representing riskier banks. If a CAMELS score exceeds a certain threshold the FDIC will, euphemistically speaking, take steps to "resolve" that bank. See section 2.4 for a brief description of the variables that help to determine the CAMELS scores.

Regressions 1-4 of Table 2.9 illustrate our CAMELS-related results. The best predictions are obtained when only management efficiency, earnings and liquidity are included (regression 1). The total success rate in terms of valid overall predictions is 80%. The model accurately predicts 73.53% of the sample crises, as well as 80.33% of the no-crisis outcomes. These results compare quite favourably with Demirgüç-Kunt and Detragiache's (1998) results where their best-performing model achieves a score of 79% in terms of overall accuracy whilst achieving a 55% correct crisis-prediction score. The addition of the other CAMELS variables diminishes the predictive power of the model as shown by regressions 2-4.

[38] These are analogous to the classical Type-I and Type-II hypothesis testing errors.

TABLE 2.9								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CAMELS - Management Efficiency	0.137***	0.017	0.061	0.009	-0.055	0.119	-0.029	
	(0.049)	(0.083)	(0.061)	(0.083)	(0.129)	(0.244)	(0.146)	
CAMELS - Earnings (ROAA) %	-0.474***	-0.766***	-0.701***	-0.727***	-0.917***	-1.203***	-1.162***	
	(0.108)	(0.168)	(0.166)	(0.173)	(0.260)	(0.425)	(0.378)	
CAMELS - Liquidity Ratio	0.011***	0.011***	0.011***	0.012***	0.010**	0.008	0.010*	
	(0.003)	(0.004)	(0.004)	(0.004)	(0.005)	(0.006)	(0.005)	
GDP Growth Rate					-0.143*	-0.101	-0.194	-0.242***
					(0.086)	(0.121)	(0.119)	(0.069)
Private Credit Growth Rate					-0.017**	-0.013		-0.023***
					(0.008)	(0.010)		(0.007)
Liquid Assets to Deposits + Short Term Funds					0.012			
					(0.012)			
CAMELS - Capital to Assets (Leverage) Ratio		0.123		0.118				
		(0.086)		(0.087)				
CAMELS - Assets Quality (NPL %)			0.038	0.021				
			(0.035)	(0.039)				
House Price Index						-0.038		
						(0.058)		
3 year CAGR private credit							-0.031**	
							(0.013)	
CAMELS - Real Interest Rate								0.023
								(0.021)
Inflation								0.010
								(0.030)
No Deposit Insurance Dummy								-0.578
								(0.556)
Bank Concentration								-0.001
								(0.011)
Constant	-4.519***	-4.828***	-4.189***	-4.973***	-4.448***	-3.582***	-0.465	-2.966***
	(0.553)	(0.936)	(0.709)	(0.974)	(1.104)	(1.167)	(1.625)	(0.902)
Summary Results:								
No. Observations	700	503	499	484	623	262	332	596
No. Systemic Crisis Episodes	34	34	34	34	34	34	34	34
Akaike Information Criterion (AIC Score)	226.6	170.3	177.8	169.2	110.9	86.40	70.57	137.4
Model Chi2	35.32	25.44	30.16	30.57	27.87	17.97	24.98	37.70
Total Correct In-Sample Predictions %	80	56.14	52.29	54	84.57	32.14	43.86	77.86
Correct Crisis Predictions %	73.53	85.29	85.29	85.29	91.18	97.06	94.12	67.65
Correct No-Crisis Predictions %	80.33	54.65	50.60	52.40	84.23	28.83	41.29	78.38
Degrees of Freedom	3	4	4	5	6	6	5	6
Model Significance - P Value	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00
Log Likelihood	-111.3	-82.63	-86.38	-81.58	-51.93	-39.70	-32.29	-65.22

This table reports the results of a variety of logistic specifications the purpose of which is to attempt to find the best performing specification in terms of in-sample crisis and no-crisis predictions. Regressions 1-4 comprise only CAMEL risk-framework variables for Capital Adequacy, Asset Quality, Management Efficiency, Earnings and Liquidity as often used in USA to risk assess individual banks. To that model are added known macroeconomic determinants such as GDP growth rate, real interest rate, inflation etc as well as other sectoral variables such as bank concentration. Table 2.9 reports only a summary of many specifications that were tested (results of which are available upon request). Statistical significance is denoted by ***, **, * for the 1%, 5%, 10% levels respectively.

It should be noted that although the management efficiency variable never enters the model with statistical significance greater than 10% nevertheless the inclusion of this variable increases the predictive power of the model relative to results obtained whenever it is omitted.

To this basic framework, and taking advantage of the information provided by the results above, the model is calibrated further via the addition of sectoral and macroeconomic variables, in that specific order. Different combinations of macroeconomic, CAMELS and other sectoral variables improve the predictive power of the model to varying degrees. The model with the best in-sample predictive power occurs when GDP growth-rate, private credit growth and liquid-assets-to-deposits-plus-short-term-funding factors are added to the variables in regression 1. This is illustrated by regression 5. The significance of credit growth supports the findings of Schularick and Taylor (2012) that in the "credit" era (i.e. post 1945) systemic crises are strongly linked with credit booms that have "gone bad".

Note that only one macroeconomic factor has been included.[39] The remaining variables fall within the remit of regulators and so can be fine-tuned to help deflect embryonic crises. This model correctly predicts in-sample crises in 91.18% of cases but also achieves a successful no-crisis prediction rate of 84.23%. As such, this specification represents a significant improvement upon results achieved in earlier literature. The remaining regressions are included for illustrative purposes and show that the addition of either GDP and/or private credit growth-rates tends to improve predictive power.

Regressions 6 and 7 illustrate the dangers of improving one prediction statistic at the expense of another. In regression 6 a house price index is included, subsequent to which the model then

[39] We make the assumption that regulators prefer sectoral variables to macroeconomic variables as crisis determinants because, in general terms, macroeconomic variables fall outside their span of policy-making influence.

correctly predicts 97% of crises. However this statistic is misleading because the level of correct no-crisis predictions falls dramatically to only 28.83%. Clearly this specification results in over-predicted crises – leading to the danger of the "Boy Who Cried Wolf" whereby crises are seen at every turn. A similar result is obtained when the 3-year compound annual growth-rate of private credit is included as per regression 7. Again the model is over-predicting crises. Regression 8 is included to facilitate a direct comparison of specification 5, the best in-sample crisis prediction specification, with one of the best-performing models reported by Demirgüç-Kunt, and Detragiache (1998). Specification 8 performs quite well but is inferior to regression 5 which yields the overall optimal results.

Finally we note that an interesting result relating to bank concentration is obtained. This factor does not appear to be statistically significant, contrary to the findings of Beck et al. (2006) and Hoggarth et al. (2005a).

2.7. Robustness Checks

The results relating to the various pooled logit regressions are presented in the Tables 2.4-2.9. Whereas this has been the most common method used to identify determinants in past studies it is a somewhat restrictive model, in that an inherent assumption is made that all countries have the same relationship between crises and the corresponding set of economic factors that were present at the time.

A fixed-effects model can be utilised if we believe that inherent differences between countries can be captured by an intercept coefficient (the constant in the regression results), with a different intercept value per country catered for via the introduction of one dummy variable per country. However the use of fixed-effects estimation for bank crisis determinants is not preferred because no time-invariant factor can be used in any fixed-effects specification, a restriction which tends to result in greatly-reduced sample sizes. Another option is to use a random-effects specification, whereby an assumption is made that the individual specific differences across countries are not correlated with the explanatory variables. This overcomes the difficulty of greatly-reduced sample sizes but is a strong assumption to make. Table 2.10 presents a comparison between pooled logistic, fixed-effects and random-effects specifications.

TABLE 2.10

	Pooled Logit	Fixed Effects	Random Effects
3 Year CAGR of Tier 1 Capital %	-0.029**	0.307	-0.029**
	(0.014)	(0.240)	(0.014)
GDP Growth Rate	-0.300***	-0.390	-0.300***
	(0.079)	(0.734)	(0.079)
Real Interest Rate	-0.052	-0.306	-0.052
	(0.069)	(0.319)	(0.069)
Inflation	0.042	0.130	0.042
	(0.066)	(0.909)	(0.066)
Private Credit to GDP %	0.014***	0.312**	0.014***
	(0.005)	(0.157)	(0.005)
Constant	-3.897***		-3.896***
	(0.914)		(0.914)
Summary Results:			
No. Observations	412	118	412
No. Systemic Crisis Episodes	35	35	35
Akaike Information Criterion (AIC Score)	116.6	15.52	117.6
Model Chi2	23.84	53.19	25.02
Total Correct In-Sample Predictions %	46.72	7.650	46.58
Correct Crisis Predictions %	88.57	97.14	88.57
Correct No-Crisis Predictions %	44.62	3.156	44.48
Degrees of Freedom	5	5	5
Model Significance - P Value	0.00	0.00	0.00
Log Likelihood	-55.31	-5.258	-55.31

This table shows the effect of using different treatment types to a pooled logistic model, which is the model used in all earlier regressions. The pooled logit results are essentially identical to regression 1 of Table 2.5. It can be seen that the coefficients for the pooled model closely agree with the random effects specification but do not agree with the fixed effects specification. Only variables that change by country sub-group are permitted in a fixed effects specification hence the drop in the number of observations.

The random-effects estimates only marginally differ from their pooled counterparts, thereby greatly increasing our confidence in the earlier estimates. However the fixed-effects estimates are significantly different, with changes to the signs of the coefficients in certain cases. The primary reason for this is undoubtedly a result of the large reduction in observations available for estimation. In the example provided the observations level drops from 412 to 116, an outcome which we believe renders the coefficient estimates less reliable.

A final robustness check involves the removal of crisis episodes via the elimination of countries from panel C. Doing so ensures that the results are not driven by factor behaviour peculiar to one specific country. Starting with regression 7 of Table 2.8 as the benchmark, the data for Argentina, the United States, Germany, Sweden and Russia are removed one at a time (non-cumulatively) and the model re-estimated. Each country removed will have experienced at least one systemic crisis. The results are reported in Table 2.11. It can be seen that in all cases the significant variables retain their sign and significance status and in no case does a previously non-significant factor change its status. From this we conclude that the results are representative of the sample as a whole and are not driven by the results of one particular country.

TABLE 2.11

	Country Removed					
	Benchmark	Argentina	United States	Germany	Sweden	Russia
3 Year CAGR of Tier 1 Capital %	-0.023	0.001	-0.025	-0.021	-0.022	-0.027
	(0.016)	(0.039)	(0.017)	(0.017)	(0.016)	(0.019)
GDP Growth Rate	-0.228***	-0.205**	-0.228**	-0.217**	-0.219**	-0.237**
	(0.086)	(0.089)	(0.089)	(0.088)	(0.088)	(0.092)
Real Interest Rate	0.010	-0.051	0.006	0.034	0.012	-0.001
	(0.082)	(0.099)	(0.087)	(0.086)	(0.081)	(0.091)
Inflation	0.078	0.073	0.083	0.094	0.078	-0.016
	(0.068)	(0.066)	(0.071)	(0.069)	(0.068)	(0.119)
Private Credit to GDP %	0.012*	0.011*	0.014**	0.014**	0.012*	0.013*
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Private Credit Growth Rate	-0.023***	-0.021**	-0.023***	-0.024***	-0.020**	-0.029***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
No Deposit Insurance Dummy	-1.691*	-1.677*	-1.649	-1.741*	-1.666	-1.436
	(0.995)	(0.990)	(1.013)	(1.024)	(1.041)	(1.008)
M2 Money to Forex Reserves	0.004**	0.004**	0.003**	0.004**	0.004**	0.004**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Bank Credit to Bank Deposit %	0.006	0.006	0.007	0.007	0.006	0.003
	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.007)
Constant	-4.877***	-4.726***	-5.270***	-5.401***	-4.925***	-4.459***
	(1.399)	(1.359)	(1.508)	(1.526)	(1.418)	(1.519)
Summary Results:						
No. Observations	377	376	370	369	369	369
No. Systemic Crisis Episodes	35	34	34	34	34	34
Akaike Information Criterion (AIC Score)	105.6	102.5	98.97	99.00	104.1	95.85
Model Chi2	62.77	68.33	62.68	63.35	60.78	60.28
Total Correct In-Sample Predictions %	44.26	44.37	44.46	44.94	43.83	45.08
Correct Crisis Predictions %	94.29	88.24	91.18	88.24	94.12	94.12
Correct No-Crisis Predictions %	41.75	42.22	42.15	42.79	41.34	42.65
Degrees of Freedom	9	9	9	9	9	9
Model Significance - P Value	0.00	0.00	0.00	0.00	0.00	0.00
Log Likelihood	-47.80	-46.24	-44.48	-44.50	-47.03	-42.93

This table illustrates the effect of removing crisis episodes from the panel on a country by country basis. The benchmark regression is regression 9 of Table 2.5. Then all observations for Argentina are removed and the regression re-run. The values for Argentina are re-instated and the United States data removed and so on. This process is repeated for Germany, Sweden and Russia. Standard errors are reported in parentheses below the coefficients. Significance levels are denoted by ***, ** and * at the 1%, 5% and 10% significance levels respectively.

2.8. Conclusions

This paper uses several recent data sources and examines the determinants of systemic banking crises from a regulatory perspective over a time-frame spanning the Global Financial Crisis. We show that if banks take steps to grow Tier-1 capital levels over a 3 year period, systemic banking crises may be less likely.

However when other aspects of the regulatory system are analysed the results are not as promising. Contrary to expectations Tier-1 capital, measured in levels, is not a determinant of systemic banking crises. Neither does the fact that banking systems are under-capitalised relative to the amended Tier-1 capital threshold appear to have any systemic crisis implications. Rather, echoing Goodhart (2008), growth of Tier-1 capital is potentially important. The introduction of a liquidity measure such as the Net Stable Funding Ratio does not appear to contribute towards more resilient banking systems, however this conclusion can only be definitive when actual NSFR results have been systematically reported for several years. Likewise only a relatively small subset of the regulatory architecture is relevant vis-à-vis sectoral stability. This includes the placing of controls on overall trading restrictions, entry level requirements and restrictions on securities trading. However the latter loses efficacy when it is considered alongside capital-adequacy controls in our regressions.

We show that whereas regulatory measures restricting trading activities and raising entry requirement hurdles may result in safer banks, other regulatory standards, for example the degree to which capital-adequacy rules are enforced, do not reduce systemic bank risk-exposure levels to any great extent.

We find no evidence in support of Beck et al.'s (2006) contention that more concentrated banking sectors are more systemically stable, a result consistent with Schaeck et al. (2009). We find evidence supporting Haldane's (2012) view that simpler heuristics-based measures are equally as effective as the more complicated Basel III standards in that neither measure of the capital ratio performs better than its alternative in our regressions.

Finally, for the benefit of early-warning-system developers, a model is presented combining simple risk measures alongside sectoral and macroeconomic variables which optimises in-sample crisis prediction success rates. This "best" model reliably predicts 91% of the 34 crisis episodes included in that regression, and does so without predicting a crisis at every turn.

Chapter 3

Systemic Bank Risk Measures – Which is Best?

Evidence from UK and Irish Banks

Abstract

Since the Global Financial Crisis there have been several measures of systemic banking risk measures (SRMs) proposed in the literature. These include marginal expected shortfall (MES), systemic expected shortfall (SES) and Delta CoVaR (ΔCoVaR). Using a panel of quarterly bank balance sheet variables, prepared by extracting time series data from hundreds of bank annual and interim reports and covering the period 1997 - 2013, we assess the effectiveness of each of these systemic risk measures (SRMs) from several perspectives. Firstly, using vector-autoregression (VAR) models we identify which of the SRMs have a causality relationship with known systemic banking crisis determinants and test the hypothesis that the new SRMs merely reflect systematic (i.e. market) risk rather than systemic (i.e. involving external cost) risks. We demonstrate that, in the case of Ireland specifically, the banking crisis led to a macroeconomic crisis rather than the other way round. Secondly we test how these SRMs respond to and interact with systemic crisis determinants using impulse-response analysis. This shows which determinants' shocks have an immediate impact upon systemic risk levels, when the shock has its most significant impact and the time taken for equilibrium to be restored. Thirdly, we use single and multi-period forecasts for each of the SRMs baselined from 2008Q2 and compare forecasts with actual SRM values, highlighting which SRMs are well behaved (i.e. falling with 95% confidence intervals) and thus are most reliable in terms of anticipating future systemic risk levels. Finally, in a fixed-effects logit specification we assess the contribution of each SRM towards the likelihood of a country experiencing a systemic banking crisis because of systemic capital shortfall. We demonstrate that the risk profiles of the UK and Ireland are significantly different from each other and that whereas an SRM may prove informative in one country, this is not necessarily true with respect to all countries generally. Therefore regulators should not rely upon only a single measure of systemic risk but should use a combination of some or all of them so as to gain a full understanding of the systemic risk levels that may be accumulating and which can be indentified via bank balance sheet metrics.

3.1. Introduction

Prior to 2008 there was relatively little focus upon bank risk measures that could, in the post-Global Financial Crisis (GFC) era, be classified as truly "systemic". Working on the fallacious assumption that the risk of the sum (i.e. sectoral-level risk) is equal to the sum of the individual bank risks, micro-prudential measures such as credit ratings, value-at-risk (see Jorion (2007)), credit default swap spreads (see Brunnermeier (2008) and Rajan (2005)), Bank Z-Scores (see Altman (2000) and Beck et al. (2009)) and CAMELS ratings (see Gropp et al. (2004)) were used as proxy variables in lieu of aggregate risk level. None of these measures accurately captured the cost of externalities, these being the spillover costs to other banks which arise when one bank either fails or is allowed to fail (see Brunnermeier et al. (2009), Bisias et al. (2012) and Blancher et al. (2013)). Regulatory attention was aimed at ensuring banks retained adequate high-quality capital as a proportion of their risk-weighted assets, thereby shielding them from idiosyncratic or systematic earnings / asset shocks (see Bank for International Settlements (2005), (2011a)). In the pre-GFC period stress-testing often involved measuring the effect of macroeconomic shocks, via impulse response function analysis, upon bank loan write-off ratios (see IMF (2003) and Hoggarth et al. (2005b)). In light of the GFC the consensus now is that such practices and procedures proved to be inadequate.[40]

In this paper we examine the effectiveness and relevance of several new systemic risk measures (SRMs) in the context of the Irish and UK banking sectors and determine which SRM represents the most effective signal of systemic weakness. Having established a generalised control cluster of systemic crisis determinants (see Chapters 1 and 2) we also establish which SRM (by country)

[40] Hoggarth et al. (2005b) find that the UK banking sector is robust to very large macroeconomic shocks.

best reflects the dynamic behaviour of these determinants in a single, preferably *leading,* index of systemic risk.[41] In particular our analysis concentrates primarily upon three SRMs which have come to feature in the literature. These are 1) marginal expected shortfall (MES), 2) systemic expected shortfall (SES) and 3) ΔCoVaR (pronounced Delta CoVaR). MES quantifies an institution's expected losses on days when the market experiences extreme losses (see Brownlees and Engle (2010)). Higher levels of MES imply that a bank is more likely to be under-capitalised when the economy experiences a shock, therefore the higher the MES the greater its potential contribution to aggregate sectoral risk. SES estimates an institution's contribution towards a banking sector being undercapitalised (see Acharya et al. (2010) and Guntay and Kupiec (2014)). Alternatively, an institution's ΔCoVaR represents the difference between the value-at-risk of the financial system conditional on that institution itself being in financial distress, compared with the value-at-risk of the financial system conditional upon the same bank experiencing median returns. That is ΔCoVaR is a conditional measure of the extent to which the financial sector's value-at-risk as a whole shifts when bank "j" is in distress relative to when bank "j" experiences median returns (see Adrian and Brunnermeier (2011)). Each of these new SRMs is benchmarked against a traditional fragility gauge which is the level of non-performing loans (NPL).

We find that, when the SRMs are analysed at the country level, there is no one "best" measure. We show that the risk characteristics vary widely from country to country therefore the choice of SRM depends very much upon the purpose for which it is being used. Extrapolating from a two-country sample we believe it is unlikely that an individual SRM will prove to be optimal on any globally-consistent basis. For example, if we wish to forecast out-of-sample risk levels based

[41] We emphasise the word "leading" in the belief that a useful systemic risk measure should flag (by way of increase) the potential for a systemic crisis prior to that crisis taking place and that it ought not just reflect an increase in factor variability post-crisis, when the damage has already been done.

upon current and past data then ΔCoVaR and SES (especially in the UK) perform best, whereas MES and NPL (in particular) levels fall outside of their respective 95% forecast confidence intervals, especially in the short-term. This feature is of value if we wish to anticipate future systemic risk levels based upon current values of balance sheet indicators, making ΔCoVaR tractable to counter-cyclical policy intervention measures which may be geared toward reducing future systemic risk levels (see Adrian and Brunnermeier (2011)). Conversely, we find that MES is the SRM that interacts most comprehensively with multiple systemic-crisis determinants (including their lagged values). Thus, if one's objective is to find the measure that captures multiple risk factors simultaneously then MES appears to be a good choice. MES also contributes the largest marginal effect to the probability of a banking sector experiencing a crisis due to capital shortfalls. These results run generally counter to Benoit et al.'s (2013) theory that each of these new SRMs can be largely explained by single factors, for instance MES by its Beta and ΔCoVaR by its value-at-risk (VaR). However we find evidence that their theory is valid in the case of SES where leverage (i.e. capital-to-assets ratio) is shown to be the only systemic crisis determinant with which it has a Granger-causal relationship.

We shed light on other recent theories concerning these new SRMs. For example Guntay and Kupiec (2014) suggest that MES, SES and ΔCoVaR are all actually capturing systematic (i.e. market-related) risk, not systemic risk.[42] They can all therefore be simply replaced by the bank's respective Beta coefficient. Using empirical data they demonstrate the strong Beta explanatory power of MES and ΔCoVaR and show that different institutions and industry sectors are systemically important depending upon which SRM is analysed, with each contributing little to

[42] All three measures are presented in the introduction to their paper, however detailed empirical analysis is presented only in the case of MES and ΔCoVaR.

systemic risk in the years leading up to the GFC. However their research takes no account of any autoregressive SRM behaviour which may be present, leading to biased and inconsistent OLS coefficients in worst-case scenarios.[43] Our approach overcomes these difficulties whilst providing supporting evidence that the SRMs are inconsistent identifiers of risky institutions (and banking systems by extrapolation) vis-à-vis each other (see Billio et al. (2010), Acharya et al. (2010) and Bisias et al. (2012)).

Other contributions of the paper are as follows. We develop, for the first time as far as we are aware, quarterly time series data drawn from annual and interim annual reports of the leading banks in Ireland and the UK covering the period 1997-2013. These series facilitate new balance sheet-based research that has not been possible until now. We include an analysis of an important market-liquidity factor which has not been extensively researched to date. This is the level of undrawn (yet contractually committed) lines-of-credit made available by banks to corporate clients as well as other banks in the years preceding the GFC (see Acharya and Mora (2015)). Such facilities do not show up as balance sheet assets until they are drawn down, therefore they do not feature prominently within the remit of traditional micro-prudential risk measures. However we show that they represent a potentially grave source of bank liquidity risk if, in stressed circumstances, large clients simultaneously avail of them for working capital purposes.[44]

[43] This happens if any right-hand-side regressor in an OLS regression is contemporaneously correlated with the corresponding error term and where autocorrelation has also been detected in the error term.

[44] In 2013 the Bank for International Settlements outlined a new leverage ratio measuring capital to total exposures, thus recognising the off-balance-sheet risk inherent in various bank investment choices. The minimum leverage ratio under this measure is 3%. However the total exposures does not include contingent claims which might, when they are availed of, become listed as bank assets at some point in the future.

In order to analyse the single-factor-related issues described by Guntay and Kupiec (2014) we create our own benchmark SRM, which we term the composite risk index (CRI). The CRI reflects, by construction, an amalgamation of multiple balance sheet-related risk elements comprising both asset and liquidity-related trend deviations from their respective sample averages. High CRI values represent significant trend deviations of the risk factors in risky directions as suggested by previous determinants-related studies (see Demirgüç-Kunt and Detragiache (1998, 2002), Barth et al.(2004), Beck et al. (2006), Davis and Karim (2008), Eichler and Sobański (2012) and Chapters 1 & 2). From the individual bank-level CRIs, asset-weighted sectoral CRIs are compiled. By including the CRI in our analysis we demonstrate that the single-factor concerns of Guntay and Kupiec (2014) are somewhat overstated. In addition, our CRI performs well as a leading visual signal of systemic weakness and also performs consistently well in short-term forecasts.

The paper proceeds as follows. We describe the econometric methods used in section 3.2. Our data is presented in section 3.3, commencing with a description of how each SRM is defined and estimated. The approach we have adopted towards the various analyses undertaken is outlined in section 3.4. We then present our detailed results in section 3.5. Robustness checks are highlighted in section 3.6 and section 3.7 concludes.

3.2. Methodology

We make use of two econometric techniques to derive our results. These are the pooled logit model and the vector auto-regression model. The logit model helps to establish which SRM is most informative in terms of establishing the likelihood that a country's banking system is under-capitalised (when measured against a pre-determined minimum threshold level of capital). Acharya et al. (2012) characterise such a condition as representing a systemic banking crisis. The vector autoregression technique is used in time-series systems of equations to determine how the variables in the system interact with and help to predict future values of each other over time. Our system comprises the various SRMs we have defined and captures their dynamic relationship with the systemic banking crisis determinants as established in the literature and as referenced above.

Pooled Logit:

As we have already described the pooled logit technique in detail in Chapter 1 we do not do so here except insofar as to point out some slight differences in terms of specification to what has gone before (see Chapter 1, section 1.3). In this chapter, by including the SRMs in the logit model's vector of explanatory variables X we can determine which of the SRMs is most significantly associated with a bank's need for emergency capital / liquidity which in turn is taken as evidence of systemic distress. Unlike Chapters 1 and 2, we now include fixed effects (FE) specifications where a dummy variable is included per country because doing so does not dramatically reduce sample size as would have been the case in Chapters 1 and 2. Their inclusion helps isolate idiosyncratic differences between the two banking sectors. Our dependent variable is triggered whenever:

$$Equity_{jt} < \frac{k}{(1-k)}\,Debt_{jt}\ . \qquad \textbf{(3.1)}$$

Here equity is market value of shareholder equity in banking sector "j" during quarter "t" and debt the market value of debt. The parameter "k" represents the minimum level of capital-to-asset ratio required to ensure the system is well funded such that unexpectedly large losses may be absorbed without the need for emergency state funding. We set "k" to 12.5% according to Basel III guidelines.[45]

Vector Auto-regression Model:

Vector Auto-regression (VAR) models are an extension of univariate auto-regressive models to multivariate time series data (see Sims (1980) and Hamilton (1994)).[46] In univariate auto-regressive models the current value of a variable depends upon lagged values of itself plus some innovation / disturbance term. In a VAR we consider multi-equation systems where all of the variables are endogenous and where the current value of each variable in the system depends not only upon its own lagged values but also upon the contemporaneous as well as past values of each of the other variables in the system. The number of lagged values included defines the order "p" of the model. In general if our system of equations takes the general structural form:

$$Az_t = B_1 z_{t-1} + B_2 z_{t-2} + \ldots + B_p z_{t-p} + u_t. \tag{3.2}$$

In this expression z_t is an n-dimensional vector of the variables comprising the system at time t, u_t is a vector of white-noise disturbances impacting z_t with A and B_1 - B_p representing coefficient matrices of dimension (n x p). Given this our VAR of lag length p, i.e. (VAR(p)), can be written as:

$$z_t = A^{-1}B_1 z_{t-1} + A^{-1}B_2 z_{t-2} + \ldots + A^{-1}B_p z_{t-p} + A^{-1}u_t, \tag{3.3}$$

[45] This figure represents a fully-loaded Basel III capital adequacy requirement including 8% total capital adequacy, plus 2% for a capital conservation buffer and a further 2.5% for a counter-cyclical capital buffer.

[46] Unfortunately value-at-risk and vector autoregression share the same three letter abbreviation (VAR). To avoid confusion we designate value-at-risk as VaR and vector autoregression as VAR throughout this paper. The exposition of VAR theory which follows is drawn primarily from Hamilton (1994).

where each element of u_t is assumed to be normally distributed, i.e. $u \sim N(0, \sigma^2)$, such that $E(u_t u_\tau') = \Sigma_u$ is a diagonal variance-covariance matrix of shocks at time $t = \tau$, containing 0 values in the off-diagonal positions. The goal of VAR regression is to recover the estimates for A, B and Σ_u.

There are different types of VAR models leading to different estimation results. The reduced form VAR is one whereby each variable is expressed as a linear function of its own past values and past values of all other variables, i.e. there are no contemporaneous effects involved. Each equation in the system can be estimated by ordinary least squares (OLS) regression. However if the variables are correlated with each other then the error terms will also be correlated and OLS may yield inconsistent estimates of the coefficients. Also this form yields estimates of $A^1B_1 \ldots A^1B_p$ and $A^{-1}\Sigma_u A^{-1'}$ but we cannot easily derive A, B and Σ_u.

Instead we try to impose some order on the system and introduce some theory to estimate a "recursive" VAR.[47] In such a model the error term is constructed in such a way that each is uncorrelated with the error term in the preceding equations. This is done by estimating the equations of the VAR via the inclusion of contemporaneous values of certain variables in the system of equations and the omission of others.

For example consider a bivariate VAR(1) with 2 equations, with two right hand side variables, one of which is a systemic risk measure Y and the other a systemic crisis determinant such as GDP growth-rate R. We may describe the relationship as follows:

[47] An example of banking theory might be an assumption that a shock to bank asset values impacts non-performing loans during later periods but does not do so contemporaneously, that is to say it takes at least one quarter for asset-related shocks to impact non-performing loan levels (see Hoggarth et al. (2005b)).

$$Y_t = -a_{yr}R_t + b_{yr}R_{t-1} + b_{yy}Y_{t-1} + u_{yt}, \quad \textbf{(3.4)}$$

$$R_t = -a_{ry}Y_t + b_{rr}R_{t-1} + b_{ry}Y_{t-1} + u_{rt}, \quad \textbf{(3.5)}$$

where a_{ry}, a_{yr} and b are the structural parameters and where u_{rt} and u_{yt} are the uncorrelated structural shocks with standard deviations σ_r and σ_y. These equations cannot be estimated by OLS since they violate the assumption of no correlation between the regressors and the error term. For example it can be shown that $\mathrm{cov}(Y_t,u_{rt}) = \frac{-a_{yr}}{1-a_{yr}a_{ry}}\sigma^2_{ur}$ which is not zero unless a_{yr} is zero in which case there is no contemporaneous relationship between R_t and Y_t. If this condition is imposed upon equation (3.4) then it may be estimated via OLS. The procedure is recursive in that the equations are estimated one-by-one with the various assumptions imposed to enable OLS regressions to take place.

In practice we estimate the reduced form of each equation in the VAR and then compute the Cholesky decomposition of the variance covariance matrix of the resulting residuals. In general, for each symmetric positive definite matrix X, the Cholesky decomposition is an upper diagonal matrix U such that X=UU'. In our example if we denote $a_{ry} = \alpha$ and $\sigma_{12} = \sigma_x$ then we can write (3.4) and (3.5) in matrix format as per (3.3) as follows:

$$z_t = A^{-1}Bz_{t-1} + A^{-1}u_t\,. \quad \textbf{(3.6)}$$

Here $A^{-1}u_t$ is designated e_t so that:

$$\Sigma_e = A^{-1}\Sigma_u^{1/2}\Sigma_u^{1/2}A^{-1\prime}, \quad \textbf{(3.7)}$$

where Σ_e is the variance of the residual vector resulting from the regression in (3.6), i.e. it is the variance-covariance matrix associated with (3.6) and from which, given $a_{yr}= 0$, we can derive the following:

$$A^{-1} = \begin{bmatrix} 1 & 0 \\ -\alpha & 1 \end{bmatrix}. \quad \textbf{(3.8)}$$

From (3.8) we may re-write (3.7) thus:

$$\begin{bmatrix} \sigma_1^{\ 2} & \sigma_x \\ \sigma_x & \sigma_2^{\ 2} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ -\alpha & 1 \end{bmatrix} \begin{bmatrix} \sigma_y & 0 \\ 0 & \sigma_r \end{bmatrix} \begin{bmatrix} \sigma_y & 0 \\ 0 & \sigma_r \end{bmatrix} \begin{bmatrix} 1 & -\alpha \\ 0 & 1 \end{bmatrix}. \quad \textbf{(3.9)}$$

Multiplying the matrices on the right hand side through we find:

$$\begin{bmatrix} \sigma_1^{\ 2} & \sigma_x \\ \sigma_x & \sigma_2^{\ 2} \end{bmatrix} = \begin{bmatrix} \sigma_y & 0 \\ -\alpha\sigma_y & \sigma_r \end{bmatrix} \begin{bmatrix} \sigma_y & -\sigma_y\alpha \\ 0 & \sigma_r \end{bmatrix}, \quad \textbf{(3.10)}$$

whereby the matrices on the right hand side represent the Cholesky decomposition of the matrix on the left hand side. This results in a system of three equations which can be solved as follows:

$$\sigma_y^{\ 2} = \sigma_1^{\ 2} \quad \textbf{(3.11)}$$

$$\alpha = -\frac{\sigma_x}{\sigma_y^{\ 2}} = -\frac{\sigma_x}{\sigma_1^{\ 2}} \quad \textbf{(3.12)}$$

and $$\sigma_r^{\ 2} = \sigma_2^{\ 2} - \alpha^2\sigma_1^{\ 2}. \quad \textbf{(3.13)}$$

Thus by estimating the reduced form model and applying Cholesky decomposition to the residuals of these equations we are able to isolate the variance/standard deviation of the structural shocks.

Finally we can recover matrix A by recognizing the following:

$$A^{-1} = chol(\textstyle\sum_e)' \textstyle\sum_u^{\ -1/2}, \quad \textbf{(3.14)}$$

where chol(.) represents the Cholesky decomposition of the residuals of (3.6) and where:

$$\sum_u^{1/2} = diag(diag(chol(\sum_e \quad))) . \tag{3.15}$$

The operation diag(diag(X)) yields a diagonal matrix with the elements of X on the main diagonal. In the above example we require the A (and B) matrices to be invertible. This implies that in each of the equations there are no unit-root solutions to any of the autoregressive equations within the VAR. None of the lagged coefficients of any variable may equal "1" and also the sum of the lagged coefficients may not equal "1". If these conditions are not met then the system is not identifiable, with any coefficient having the value of "1" implying shocks have permanent effects. Therefore, before any time series variable is included in any VAR we perform a range of visual inspections of the series as well as formal augmented Dickey-Fuller tests, taking corrective action (e.g. using growth-rates of variables rather than levels, or first differences of variables) where appropriate (see Dickey and Fuller (1979)).

Impulse Response Function Analysis:

The use of the Cholesky decomposition technique has important implications in terms of stress testing banking systems. The technique is useful in terms of identifying shocks which are orthogonal (i.e. have no effect upon) to each other, so that we can trace the dynamic effect of that shock as it propagates the system from quarter to quarter. This technique, known as orthogonal impulse response function analysis also helps us to identify the maximum effect of a shock to one variable (e.g. loans-to-deposits ratio) upon the SRM being analysed and also in what quarter (forward lag) the shock impacts most. We are then able to graph and/or tabulate these orthogonal impulse response functions such that the dynamic effect of a unit (or a single standard-deviation) shock associated with the impulse variable can be measured upon all the variables in the system over time.

Note, from (3.6) we have recovered the coefficient matrix representing $A^{-1}B$ and we have also recovered A^{-1} via Cholesky decomposition. Therefore if we were to assign a unit value to one of the shocks at time t=0 in our U vector (see equation (3.6)) while setting the other shocks to a value of 0 we can trace the path of our Z vector variables over time, assuming they start from an (assumed) equilibrium value of 0. Hence we have:

$$z_0 = A^{-1} u_0, \tag{3.16}$$

and for every s>0,

$$z_s = A^{-1}Bz_{s-1}. \tag{3.17}$$

In this way we can trace out the path through time of our variables of interest following an individual shock to one of the variables in the system.

Granger-Causality:

As outlined above each random shock in a VAR influences all of the endogenous variables. Nevertheless random shocks may impact some variables later or earlier than others. Granger-causality tests check a VAR for such evidence of temporal ordering by testing whether lagged values of one variable (e.g. loans-to-deposit ratio) improve the forecast of another variable (e.g. MES) after the lagged effects of past values of MES have been taken into account. This takes the form of a hypothesis test that the all regression coefficients of the lagged explanatory variable are jointly equal to 0. If true the variable does not Granger-cause the dependent (sometimes called the "Equation") variable. In the example given we would say that loans-to-deposits do not Granger-cause MES. We make use of Granger-causality tests to help us identify the order in which our VAR variables are formed within the VAR and to base our assumptions of no contemporaneous effect between certain variables upon sample evidence.

3.3. Data

The SRMs are the focal point of this paper, therefore we commence this section by providing an overview of each, including their data source and method of calculation.

Marginal Expected Shortfall (MES):

Brownlees and Engle (2010) define MES as the marginal contribution of bank "j" to the expected shortfall of the financial system. More specifically, the MES of bank "j" is the expected value of the stock return $\tilde{R}_j$ conditional upon the market portfolio return $\tilde{R}_m$ being at or below the sample p-percent quantile (see Acharya et al. (2012) and Guntay and Kupiec (2014)). Hence the MES per quarter "t" per bank "j" is given as:

$$MES(R_{jt}, p) = E(R_{jt} \mid R_{mt} \leq VaR(R_{mt}, p)), \tag{3.18}$$

where VaR is the market's 99% value-at-risk, i.e. maximum loss not exceeded with 1-p confidence (probability) where p is set to 1%. For estimation purposes we make the conventional assumption that the 99% VaR for market returns is best approximated by daily losses meeting or exceeding 2% of the relevant market index, these being the ISEQ in the case of Ireland and the FTSE in the case of the UK. Therefore the analogue $MES_{j,t}$ for bank "j" in quarter "t" is calculated as the average of the returns (calculated via daily stock prices) realised by bank "j" on those days during quarter "t" in which the market index recorded losses of 2% or greater. An institution's MES thus provides an estimate of the scale of losses a bank may experience during turbulent periods, representing an improvement over traditional value-at-risk measures which merely provide a confidence level that the bank's losses will not exceed a threshold with a pre-specified confidence level.

Systemic Expected Shortfall (SES):

SES represents a transformation of MES in that it provides an approximation of the additional capital a financial institution will require whenever markets experience extreme lower distributional tail events and in order to return capital levels to a minimum required threshold. Acharya et al. (2010, 2012) define SES as the expected under-capitalisation of bank "j" when the aggregate banking system as a whole is undercapitalised, with aggregate Tier-1 capital having fallen below threshold "λ" of risk-weighted assets. More specifically they define:

$$SES_j = \max(0, \text{Equity}_j * [\lambda * \text{Leverage}_j - (1-\lambda) * \exp(-18*\text{MES}_j)]), \qquad \textbf{(3.19)}$$

where Equity_j is the market capitalisation of bank "j" and Leverage_j is the book value of "j's" debt divided by equity.[48] Guntay and Kupiec (2014) observe that SES modifies MES so that a bank's systemic risk is related to its stock return tail dependence, but the strength of the systemic risk also depends on the bank's current capital position relative to the projected capital the bank would need to survive a financial crisis. Note SES is increasing where debt/equity ratios exceed scaled (crisis) MES. Therefore the projected unencumbered (Tier-1) capital required is estimated by comparing a bank's current high-quality equity to a scaled-up MES estimate where the scaling factor adjusts sample MES estimates for true financial crisis conditions. In this sense, scaled MES acts as a proxy variable for expected losses on financial crisis days. For our analysis we follow convention and choose λ = 8% (see Bank for International Settlements (2011a)) with the Tier-1 capital data drawn from bank annual and interim reports and interpolated quarterly. MES is calculated as per the above.

[48] Equation (3.19) makes use of Acharya et al.'s (2012) suggestion, based upon empirical studies, that long-run MES, may be approximated as 1-exp(-18*MES). Thus long-run MES is factored into (3.19). See also Guntay and Kupiec (2014).

Delta CoVaR (ΔCoVaR):

Jorion (2007) defines the value-at-risk of bank "j" as the maximum losses that may be expected with probability (1-q) based upon the bank's distribution of stock price returns. More formally if, based upon bank "j's" past distribution of returns $Rj \sim N(\overline{R}_j, \sigma_j^2)$, we can define the critical point z with probability q (usually 1%) such that:

$$\text{Probability } (Rj \leq z) = q, \qquad \textbf{(3.20)}$$

then z is defined as the value-at-risk for bank j with (1-q)% certainty, i.e. $z = (VaR_{j,q})$.[49] For our purposes, conditional value-at-risk measures the value-at-risk of the financial services sector conditional upon bank "j" experiencing a particular return event. For example assuming bank j experiences its value-at-risk returns, with certainty "q", then we define bank "j's" CoVaR as:

$$\text{Probability } (R_{fs} \leq VaR(R_{fs}|j,q) \mid R_j \leq VaR(R_{j,q})) = q\,, \qquad \textbf{(3.21)}$$

where R_{fs} represents the return of the financial services sector and R_j the return for bank "j" and q is usually a low percentage such as 1%. Measuring the CoVaR of the financial services sector when bank j has met or exceeded its value-at-risk returns and again when bank j has experienced median returns we define the Delta CoVaR for bank "j" as the difference between the two CoVaR measures (see Adrian and Brunnermeier (2011)). More specifically:

$$\Delta CoVaR(R_{fs|j},q) = CoVaR(R_{fs|j},q) - CoVaR(R_{fs|j}, 50\%), \qquad \textbf{(3.22)}$$

Adrian and Brunnermeier (2011) describe a method by which ΔCoVaR can be estimated using quantile regressions. The quantile regression is characterised by the following equation

[49] Rj is assumed to have a Normal Distribution.

$y_i = x_i'\beta_q + \varepsilon_i$ where β_q is a vector of unknown parameters associated with the qth quantile. In ordinary least squared regression models the β_q are chosen to minimise the sum of squared model prediction errors $\Sigma\varepsilon_i^2$ whereas with quantile regression the β_q are chosen to minimise the following objective function Q(.):

$$\sum_{i:y_i \geq x_i'\beta_q}^{N} q\,|\,y_i - x_i'\beta_q\,| + \sum_{i:y_i < x_i'\beta_q}^{N} (1-q)\,|\,y_i - x_i'\beta_q\,| \text{ , where } (0 < q < 1). \quad \textbf{(3.23)}$$

This function represents a summation whereby asymmetric penalties are applied to predictions, $q|\varepsilon_i|$ in the case of under-predictions and $(1\text{-}q)|\varepsilon_i|$ in the case of over-predictions. In the case of quantile regressions β_q measures the marginal effect of a change in one of the vector X variables upon the dependent variable y, for values which fall within the qth quantile of the sample distribution of y. Having estimated the parameters, the predicted $\hat{y}_i$ values are easily generated and can be used as conditioning variables in subsequent regressions.

Therefore, using past returns for the market, the financial services sector and individual banks we can use (3.21) to estimate the value-at-risk for each bank j (e.g. predicted returns for j representing a 1% VaR, whereby q=1%). We then estimate the conditional value-at-risk for the financial services sector conditioned upon bank "j" experiencing its 1% VaR (the predicted 1% VaR for bank "j" being included as a conditioning variable in the quantile regression for the financial services sector). Having done so we re-run those regressions and generate predicted median values of bank "j's" returns (i.e. q=50) and re-estimate the financial system's 1% VaR conditional upon bank "j" experiencing median returns.

Composite Risk Index (CRI):

The purpose of the composite risk index is to capture multiple sources of banking sector risk in one variable, with the index dependent upon deviations of key balance-sheet-based ratio trends from their sample averages. The ratios considered include: 1) the debt-to-GDP ratio of the banking sector, 2) the banking sector's Z-Score (distance-to-default), 3) undrawn (but contractually committed) credit facilities to shareholder equity ratio, 4) the sectoral loans-to-deposits ratio and 5) non-performing loans as a proportion of total loans. As such the CRI captures data on lending bubbles (via loans to GDP), asset price shocks (via Z-Score which includes capital-to-asset ratios as well as sectoral profitability via return on assets), liquidity shocks whereby large bank clients avail of credit lines in circumstances where suppliers increase their debtor days outstanding and also via the traditional liquidity measure of loans-to-deposits and finally credit risk as captured by the non-performing loan percentages. Undrawn credit facilities do not feature in traditional micro or macro-prudential risk measures however they represent a significant source of sectoral liquidity risk (see Brunnermeier et al. (2009)).

The CRI per quarter for a country's banking sector is based upon assessing the current level of each factor relative to the sample average and penalising / rewarding deviations depending upon whether or not the deviation represents a risk contribution / mitigation. The various CRI-contributing-factor series are transformed via Hodrick-Prescott filters to isolate cycles from trends, with the trend component compared to the sample average. So, for example, if the Z-Score's trend, representing the distance-to-default of the banking system is two standard deviations lower (i.e. the system is riskier) than the sample average then that contributes 3 units to the CRI, if the Z-Score is two standard deviations higher than the average that contributes a score of -3 units to the CRI for that quarter.

Ex-ante known systemic banking crisis determinants (see Chapters 1 and 2) are given higher scores than their unproven counterparts. Thus the full CRI per quarter is the aggregate score based upon the following table:-

TABLE 3.1

Variable Name	Contribution Towards CRI per quarter				
	<= 2σ below avg	<=σ below avg	within σ from avg	>= σ above avg	>=2σ above avg
Total loans to GDP ratio	-3	-1.5	0	1.5	3
Banking Sector Z-Score	3	1.5	0	-1.5	-3
Undrawn (contractually committed) credit facilities to shareholder equity	-1.5	-0.75	0	0.75	1.5
Loans to deposit ratios	-3	-1.5	0	1.5	3
Non-performing-loan ratios	-3	-1.5	0	1.5	3

This table demonstrates the composition of the Composite Risk Index (CRI). Each of the variables trends is isolated via Hodrick-Prescott filters and compared with their sample average. Deviations in the direction of risk add a score to the CRI, deviations away from risk reduce the score. There are five factors contributing to the CRI. These are loans to GDP ratios of the banking system, distance to default (sectoral Z-Score), undrawn credit facilities to shareholder equity ratio, loans to deposits ratio and non-performing-loans as a percentage of total loans ratio. The "risky" direction is based upon existing systemic crisis determinants literature (see Chapter 1) where known significant determinants are given higher scores

Non-performing-loans ratio (NPL):

Hoggarth et al. (2005b) use the banking system's loan write-off ratio as a measure of systemic risk in a VAR model comprising macroeconomic variables. They use the model's orthogonalised impulse response functions (IRFs) as their basis for stress testing the UK banking system and conclude that the sector is robust to extremely large macroeconomic shocks. In our view write-off ratios are as much an outcome of bank policy as they are a signal of sectoral distress and tend to increase only in quarters subsequent to the onset of a crisis, rather than in advance of a crisis. Government policy may also mandate a lengthy arbitration procedure to be followed prior to loans being declared as written-off. Therefore we prefer to benchmark the performance of our other SRMs against non-performing-loans rather than write-off ratios, where a loan is considered non-performing if it has not been serviced within the preceding 90 days. This information is drawn from bank annual and interim reports and interpolated quarterly where necessary.

Sample Data:

We maintain a panel of data covering the period 1997-2013 and comprising the leading banks in Ireland and the UK. The Irish banks are Bank of Ireland, Allied Irish Bank, Permanent TSB and, for the years during which data was available, Anglo Irish Bank (shares suspended from trading in Dec. 2008 and subsequently liquidated in 2013). The UK banks are Barclays, Lloyds, Royal Bank of Scotland Group, HSBC and Standard Chartered. Note Ulster Bank, operating in Northern Ireland as well as the Republic of Ireland, reports its results as part of Royal Bank of Scotland's consolidated annual reports. Collectively these banks are representative of their respective banking sectors given that their collective assets comprise a significant proportion of the total banking assets in their respective countries (see Table 3.2). The balance-sheet-based determinants were compiled by examining and extracting data from annual and interim reports on a bank-by-bank basis. Up to 2008 it was sometimes necessary to interpolate values (via estimated growth-rates) for certain quarters, however since 2008 banks have been reporting results on a quarterly basis. We present summary statistics for this data in Tables 3.2 – 3.4 below.

Table 3.2 presents summary information on the respective composition of the banking sectors of Ireland and the UK, over the final six years (2008 – 2013) of our sample's timeframe. The UK banking sector is approximately ten times as large as the Irish in 2013, albeit with the Irish banking sector having experienced significant de-leveraging of assets since its 2008 peak level. In spite of this wholesale sell-off of assets the leverage ratio of Ireland remains generally higher over this period than is the case in the UK, although both banking systems show the results of increasing levels of capital and reserves since the start of the GFC. The Irish banking system operates on tighter interest margins than the UK does but it is also more efficient as the expenses-to-gross-income ratio shows. The most common measure of bank liquidity, i.e. the loans-to-deposit ratio, indicates that banks in Ireland are more liquidity-constrained on aggregate than the UK banks are. However, in spite of their relatively lower lending levels, the UK banks experience positive (though moderate) returns on assets whereas the Irish banks report significant losses during this period. This occurs due to the combination of relatively higher non-interest income of UK banks, coupled with higher levels of loan quality on aggregate.

These aggregate results are somewhat masked by the presence of foreign-owned banks who have an Irish presence but who do not operate a retail banking business in Ireland. These include large banks such as Citibank Europe, Depfa Bank and Commerzbank amongst others, and their inclusion in the aggregate picture can obscure the picture at the retail banking level. We therefore compare the banking systems at the sample composition level as outlined in Table 3.3.

Once again we observe the difference in scale between the two banking sectors with the largest Irish banks (Allied Irish Bank and Bank of Ireland) still smaller on average than the smallest UK bank considered, i.e. Standard Chartered. In terms of average assets over the period Anglo Irish Bank is actually the smallest bank (average assets of €43bn) however its central role in the precipitation of the Irish banking crisis has been well documented (see Mody (2009) and Whelan (2013)). Where Anglo's risk profile stands out is in terms of the enormous average returns on assets relative to the other banks, this being more than four times larger than any other bank in the sample. Anglo also maintained the highest liquidity ratio (loans-to-deposits) of any bank and had the lowest average capital-to-asset ratio (11.33%). In addition it was the most generous of the Irish banks in terms of making credit facilities available (as a proportion of shareholder equity) and also had the largest standard deviation of such facilities compared to all the other banks.

TABLE 3.2

Summary Information	Irish Banking System						UK Banking System					
	2008	2009	2010	2011	2012	2013	2008	2009	2010	2011	2012	2013
Balance Sheet												
Bank Assets	1,534,136	1,384,676	1,187,808	1,109,128	1,025,100	820,056	6,434,575	8,853,495	8,844,142	9,017,405	8,886,548	8,207,271
Bank Capital and Reserves	51,235	66,309	56,215	62,775	64,749	54,618	245,566	402,385	425,555	439,085	465,401	458,937
Bank Loans	850,209	798,651	600,148	472,465	432,449	353,676	3,841,122	4,045,351	3,509,163	3,340,966	3,471,536	3,344,341
Bank Deposits	321,636	324,099	258,608	222,120	243,693	230,360	2,321,876	2,971,199	2,920,431	2,897,017	3,176,084	3,295,287
Income Statement												
Net Interest Income	13,760	11,901	8,168	6,155	6,055	5,555	72,826	85,064	84,157	79,819	75,767	77,312
Noninterest Income, Net	2,375	1,582	1,893	2,148	2,053	1,775	39,071	52,581	51,975	51,729	47,945	51,306
Gross Income	16,135	13,483	10,061	8,303	8,107	7,330	111,897	137,644	136,134	131,547	123,712	128,618
Operating Expenses	7,684	6,773	6,476	6,024	7,030	6,002	72,255	99,300	106,009	103,045	106,980	111,875
Provisions, Net	-2,716	-62	735	372	-102	-41	-48,603	-75,248	-41,949	-40,366	-30,032	-28,240
Profit Before Tax	757	-24,836	-38,984	-9,892	-9,585	-7,746	-23,915	605	27,355	26,504	15,786	18,995
Net Income	8,517	11,043	-4,904	8,740	550	-	50,445	75,835	69,903	66,214	45,643	-
Balance Sheet Ratios												
Provisions/ Bank Loans (%)	(0.32)	(0.01)	0.12	0.08	(0.02)	(0.01)	-1.27	(1.86)	(1.20)	(1.21)	(0.87)	(0.84)
Capital and Reserves/ Bank Assets (%)	3.34	4.79	4.70	5.70	6.30	6.70	3.82	4.50	4.80	4.90	5.20	5.60
Bank Loans/ Bank Assets (%)	55.42	57.68	50.50	42.60	42.20	43.10	59.7	45.70	39.70	37.10	39.10	40.70
Bank Loans/ Bank Deposits (%)	264.34	246.42	232.10	212.70	177.50	153.50	165.43	136.20	120.20	115.30	109.30	101.50
Provisions, Net/ Bank Assets (%)	(0.18)	0.00	0.10	0.00	0.00	0.00	-0.76	(0.80)	(0.50)	(0.40)	(0.30)	(0.30)
Profitability												
Return On Assets (%)	0.05	(1.79)	(3.30)	(0.90)	(0.90)	(0.90)	-0.37	0.00	0.30	0.30	0.20	0.20
Net Interest Margin (%)	0.90	0.86	0.70	0.60	0.60	0.70	1.13	1.00	1.00	0.90	0.90	0.90
Operating Expenses/ Gross Income (%)	47.63	50.23	64.40	72.60	86.70	81.90	64.57	72.10	77.90	78.30	86.50	87.00
Nonint Inc/ Gross Income (%)	14.72	11.73	18.80	25.90	25.30	24.20	34.92	38.20	38.20	39.30	38.80	39.90
Nonint Inc/ Op Exp (%)	30.91	23.36	29.20	35.60	29.20	29.60	54.07	53.00	49.00	50.20	44.80	45.90
Operating Expenses/ Bank Assets (%)	0.50	0.49	0.50	0.50	0.70	0.70	1.12	1.10	1.20	1.10	1.20	1.40
Noninterest Income/ Bank Assets (%)	0.16	0.11	0.20	0.20	0.20	0.20	0.61	0.60	0.60	0.60	0.50	0.60

This table presents aggregate banking sector details for Ireland and the UK. Included are totals for Balance Sheet and Income Statement aggregated by all banks operating in each country. Also presented are important Balance Sheet and Income Statement operational ratios which are indicative of the relevant strength and weaknesses of each sector as a whole. Millions are the unit of measure.

Net-interest-margins, leverage ratios and liquidity ratios are broadly comparable across the two bank groups.

The Irish banks' average distance-to-default (Z-Score) is higher (at 25.31) than the UK equivalent (21.48) but this is driven by the relatively high Z-Scores of Bank of Ireland and Permanent TSB relative to their peers. By this measure Allied Irish Bank and RBSG are the two banks most susceptible to returns / capital shocks.

The UK banks provide more than twice the levels of undrawn credit facilities as the Irish banks (as a proportion of shareholder equity) so that, even though their capital and net-interest-margin exposures are broadly comparable, the UK banks are more likely to become embroiled in a liquidity/asset downward spiral as clients avail of credit facilities during periods of more challenging inter-bank lending conditions and where banks cannot roll-over short-term finance. Such a liquidity spiral can result in a fire-sale of assets leading to even greater liquidity strains at a systemic level (see Brunnermeier et al. (2009)). Against this we observe that the Irish banks, consistent with Table 3.2, have higher loans-to-deposit ratios than the UK's (1.84 versus 1.01) leaving them relatively more exposed to other forms of asset-valuation shocks (i.e. not necessarily driven by liquidity stresses, for instance the bursting of a real-estate bubble).[50]

The individual systemic risk measures for each of our sample banks are presented in Table 3.4. Details presented include NPL ratios (% of total loans), MES, ΔCoVaR, SES and our newly-created composite risk index (CRI).

[50] Some commentators believe the Irish property bubble started to burst when a Government minister announced that state funding via property-related stamp-duty was no longer required. Market activity immediately ceased as buyers anticipated a reduction of stamp-duty in an upcoming budget and property prices started to decline. This preceded the GFC by approximately 3 quarters (see Whelan (2013)).

TABLE 3.3

	Total Assets (Billion)		Return on Assets (%)		Capital to Asset Ratio (Leverage Ratio %)		Net Interest Margin (%)		Total Loans Extended (Billion)		Total Deposits		Loans to Deposits (Liquidity Ratio)		Bank Z-Score (Distance to Default)		Undrawn Credit to S/holder Equity	
Bank Name	**Avg**	**S.D**	**Avg**	**S.D.**	**Avg**	**S.D.**	**Avg**	**S.D.**	**Avg**	**S.D.**	**Avg**	**S.D.**	**Avg**	**S.D.**	**Avg**	**S.D.**	**Avg**	**S.D.**
Allied Irish Bank	113	44.57	0.12	1.94	12.04	3.13	2.39	0.78	70	32.16	57	16.67	1.17	0.22	6.28	1.41	2.76	1.30
Anglo Irish Bank	42	34.52	4.15	1.76	11.33	2.22	2.76	1.57	22	21.85	17	16.40	2.92	5.58	8.07	1.31	3.99	5.59
Bank of Ireland	122	54.60	0.12	0.33	12.43	1.66	2.02	0.61	81	36.26	59	18.76	1.32	0.26	37.66	4.70	3.34	1.28
Permanent TSB	48	25.17	0.09	0.25	12.16	3.07	1.33	0.46	25	12.20	12	3.96	1.95	0.59	49.23	11.98	0.16	0.11
Barclays Bank	884	558.62	0.38	0.34	13.06	2.34	2.11	0.71	281	133.33	245	105.15	1.11	0.13	14.44	3.69	6.33	1.78
HSBC	933	538.00	1.03	0.42	13.75	1.27	2.77	0.35	289	119.81	357	120.70	0.80	0.11	18.71	4.95	5.18	1.50
Lloyds PLC	466	332.24	0.26	0.27	12.06	2.96	2.86	0.65	279	209.92	212	141.46	1.25	0.17	10.00	2.82	5.29	2.51
RBSG	856	621.37	0.23	0.25	12.58	1.52	2.57	0.40	342	207.21	295	156.74	1.08	0.17	6.95	1.96	5.12	1.27
Standard Chartered	170	131.11	0.48	0.18	15.13	1.62	2.72	0.43	78	55.31	97	73.28	0.83	0.06	18.42	6.03	4.31	2.42
Summary Statistics:																		
Irish Average	81.33	39.72	1.12	1.07	11.99	2.52	2.12	0.86	49.50	25.62	36.25	13.95	1.84	1.66	25.31	4.85	2.56	2.07
Irish Std. Deviation	42.00	12.70	2.02	0.90	0.47	0.71	0.61	0.49	30.38	10.81	25.21	6.74	0.79	2.62	21.48	5.01	1.68	2.41
UK Average	661.80	436.27	0.47	0.29	13.32	1.94	2.61	0.51	253.80	145.12	241.20	119.47	1.01	0.13	13.70	3.89	5.25	1.90
UK Std. Deviation	331.98	202.19	0.32	0.09	1.19	0.69	0.30	0.16	101.61	65.00	97.42	32.45	0.20	0.05	5.17	1.63	0.72	0.55
Pooled Average	403.81	260.02	0.76	0.64	12.73	2.20	2.39	0.66	163.00	92.01	150.11	72.57	1.38	0.81	18.86	4.32	4.06	1.97
Pooled Std. Deviation	386.48	253.34	1.30	0.69	1.13	0.72	0.50	0.37	130.78	78.25	129.04	60.30	0.67	1.80	14.96	3.32	1.82	1.53

This table summarises the various systemic crisis determinants data, drawn from balance sheet time series data , that we interact with the Systemic Risk Measures in a vector autoregressive model. For each of the main banks in the UK and Ireland we report data on size (assets), profitability (ROA), leverage (capital to asset ratio), interest rate exposure (net interest margin), credit extended (total loans), deposit funding, liquidity (loans to deposit ratio), default risk / credit worthiness (Bank Z-Score) and exposure to a liquidity shock (undrawn credit to shareholder equity). The data spans the time-frame 1997-2013. Summary statistics for each geography are provided as well as pooled summary statistics.

Later these measures will be aggregated into country-level measures of systemic risk with appropriate SRMs for the Irish and UK banking sectors taken as a whole.

In the case of both NPL and CRI the SRMs represent asset-weighted aggregates of their underlying individual bank counterparts. The remaining SRMs are drawn from individual bank market returns data, asset-weighted as before, so as to yield the sectoral SRM equivalent. The non-performing-loan and composite risk index data are drawn, like the determinants data of Table 3.3, from annual and interim reports whereas the other market-return based SRMS are sourced via DataStream.

The average NPL level of the Irish banking sector is more than three times that of the UK and with almost twice the standard deviation. Given the enormous impact of the GFC on the Irish economy this is to be expected. Anglo Irish Bank is once again the most exposed with average NPL levels of 12.2%, which are almost three times that of Bank of Ireland. Allied Irish Bank also reports very high NPL levels of 7.45% on average over this period – reflecting why its nationalisation was necessary by 2010.

The relative fragility of the Irish banks is also highlighted by the enormous difference between the MES of the Irish banks and that of the UK (-3.05% vs. 0.02%). These figures illustrate the extent to which the stock market in Ireland was driven by financial services sector returns and how the UK markets were less vulnerable to such financial sector shocks during this period. However a slightly different picture emerges when extreme shocks (i.e. extreme tail events) are considered. Looking at the ΔCoVaR measure we see the UK financial sector is most susceptible to returns disturbances involving HSBC and Barclays.

Not surprisingly the Irish financial sector is most exposed to large shocks involving Allied Irish Bank and Bank of Ireland, the so-called Pillar banks.

TABLE 3.4

	Non-performing loan ratio (NPL)			Marginal Expected Shortfall (MES)			Delta-CoVaR (ΔCoVaR)			Systemic Expected Shortfall (SES)			Composite Risk Index (CRI)		
Bank Name	**Avg**	**Min**	**Max**	**Avg**	**Min**	**Max**	**Avg**	**Min**	**Max**	**Avg**	**Min**	**Max**	**Avg**	**Min**	**Max**
Allied Irish Bank	7.45	0.70	34.90	-3.41	-12.84	0.989	-0.142	-4.26	2.79	131	0	8935	2.17	-1.00	6.50
Anglo Irish Bank	12.20	0.50	65.45	-2.38	-10.14	3.922	-1.938	-14.09	7.78	41	0	1285	3.34	0.50	10.75
Bank of Ireland	4.13	0.50	17.80	-3.40	-13.43	0.000	-1.690	-17.81	9.18	166	0	3408	2.26	-1.00	6.50
Permanent TSB	3.31	0.20	25.60	-3.02	-18.27	0.712	1.916	-5.52	12.94	43	0	2907	2.48	-1.75	6.25
Barclays Bank	2.87	1.19	5.10	-0.04	-3.87	2.844	-6.595	-83.79	45.71	11221	0	62789	1.71	-2.50	5.94
HSBC	2.24	0.70	4.00	0.08	-3.31	3.774	-8.241	-37.29	30.77	7546	0	31154	1.93	-1.25	4.25
Lloyds PLC	1.11	0.50	2.49	0.06	-5.89	4.068	0.146	-1.06	1.90	6510	0	34605	1.56	-0.63	3.50
RBSG	1.93	0.29	5.40	-0.01	-3.89	7.102	0.599	-4.35	7.84	5425	0	52620	1.96	-2.13	5.25
Standard Chartered	1.30	0.69	2.57	-0.02	-4.89	3.710	8.360	-26.68	46.82	1637	0	8351	2.30	-0.44	5.75
Summary Statistics:															
Irish Average	6.77	0.48	35.94	-3.05	-13.67	1.41	-0.46	-10.42	8.18	95	0.00	4134	2.56	-0.81	7.50
Irish Std. Deviation	4.04	0.21	20.88	0.48	3.38	1.73	1.77	6.58	4.20	63	0.00	3327	0.53	0.94	2.17
UK Average	1.89	0.67	3.91	0.02	-4.37	4.30	-1.15	-30.63	26.61	6468	0.00	37904	1.89	-1.39	4.94
UK Std. Deviation	0.71	0.33	1.37	0.05	1.02	1.63	6.62	33.36	20.94	3471	0.00	21009	0.28	0.91	1.04
Pooled Average	4.06	0.59	18.15	-1.35	-8.50	3.01	-0.84	-21.65	18.42	3636	0.00	22895	2.19	-1.13	6.08
Pooled Std. Deviation	3.60	0.29	21.20	1.64	5.37	2.19	4.82	26.19	17.89	4160	0.00	23273	0.52	0.91	2.03

This table summarises the various systemic risk measures relating to the banking sectors of Ireland and the UK over the period 1997 to 2013. The data for MES, Delta CoVaR and Systemic Expected Shortfall is derived from returns data taken from Datastream. Non-performing loan and composite risk index data is drawn from annual / interim bank reports published during this period. The measures themselves are described in section 3 of the paper. Here we present summary statistics comprising average, minimum and maximum values for each of the institutions considered. We also provide summary statistics of these SRMs aggregated by asset weight in each jurisdiction. Finally, full sample summary statistics are also provided.

We also note that the relatively small banks (per country) sometimes report positive values, as is the case with both Standard Chartered and Permanent TSB. This means these banks carry relatively low levels of systemic risk according to the ΔCoVaR measure.

By its nature the average values of SES are somewhat misleading, the maximum values should be considered instead. These represent the amount of bank capital required, in millions, during periods when the banking sector as a whole is undercapitalised (relative to Basel III capital-adequacy rules). Most of the time there is no shortfall so the minimum values are reported as zero. Barclays reports a maximum SES value of almost £63bn followed by RBSG's figure of almost £53bn. Allied Irish Bank is the worst-performing Irish bank, with its largest shortfall being just under €9bn. It should be noted that Anglo Irish Bank's figures do not take into account actual losses incurred upon the liquidation of the company as trading in Anglo was suspended prior to liquidation. In that sense its SES figures are also somewhat misleading, leaving the measure itself open to the criticism that it may not accurately capture the full extent of the systemic risk posed by an individual bank during a crisis episode. We present further evidence of this in the results section below. Finally, the CRI measures are also shown. As this has been constructed to represent trend deviations in risky directions away from sample averages it is not surprising that we now see greater homogeneity between the two banking systems. The Irish banking sector carries more risk than the UK over this period – as expected. Yet again Anglo Irish Bank is prominent as the most risky Irish bank on average. Standard Chartered is the most risky UK equivalent, followed closely by RBSG. These individual CRI scores are asset-weighted to determine the sectoral counterparts, thus the impact of high CRI scores in relatively low asset-holding banks is lessened when consolidated at the overall banking sector level. In Figs. 1 and 2 we show the time path of the CRI for each of the banks. Note the increase in the CRI of each bank in the run-up to the GFC, represented as a vertical red line as of 2008Q2 (see

Laeven and Valencia (2013)). The trend lines for Allied Irish Bank and Bank of Ireland are very similar. Permanent TSB also follows a very similar pattern from 2001 onwards but its CRI score came from a plateau in the year 2000 when it was higher than its GFC-based level.

Once again Anglo Irish Bank is markedly different to its peers. Its distinctive U-shape illustrates how Anglo moved from a relatively high position around the year 1997 and declined until the start of the Irish property bubble circa 2004. From then it increased and kept rising until it was eventually liquidated. In contrast, the Pillar banks reached their peak values around 2009 after which changes to bank regulation, sovereign aid and other intervention measures took hold and their respective CRI values declined. In the UK Barclays, Lloyds and HSBC follow similar patterns to those of the Irish banks, however in the case of the latter their peak values are realised prior to the GFC, unlike Barclays which peaks post-2008. This suggests those banks recognised and took action to mitigate their risk levels following the Northern Rock bank run in 2007.

These national differences can be seen graphically in Fig. 3 where the SRMs for the Irish and UK banking sectors are presented alongside each other. Evidence for our assertion that the risk signature, in the form of scale, timing and direction, of the two banking sectors' risk were radically different is clearly visible. For example, in the case of Ireland the scale of the NPL graph is ten times that of the UK but we see that, in each case, the NPL levels rise in the wake of the GFC. There is no clear pre-crisis signal of sectoral weakness emanating from the NPL channel, especially in the case of Ireland. This result may explain Hoggarth et al.'s (2005b) finding that the UK banking system is robust, even to large macroeconomic shocks.

The MES graph demonstrates how dependent the ISEQ is upon the returns of the Irish banks. When the ISEQ is experiencing large losses the MES levels of the Irish banking system is almost always increasing (larger negative values) in unison. By contrast, the UK-related graphs provide evidence of how relatively loosely-coupled the FTSE and the UK banking sector were, where banks risk levels actually reduced on occasion (positive MES values) even though the FTSE was performing poorly. The SES graphs show the UK banking system experienced under-capitalisation episodes more frequently than occurred in Ireland. However neither banking system was reported as being under-capitalised as of 2008Q2. The UK banks were most under-capitalised around the time of the Northern Rock deposit run, whereas the risk in Ireland appeared greatest in 2004-2005. SES does not appear to provide a good pre-crisis signal, however ΔCoVaR fares better. In each country there were prolonged periods of extreme left-tail distributional shifts associated with increasing systemic risk levels, especially in the years leading up to the crisis, with the scale of these risks being broadly similar. The CRI graphs echo this feature where evidence is also seen of increasing bank risk. There are clear signs that key management ratios were trending further and further away from sample averages, always in the direction of increasing risk, during the years just prior to the GFC. In the UK, these risks were brought under control far earlier than they were in Ireland where the ineffectiveness of the blanket bank guarantee, the creation of NAMA and other government intervention is evident.

3.4. Approach

The systemic banking crisis literature shows that risks have multiple sources. Therefore to establish which of the SRMs is "best" we need to consider how each performs from a variety of perspectives. One approach is to analyse the extent to which the SRM interacts with a cluster of known systemic crisis determinants. This echoes Hoggarth et al's. (2005b) approach where the SRM analysed is the UK banking sector's loan write-off ratio. Their control variables include: 1) GDP output gap, 2) nominal short-term interest rate, 3) inflation and 4) real exchange rate. A difficulty arises as there is no standard method of calculating actual GDP output gap, a fact the authors acknowledge. They select a Cobb-Douglas production function to measure potential

GDP but do not explain how the capital and labour parameters are determined. There are several studies showing how GDP growth-rates, short-term interest rates and inflation are frequently associated with periods of systemic banking stress (see Demirgüç-Kunt and Detragiache (1998 and 2002), Beck et al. (2009) and Eichler and Sobański (2012)) so the inclusion of these variables by Hoggarth et al. (2005b) appears valid. However other literature shows that sectoral variables such as debt-to-GDP ratio (credit extended), Bank Z-Score, leverage ratio and liquidity ratio are equally important systemic crises determinants (see Eichler and Sobański (2012), Davis and Karim (2008) and Chapter 2), therefore we need to discriminate between the choices available at the macroeconomic and sectoral levels.

It would not be appropriate or practical to simply include all known determinants in a vector autoregressive model, for several reasons. First, these determinants are based upon global studies involving pooled data analyses spanning, in most cases, dozens of banking sectors. These studies make little allowance for differences between the various banking sectors insofar as what may be a determinant in country A may not feature at all in terms of country B. Second, these studies are often pooled logit models which are not geared toward an examination of causality, they simply report which variables happen to be associated with systemic crises.

Another complicating factor is that systemic crisis determinants may become endogenously determined during crisis years and may bias the results of such pooled logit regressions. For these reasons it is not possible to determine whether a sovereign crisis has resulted in a banking crisis or the other way around. If it is the former then the selection of macroeconomic variables should take precedence in our models. If it is the latter, then it would be reasonable to focus our attention on sectoral variables at the expense of macroeconomic factors. A final difficulty lies in the fact that we wish our VAR models to be parsimonious, including only variables we know for certain to be systemic crisis determinants as far as Ireland and the UK in particular are concerned. The more variables we add to the VAR the more cumbersome and, potentially, unstable it becomes as lagged values are added.

To overcome these difficulties we commence by examining the behaviour of the most commonly-reported systemic banking crisis determinants in separate VAR models, one VAR per country. This allows us to examine their dynamic interaction and to select only the most significant factors for further analysis. Once we have identified a meaningful set of control variables (i.e. crisis determinants) for each country we then bring these forward into our SRM-based VARs. The advantage of this approach is that it allows us to demonstrate whether or not a particular SRM is affected by single or multiple determinants. Knowing a-priori that these global crisis determinants are mutually significant in the case of a specific country means we can be certain that, when examined in the context of a particular SRM, we can test two related hypotheses : 1) that the SRM is Granger-caused by one or more systemic crisis determinants and 2) that the SRM in turn Granger-causes any systemic crisis determinants. Thus not only can we establish if the SRM is capturing and reflecting multiple components of systemic risk but also whether or not the SRM is more than just a passive indicator of risk, inherently representing a risk channel by which systemic banking crisis determinants are influenced more generally (see Guntay and Kupiec (2014)).

Another aspect of our SRM appraisal is via the evaluation of shock transmission dynamics in such VARs. This is accomplished via impulse-response function (IRF) analysis which often accompanies VAR output. In our analysis the IRFs show how a one-standard-deviation shock to a particular determinant impacts the other variables in the VAR, including the SRMs. We can identify the specific quarter when a shock has its largest effect upon the remaining variables, the maximum extent of the shocks and the direction (path) followed by the variables in the wake of a shock. The inclusion of two banking sectors in our evaluation allows us to understand whether shocks result in similar behaviour across each country or if there are important differences. We include detailed IRF analysis in our results with particular emphasis placed upon the impulse and response of the various SRMs.

Naturally, understanding how systemic crises emerged in the past and how they unfold are useful aspects of any crisis-related paper. But it is also important to establish whether a particular SRM functions well as a forecasting tool. Ideally, forecasts should have 95% confidence intervals closely matching actually-observed values, otherwise the forecasts may be considered unreliable. The Granger-causality tests / IRFs described above rely upon quarterly data drawn from the 1997-2008 time-frame, following which we develop 5-year forecasts (i.e. 20 quarters) covering the period 2009-2013 when the GFC was full-blown. Because we have observed values for the SRMs in these years our 2008 forecasts may be benchmarked and contrasted for accuracy and effectiveness purposes. The forecast results are also presented below.

A final attribute of the "best" SRM is to identify which SRM is most closely associated with the likelihood of a banking sector experiencing a systemic crisis due to being under-capitalised and therefore being less robust to earnings shocks. We test the contribution of each SRM towards the probability of such crises using the pooled logit model described above, but making use of fixed effects specifications in the regressions to eliminate inherent differences between the two banking systems (e.g. management effectiveness / cultural differences etc.). We establish the statistical significance of each SRM and also its marginal effect, thus allowing us to rank the SRMs accordingly.

3.5. Results

Determinants VAR:

We present the process by which the most representative Irish systemic crisis determinants are selected in Table 3.5. As is the case in all time-series analysis care is taken to ensure the stationarity of the variables in the model so as to avoid spurious regression results. All our data series are tested for stationarity with appropriate corrective action taken where necessary. In general, to avoid the stationarity problem we measure variables as growth-rates rather than in levels. These tend to be stationary, though confirmation is established via formal Dickey-Fuller tests. We identify the appropriate number of lags to include in each VAR (using a variety of Information Criteria) whilst also ensuring the stability of the VAR as a system. Having run the VAR with the appropriate number of lags (4 in the case of Table 3.5), the phase 1 column of Table 3.5 outlines the results of a Granger-causality test involving all common macroeconomic and sectoral crisis determinants. We call every iteration of the VAR a "Phase". From here we progressively reduce the number of variables in the VAR at the end of each phase, using the Granger-causality results and banking theory to isolate exogenous variables or those with limited explanatory power. By phase 5 we arrive at a four-factor model for Ireland comprising the following determinants: 1) undrawn credit to shareholder equity, 2) leverage, 3) liquidity and 4) debt-to-GDP ratio. Interestingly, in the case of Ireland, all remaining determinants are drawn from the banking sector, rather than from the wider macro-economy. This outcome suggests that, from Ireland's perspective, the GFC manifested itself as a banking crisis which ultimately damaged the wider economy rather than the other way around.

Table 3.5 should be considered in the following way. For each iteration/phase of the VAR model we consider a number of variables. In phase 1 all variables are considered. The model works by considering how the removal of one variable at a time affects the dependent variable listed in the "Equation" column (having isolated the lagged effects of that variable upon itself, as per the methodology outlined in section 3.2 above). For each variable excluded we present the appropriate Chi-squared coefficient, degrees of freedom and corresponding p-value. If the p-value is less than .01 that variable is said to Granger-cause the Equation variable, i.e. the lagged effects of the Granger-causing variable help to predict future values of the Equation variable. Thus we see that in phase 1, GDP growth-rate Granger-causes the Undrawn-Credit-to-Equity ratio at the 1% level of significance, but the growth of the leverage ratio (Capital-to-assets ratio) does not. The bank Z-Score coefficient has border-line significance at the 1% level.

For each Equation variable the row labelled ALL describes the effect of jointly removing ALL variables in terms of predicting future values of the Equation variable. The fact that, in all equations and in all phases, this value is significant at the 1% level shows how important these variables are with respect to each other and how interconnected they become in periods up to and including systemic crises. There is one exception to this which we address below.

We exclude GDP growth-rate in phase 2. This is because it only Granger-causes two variables (Undrawn-credit-to-Equity and International Capital Flows) in the VAR at the 1% level of significance and is itself not Granger-caused by any other variable at the 1% level. We feel it is necessary to set the bar high (i.e. at 1%) in terms of statistical significance if we are to reach our goal of a more parsimonious vector of determinants. Short-term interest rates are excluded in phase 3 because they are not jointly determined by the other variables in the VAR (e.g. excluding ALL variables only impacts short-term rates at the 5% level of significance). Whereas it Granger-causes Bank Z-Scores and the leverage ratio at the 1% level we find it does so exogenously.

TABLE 3.5

Equation	Granger Causing Variable	Phase 1			Phase 2			Phase 3			Phase 4			Phase 5		
		chi2	**df**	**Prob**	**chi2**	**df**	**Prob**	**chi2**	**df**	**Prob**	**chi2**	**df**	**Prob**	**chi2**	**df**	**Prob**
Undrawn Credit to Equity Ratio	GDP Growth Rate	18.908	4	0.001												
	Intl. Capital Flows	18.923	4	0.001	10.645	4	0.031	16.016	4	0.003	10.265	4	0.036			
	Bank Z-Score	13.293	4	0.010	12.05	4	0.017	16.861	4	0.002						
	Leverage Ratio Growth	12.309	4	0.015	15.824	4	0.003	20.541	4	0.000	7.8573	4	0.097	10.076	4	0.039
	Short Term Interest Rates	14.421	4	0.006	11.72	4	0.020									
	Debt to GDP Ratio	23.667	4	0.000	15.584	4	0.004	17.221	4	0.002	15.933	4	0.003	22.046	4	0.000
	Loans to Deposit Ratio	33.839	4	0.000	15.504	4	0.004	11.649	4	0.020	8.5643	4	0.073	8.8444	4	0.065
	ALL	**173.77**	**28**	**0.000**	**106.74**	**24**	**0.000**	**80.117**	**20**	**0.000**	**49.9**	**16**	**0.000**	**34.082**	**12**	**0.001**
Leverage Ratio Growth	GDP Growth Rate	13.181	4	0.010												
	Intl. Capital Flows	9.8179	4	0.044	15.776	4	0.003	14.924	4	0.005	17.676	4	0.001			
	Bank Z-Score	13.52	4	0.009	14.401	4	0.006	11.711	4	0.020						
	Undrawn credit to equity	13.504	4	0.009	18.966	4	0.001	10.224	4	0.037	10.009	4	0.040	6.0366	4	0.196
	Short Term Interest Rates	25.285	4	0.000	19.207	4	0.001									
	Debt to GDP Ratio	10.567	4	0.032	10.004	4	0.040	8.3839	4	0.078	8.4471	4	0.077	11.692	4	0.020
	Loans to Deposit Ratio	38.308	4	0.000	62.898	4	0.000	46.525	4	0.000	39.5	4	0.000	28.053	4	0.000
	ALL	**171.97**	**28**	**0.000**	**148.94**	**24**	**0.000**	**99.422**	**20**	**0.000**	**73.963**	**16**	**0.000**	**43.954**	**12**	**0.000**
Loans to Deposit Ratio	GDP Growth Rate	9.1707	4	0.057												
	Intl. Capital Flows	12.156	4	0.016	21.915	4	0.000	22.851	4	0.000	20.493	4	0.000			
	Bank Z-Score	14.941	4	0.005	11.072	4	0.026	10.413	4	0.034						
	Undrawn credit to equity	8.4519	4	0.076	8.2266	4	0.084	8.2048	4	0.084	8.5758	4	0.073	5.8383	4	0.212
	Leverage Ratio Growth	17.556	4	0.002	16.195	4	0.003	15.114	4	0.004	8.1267	4	0.087	10.644	4	0.031
	Short Term Interest Rates	6.9306	4	0.140	1.6359	4	0.802									
	Debt to GDP Ratio	8.1326	4	0.087	17.703	4	0.001	19.232	4	0.001	16.024	4	0.003	16.567	4	0.002
	ALL	**120.52**	**28**	**0.000**	**97.575**	**24**	**0.000**	**93.511**	**20**	**0.000**	**71.312**	**16**	**0.000**	**38.345**	**12**	**0.000**
Debt to GDP Ratio	GDP Growth Rate	4.1765	4	0.383												
	Intl. Capital Flows	29.992	4	0.000	14.68	**4**	**0.005**	**12.626**	**4**	**0.013**	**14.482**	**4**	**0.006**			
	Bank Z-Score	25.256	4	0.000	10.826	4	0.029	6.1853	4	0.186						
	Undrawn credit to equity	18.143	4	0.001	20.637	4	0.000	20.338	4	0.000	18.942	4	0.001	13.513	4	0.009
	Leverage Ratio Growth	7.6632	4	0.105	11.429	4	0.022	14.436	4	0.006	22.985	4	0.000	12.675	4	0.013
	Short Term Interest Rates	22.136	4	0.000	11.973	4	0.018									
	Loans to Deposit Ratio	35.922	4	0.000	21.729	4	0.000	21.233	4	0.000	28.033	4	0.000	24.345	4	0.000
	ALL	**167.89**	**28**	**0.000**	**113**	**24**	**0.000**	**84.892**	**20**	**0.000**	**71.67**	**16**	**0.000**	**46.499**	**12**	**0.000**
International Capital Flows	GDP Growth Rate	13.705	4	0.008												
	Bank Z-Score	18.046	4	0.001	15.606	4	0.004	12.683	4	0.013						
	Undrawn credit to equity	3.8269	4	0.430	0.6879	4	0.953	1.9026	4	0.754	2.1792	4	0.703			
	Leverage Ratio Growth	10.297	4	0.036	7.491	4	0.112	6.4808	4	0.166	2.2054	4	0.698			
	Short Term Interest Rates	11.207	4	0.024	5.9154	4	0.206									
	Debt to GDP Ratio	6.3917	4	0.172	0.85566	4	0.931	1.2781	4	0.865	3.8554	4	0.426			
	Loans to Deposit Ratio	22.531	4	0.000	22.577	4	0.000	17.182	4	0.002	10.776	4	0.029			
	ALL	**76.933**	**28**	**0.000**	**51.889**	**24**	**0.001**	**42.027**	**20**	**0.003**	**24.427**	**16**	**0.081**			
Bank Z-Score	GDP Growth Rate	3.1316	4	0.536												
	Intl. Capital Flows	2.3442	4	0.673	3.85	4	0.427	3.1833	4	0.528						
	Undrawn credit to equity	29.226	4	0.000	23.024	4	0.000	11.78	4	0.019						
	Leverage Ratio Growth	10.968	4	0.027	12.771	4	0.012	8.6403	4	0.071						
	Short Term Interest Rates	19.59	4	0.001	24.552	4	0.000									
	Debt to GDP Ratio	4.523	4	0.340	10.491	4	0.033	8.4609	4	0.076						
	Loans to Deposit Ratio	53.089	4	0.000	59.891	4	0.000	37.211	4	0.000						
	ALL	**175.76**	**28**	**0.000**	**156.93**	**24**	**0.000**	**95.254**	**20**	**0.000**						
Short Term Interest Rates	GDP Growth Rate	8.3761	4	0.079												
	Intl. Capital Flows	8.3794	4	0.079	8.4032	4	0.078									
	Bank Z-Score	17.513	4	0.002	4.1841	4	0.382									
	Undrawn credit to equity	12.451	4	0.014	7.3995	4	0.116									
	Leverage Ratio Growth	7.1953	4	0.126	2.3805	4	0.666									
	Debt to GDP Ratio	3.5652	4	0.468	8.4423	4	0.077									
	Loans to Deposit Ratio	13.599	4	0.009	6.5631	4	0.161									
	ALL	**66.578**	**28**	**0.000**	**38.494**	**24**	**0.031**									
GDP Growth Rate	Intl. Capital Flows	12.535	4	0.014												
	Bank Z-Score	11.527	4	0.021												
	Undrawn credit to equity	12.897	4	0.012												
	Leverage Ratio Growth	2.6723	4	0.614												
	Short Term Interest Rates	7.8857	4	0.096												
	Debt to GDP Ratio	7.4398	4	0.114												
	Loans to Deposit Ratio	8.2891	4	0.082												
	ALL	**84.094**	**28**	**0.000**												

This table illustrates how ex-ante known systemic crisis determinants (see Chapter 2) interact with each other in the Irish macroeconomic / banking sector. The objective is to arrive at a parsimonious set of macroeconomic / sectoral variables that are shown to be significant causal factors of each other and against which the effectiveness of the various systemic risk measures may be assessed in vector autoregression models. In Phase 1 GDP growth rate does not Granger cause any variable at the 1% level of significance apart from international capital flows and undrawn credit to equity (which is not known ex-ante as a systemic crisis determinant). Therefore GDP growth rate is not considered in Phase 2 and drops out. A full description of the rationale behind the removal of variables at particular stages is provided in the paper. The "Prob" score indicates the significance level, variables less than .01 are significant at the 1% level as per usual. We arrive at a model comprising 4 sectoral variables in Phase 5 which can be used to test the SRMS at a later stage of the analysis.

By phase 4 we remove the Bank Z-Score. The only variable it Granger-causes is Undrawn-credit-to-Equity. By phase 5 our International Capital Flows variable is removed as, once again, it is shown to be exogenous in that it is not jointly determined by the remaining VAR components.

Finally in phase 5 we see that all variables Granger cause at least 1 other variable at the 1% level and all the variables are significantly jointly determined by each other. A case might be made for the exclusion of Undrawn-credit-to-Equity at this stage however one of our goals is to examine the impact of this factor upon the SRMs so we retain it for that reason.

We have chosen to include maximally correlated variables in our VAR analysis prior to the introduction of the various SRMs. There are several reasons for this ; 1) each variable in our VAR is a systemic crisis determinant and each Granger-causes the other, therefore to omit those variables from the SRM VARs might lead to important factors being overlooked, 2) the purpose of VAR analysis is to try to allow for endogenous variables to be analysed and shocks to each interpreted. Thus our goal is to model the interaction of a parsimonious yet significant set of endogenous variables in our VARs such that their high degree of interconnectedness helps to determine the systemic risk impact of various shocks upon a banking system.

We repeat this exercise for the UK banking sector, reporting our results in Table 3.6. Commencing with the same variables in phase 1 as were analysed in the case of Ireland we repeat the process until, by phase 5, we have also reached a point whereby we have 4 determinants all jointly Granger-causing each other at a 1% level of significance. However the four remaining determinants are not the same as those remaining in the case of Ireland. This re-emphasises the differences in risk profile between Ireland and the UK. For example Undrawn-credit-to-Equity features prominently in the case of Ireland, but does not do so in the case of the UK. Another liquidity measure, i.e. the loans-to-deposits ratio is also of importance in an Irish context, unlike the UK where asset values and the performance of the wider economy are the two key risks. Our results tell us that liquidity risk was one of the central issues affecting Irish banks leading up to the GFC, whereas the liquidity intervention of the British government subsequent to the Northern Rock deposit run appears to have had the required effect. Consistent with this result we observe how distance-to-default (i.e. the extent to which assets must fall before a bank is insolvent as measured by Bank Z-Score) features significantly in the UK, but not in Ireland.

Brunnermeier et al. (2009) describe the mechanism by which liquidity imbalances may amplify and exacerbate asset-valuation issues downstream. The Irish banks demonstrate clear evidence of this in that liquidity risk is signalled in two of our four most important determinants, whereas asset valuations are not. Asset risk is captured only via the leverage ratio in case of the Irish banks.

There are areas whereby risk is common to both Irish and UK banks. Risk channelled via the wider economy is reflected via GDP measures, GDP growth-rate and debt-to-GDP in the case of the UK, but only via debt-to-GDP ratios in the case of Ireland. Also, leverage ratios are important in each country as measured by the capital-to-asset ratio, results which reinforce the importance of measures that take both credit growth and GDP growth into account in such studies.

Granger-causality Tests:

Having selected the appropriate VAR variables we commence with the analysis of the Irish banking-sector's SRMs. We later repeat this analysis with respect to the UK banks. As stated earlier our analysis focuses upon the years leading up to the crisis (benchmarked as of 2008Q2)

TABLE 3.6

Equation	Granger Causing Variable	Phase 1			Phase 2			Phase 3			Phase 4			Phase 5		
		chi2	df	Prob	chi2	df	Prob	chi2	df	Prob	chi2	df	Prob	chi2	df	Prob
GDP Growth Rate	Bank Z-Score	10.515	3	0.015	9.3317	3	0.025	9.6668	3	0.022	12.371	3	0.006	10.883	3	0.012
	Leverage Ratio Growth	7.1779	3	0.066	6.2426	3	0.100	6.9008	3	0.075	8.8649	3	0.031	7.999	3	0.046
	Debt to GDP Ratio	18.11	3	0.000	17.854	3	0.000	16.441	3	0.001	16.929	3	0.001	15.636	3	0.001
	Short Term Interest Rates	3.9188	3	0.270	5.9724	3	0.113	7.4072	3	0.060	5.4791	3	0.140			
	Intl. Capital Flows	2.611	3	0.456	5.5264	3	0.137	6.8538	3	0.077						
	Undrawn credit to equity	1.3805	3	0.710	1.2395	3	0.744									
	Loan to Deposit Ratio	1.1962	3	0.754												
	ALL	**47.321**	**21**	**0.001**	**45.278**	**18**	**0.000**	**43.202**	**15**	**0.000**	**32.832**	**12**	**0.001**	**25.196**	**9**	**0.003**
Bank Z-Score	GDP Growth Rate	12.455	3	0.006	9.3537	3	0.025	11.562	3	0.009	13.869	3	0.003	14.262	3	0.003
	Leverage Ratio Growth	22.486	3	0.000	18.846	3	0.000	20.228	3	0.000	23.56	3	0.000	26.537	3	0.000
	Debt to GDP Ratio	22.883	3	0.000	21.616	3	0.000	14.798	3	0.002	14.347	3	0.002	14.322	3	0.002
	Short Term Interest Rates	5.5281	3	0.137	5.4883	3	0.139	1.6274	3	0.653	1.4341	3	0.698			
	Intl. Capital Flows	0.52653	3	0.913	1.5338	3	0.674	0.51124	3	0.916						
	Undrawn credit to equity	15.448	3	0.001	12.821	3	0.005									
	Loan to Deposit Ratio	5.2601	3	0.154												
	ALL	**109.3**	**21**	**0.000**	**96.137**	**18**	**0.000**	**69.41**	**15**	**0.000**	**68.353**	**12**	**0.000**	**65.452**	**9**	**0.000**
Leverage Ratio Growth	GDP Growth Rate	9.8562	3	0.020	7.6091	3	0.055	10.253	3	0.017	11.715	3	0.008	11.766	3	0.008
	Bank Z-Score	18.648	3	0.000	16.887	3	0.001	17.418	3	0.001	18.21	3	0.000	20.35	3	0.000
	Debt to GDP Ratio	22.829	3	0.000	21.815	3	0.000	14.927	3	0.002	15.072	3	0.002	15.033	3	0.002
	Short Term Interest Rates	5.9471	3	0.114	6.4236	3	0.093	1.876	3	0.599	2.0421	3	0.564			
	Intl. Capital Flows	0.5884	3	0.899	0.47959	3	0.923	0.9998	3	0.801						
	Undrawn credit to equity	16.758	3	0.001	14.655	3	0.002									
	Loan to Deposit Ratio	4.3694	3	0.224												
	ALL	**111.71**	**21**	**0.000**	**100.48**	**18**	**0.000**	**69.832**	**15**	**0.000**	**67.773**	**12**	**0.000**	**63.699**	**9**	**0.000**
Debt to GDP Ratio	GDP Growth Rate	2.4902	3	0.477	1.8248	3	0.610	1.816	3	0.611	3.2718	3	0.352	2.5329	3	0.469
	Bank Z-Score	8.1356	3	0.043	10.044	3	0.018	9.3911	3	0.025	7.4482	3	0.059	8.8143	3	0.032
	Leverage Ratio Growth	3.7464	3	0.290	4.96	3	0.175	4.673	3	0.197	3.4509	3	0.327	4.2628	3	0.234
	Short Term Interest Rates	0.27304	3	0.965	0.62318	3	0.891	1.7933	3	0.616	2.0781	3	0.556			
	Intl. Capital Flows	2.3657	3	0.500	6.6275	3	0.085	4.1143	3	0.249						
	Undrawn credit to equity	13.856	3	0.003	12.569	3	0.006									
	Loan to Deposit Ratio	3.8071	3	0.283												
	ALL	**62.203**	**21**	**0.000**	**55.118**	**18**	**0.000**	**35.564**	**15**	**0.002**	**29.55**	**12**	**0.003**	**26.608**	**9**	**0.002**
Short Term Interest Rates	GDP Growth Rate	6.0917	3	0.107	5.1199	3	0.163	1.9149	3	0.590	3.106	3	0.376			
	Bank Z-Score	0.87089	3	0.832	0.97491	3	0.807	2.3013	3	0.512	2.5	3	0.475			
	Leverage Ratio Growth	1.8656	3	0.601	1.9147	3	0.590	3.0917	3	0.378	3.3861	3	0.336			
	Debt to GDP Ratio	0.34499	3	0.951	0.43248	3	0.933	1.3995	3	0.706	1.5541	3	0.67			
	Intl. Capital Flows	0.76278	3	0.858	1.7022	3	0.636	3.4654	3	0.325						
	Undrawn credit to equity	14.733	3	0.002	14.41	3	0.002									
	Loan to Deposit Ratio	1.2221	3	0.748												
	ALL	**40.36**	**21**	**0.007**	**38.404**	**18**	**0.003**	**19.584**	**15**	**0.188**	**15.291**	**12**	**0.226**			
International Capital Flows	GDP Growth Rate	5.734	3	0.125	7.1499	3	0.067	4.7766	3	0.189						
	Bank Z-Score	1.804	3	0.614	1.5356	3	0.674	1.4182	3	0.701						
	Leverage Ratio Growth	0.07255	3	0.995	0.03183	3	0.999	0.4625	3	0.927						
	Debt to GDP Ratio	12.019	3	0.007	12.458	3	0.006	5.3604	3	0.147						
	Short Term Interest Rates	0.59942	3	0.897	0.81145	3	0.847	0.75189	3	0.861						
	Undrawn credit to equity	18.291	3	0.000	19.926	3	0.000									
	Loan to Deposit Ratio	1.018	3	0.797												
	ALL	**40.162**	**21**	**0.007**	**38.531**	**18**	**0.003**	**14.187**	**15**	**0.511**						
Undrawn Credit to Equity Ratio	GDP Growth Rate	6.0723	3	0.108	2.8221	3	0.420									
	Bank Z-Score	3.3094	3	0.346	2.5715	3	0.463									
	Leverage Ratio Growth	4.1447	3	0.246	2.8489	3	0.416									
	Debt to GDP Ratio	6.334	3	0.096	7.5534	3	0.056									
	Short Term Interest Rates	0.95831	3	0.811	2.6329	3	0.452									
	Intl. Capital Flows	1.8116	3	0.612	1.1679	3	0.761									
	Loan to Deposit Ratio	8.721	3	0.033												
	ALL	**35.248**	**21**	**0.027**	**23.346**	**18**	**0.178**									
Loans to Deposit Ratio	GDP Growth Rate	0.91405	3	0.822												
	Bank Z-Score	2.9525	3	0.399												
	Leverage Ratio Growth	2.0463	3	0.563												
	Debt to GDP Ratio	1.3528	3	0.717												
	Short Term Interest Rates	1.4297	3	0.699												
	Intl. Capital Flows	12.949	3	0.005												
	Undrawn credit to equity	1.6611	3	0.646												
	ALL	**26.805**	**21**	**0.177**												

This table illustrates how ex-ante known systemic crisis determinants (see Chapter 2) interact with each other in the UK macroeconomic / banking sector. The objective is to arrive at a parsimonious set of macroeconomic / sectoral variables that are shown to be significant causal factors of each other and against which the effectiveness of the various systemic risk measures may be assessed in vector autoregression models. In Phase 1 loans to deposits ratio does not Granger cause any variable at the 1% level of significance. Therefore that ratio is not considered in Phase 2 and drops out. A full description of the rationale behind the removal of variables at particular stages is provided in the paper. The "Prob" score indicates the significance level, variables less than .01 are significant at the 1% level as per usual. We arrive at a model comprising 4 sectoral variables in Phase 5 which can be used to test the SRMS at a later stage of the analysis.

because we are primarily interested in the dynamic interchanges between known systemic-crisis determinants and the new systemic risk measures in the years leading up to the GFC.

For each SRM examined, one of our primary areas of interest is to examine and understand the extent to which the SRM interacts with and is determined by the various systemic crisis determinants from a Granger-causality perspective. Understanding whether the SRM has a significant Granger-causal relationship with zero, one or several crisis determinants is important, as is knowing whether the SRM is passive or active in these relationship, that is whether the SRM simply reflects risk or if SRM-related disturbances Granger-cause the determinants in turn. Before presenting the summary findings we present an example of one of the VAR outputs in detail, highlighting the important results as appropriate.

We first consider the case of non-performing loan rates in the case of the Irish banks, with corresponding results reported in Table 3.7. Information Criterion analysis (LR, AIC and HQIC) suggests that seven lags of the variables is optimal, however further analysis indicates that the VAR as a whole is not stable whenever more than 3 lags are included, especially when we include short-term interest rates and international capital flows as exogenous variables in the VAR (see Table 3.5 above), therefore this VAR is estimated based upon 3 lags of the variables. Looking at the phase 1 column we see that the inclusion of NPL appears to weaken the Granger-causality effects we observed earlier in Table 3.5.

Considered jointly, the variables marginally Granger-cause Irish NPL levels at the 1% level of significance however NPL growth-rates in turn do not determine any systemic crisis determinant at even a 10% level of significance (leverage ratio growth excepted). It could be argued that undrawn-credit-to-shareholder-equity is now exogenous in this system as is debt-to-GDP, and indeed NPL itself. In fact only two variables have any Granger-causality impact upon another (at the 1% significance level). These are the effect of leverage ratio on 1) non-performing loans and 2) undrawn-credit-to-equity. Coupled with our Table 3.5 findings we conclude that NPL growth-rates do not interact strongly with systemic crisis determinants prior to 2008 Q2. Thus, the NPL SRM is a weak leading signal of the GFC in Ireland.

TABLE 3.7

Equation	Granger Causing Variable	Phase 1			Phase 2		
		chi2	df	Prob	chi2	df	Prob
Non-Performing Loan Ratio	Loan to Deposit Ratio	7.4469	3	0.059	6.7415	3	0.081
	Debt to GDP Ratio	2.9359	3	0.402	3.0966	3	0.377
	Leverage Ratio Growth	11.48	3	0.009	12.051	3	0.007
	Undrawn credit to equity	2.7445	3	0.433			
	ALL	**26.214**	**12**	**0.010**	**21.997**	**9**	**0.009**
Loan to Deposit Ratio	Non-Performing Loan Ratio	2.7459	3	0.432	4.0369	3	0.258
	Debt to GDP Ratio	3.3169	3	0.345	3.5874	3	0.310
	Leverage Ratio Growth	2.8177	3	0.421	3.2523	3	0.354
	Undrawn credit to equity	0.71855	3	0.869			
	ALL	**10.537**	**12**	**0.569**	**9.6496**	**9**	**0.380**
Debt to GDP Ratio	Non-Performing Loan Ratio	2.6578	3	0.447	1.8466	3	0.605
	Loan to Deposit Ratio	5.1959	3	0.158	3.5049	3	0.320
	Leverage Ratio Growth	4.156	3	0.245	4.6137	3	0.202
	Undrawn credit to equity	2.4807	3	0.479			
	ALL	**18.38**	**12**	**0.105**	**14.992**	**9**	**0.091**
Leverage Ratio Growth	Non-Performing Loan Ratio	6.3539	3	0.096	4.2829	3	0.232
	Loan to Deposit Ratio	0.53999	3	0.910	0.16199	**3**	0.983
	Debt to GDP Ratio	0.93183	3	0.818	1.6642	3	0.645
	Undrawn credit to equity	4.6166	3	0.202			
	ALL	**11.598**	**12**	**0.478**	**6.275**	**9**	**0.712**
Undrawn Credit to Equity Ratio	Non-Performing Loan Ratio	5.7862	3	0.122			
	Loan to Deposit Ratio	4.747	3	0.191			
	Debt to GDP Ratio	0.82609	3	0.843			
	Leverage Ratio Growth	7.1783	3	0.066			
	ALL	**10.431**	**12**	**0.578**			

This table illustrates how ex-ante known systemic crisis determinants (see Chapter 2) interact with the Non-performing loan SRM in the context of the Irish banking sector. The "Prob" column tells whether the Granger Causing Variable and its lags signficantly determines the current value of the Equation variable. In the first iteration of the VAR (Phase 1) we see that Undrawn credit is not Granger caused by any other variable at even the 10% level of significance and vice versa. It is classified as exogenous and the the second iteration (Phase 2) occurs.

Omitting Undrawn-credit-to-Equity from the second VAR model makes little difference. Now NPL growth-rate is only marginally explained by the crisis determinants at the 1% level, this result largely being driven by the inclusion of leverage ratio growth-rates in the model. In general, these results reconfirm our earlier observations regarding NPL (see section 3.3 above).

Having repeated these VARs for each of MES, SES, ΔCoVaR and CRI for both Irish and UK banks, we present a summary of the Granger-causality results in Table 3.8. With the exception of SES we see that the SRMs interact with and Granger-cause multiple systemic crisis determinants. This is especially true in the case of MES and NPL, but strong evidence for ΔCoVaR (especially in the case of Ireland) can also be seen. Our result is contrary to Benoit et al.'s (2013) conclusion that the new SRMs can be explained by single micro-prudential risk factors. Clearly they find evidence of a strong relationship between the SRMs and certain risk measures, but we have shown two things: 1) the SRMs are linked and have causality relationships with several risk sources and 2) shocks to these SRMs propagate across financial systems, leading to increased risk levels in well-established systemic crisis determinants in each country.

Based upon these findings we argue that the SRMS have an important role to play in understanding how systemic risk exists and spreads throughout banking systems, i.e. that they are not merely passive risk indicators, such as, for example, a bank's Beta score might be. We present further evidence of this shock propagation behaviour in the next section.

Impulse Response Functions:

As per the Granger-causality results our main focus is to understand how systemic crisis determinants' disturbances impact the SRMs and vice versa. We are interested in the direction, extent and timing of such disturbances. As there are five SRMs per country to consider, interacting with four systemic crisis determinants which are not common to each country, we do not present detailed commentary on each specific IRF, rather we restrict comments to the most striking and interesting aspects of the IRF results. These are depicted in Figs. 4a, 4b, 5a and 5b and represent the graphic form of equation (3.17) where vector z comprises our SRM and determinants variables.

A Note on VAR variable order:

As mentioned above the results of the VAR analysis are sensitive to the order of the variables in the VAR (see section 3.2 for details). According to Becketti (2013) "The data may not support a definitive ordering of events. Or more precisely, the data may be consistent with multiple orderings". Our Granger-causality results reinforce this view because for example, leverage

Granger-causes the loan-to-deposit ratio and vice versa. However, the Granger-causality results are order independent meaning they can be used to guide our ordering to a certain extent. Because different VAR orderings are possible for the sake of clarity we present those used in our analysis and then present the rationale for each. A case may be made for different ordering(s) of the variables but each is open to interpretation and critique and is, due to its pseudo-scientific nature, subjective.

Table 3.7a - VAR Ordering of Variables

	Ireland	UK
1	Systemic Risk Measure	Systemic Risk Measure
2	Loan to Deposit Ratio	GDP Growth
3	Debt to GDP Ratio	Z-Score
4	Leverage	Leverage
5	Undrawn Credit to Equity Ratio	Debt to GDP Ratio

This table shows the ordering of the variables in the VARs for each country. Thus a shock to variable 3 has a contemporaneous impact upon variables 3,4 and 5 but no contemporaneous impact (by construction) upon variables 1 and 2 etc.

The systemic risk measure is placed at the top of the order in each VAR because it is the main variable of interest and we wish to see the contemporaneous impact of a shock to each SRM upon the other variables in the VAR. In the case of Ireland we place the loan-to-deposit ratio ahead of the other variables for two reasons; 1) the Granger-causality results support the view that this variable more significantly Granger-causes the other variables than the converse (e.g. compare the Granger-causality impact of loan-to-deposit upon leverage in Ireland versus the other way around) and 2) in recognition that the 2008 crisis initially started as a liquidity problem ("liquidity crunch") before spreading into a bank solvency / real-economy crisis. Debt-to-GDP could feature either before or after leverage according to the results shown in Table 3.5. Recognising the role GDP plays in systemic banking crises in the literature we give it a relatively higher order. We place undrawn-credit-to-equity at the foot of the order as this variable is the least studied in the literature and limited evidence exists that, once shocked, it has contemporaneous impact upon the other variables in our system.

A similar rationale applies in the case of the UK where the importance of GDP growth is accounted for. We assume GDP shocks affect the other variables contemporaneously. The Z-score has a leverage component to it, so these variables could swap places. We go with the order shown on the basis that GDP shocks translate into returns / earnings shocks which will be captured by the Z-Score. This will in turn contemporaneously impinge upon the leverage ratio as earnings shocks are absorbed by shareholder equity, so we place that above leverage. Debt to GDP is placed lower in the order because we assume that shocks to that variable are responded to in later periods by the other variables in the VAR, especially as borrowing-related variables are only reported upon periodically by the banks and it takes time for their shock-related implications to be absorbed.

Fig. 4a shows the response of the SRMs to systemic crisis determinants' shocks in the case of Ireland during the years preceding the GFC. There are five sub-graphs, one per SRM, and five IRF charts per SRM, showing the response of the SRM to a specific determinant shock. The charts are based upon orthogonal (i.e. isolated effects) shocks as described above, tracing the path of the SRM subsequent to a one-standard-deviation determinant disturbance over time (measured in quarters).

We see that none of the determinants has any significant impact upon the Irish NPL levels during this period. However the other SRMs are more responsive to such disturbances. For example a shock to leverage (capital-to-asset ratio) triggers a 2% worsening of MES within one quarter.

TABLE 3.8

	Ireland					UK				
Sign.	NPL	CRI	MES	SES	ΔCoVaR	NPL	CRI	MES	SES	ΔCoVaR
1%	Loan to Deposit Leverage			Leverage		GDP Growth	GDP Growth Debt to GDP			
5%	Debt to GDP		Debt to GDP			Z-Score Leverage	Leverage		Leverage	
10%		Undrawn Credit Leverage			Loan to Deposit			Debt to GDP	GDP Growth Z-Score	
1%	Loan to Deposit	Leverage	Debt to GDP		Undrawn Credit Leverage	Z-Score Leverage		Debt to GDP		
5%	Leverage		Undrawn Credit		Loan to Deposit					
10%			Loan to Deposit			GDP Growth	GDP Growth	GDP Growth		

This table illustrates how Systemic Risk Measures interact with previously known global systemic crisis determinants in each of the UK and Irish banking systems. The top panel shows which determinants Granger Cause the systemic risk measure at the 1%, 5% and 10% levels of significance. The bottom panel shows which SRM Granger causes the systemic crisis determinants. In the case of the latter we observe whether or not the SRM is passive in the process or whether shocks to the SRM propagate across known systemic crisis determinants.

Whereas the effects of the shock have largely dissipated within 6 months, they do not disappear entirely. A debt-to-GDP shock initially causes MES to improve but then its path traces a worsening MES below equilibrium within three quarters. MES is similarly affected by undrawn-credit-to-equity shocks. With the exception of NPL each of the SRMs is impacted by both leverage and debt-to-GDP shocks. Although equilibrium, ceteris paribus, is generally restored within 3-4 quarters we can see evidence of increased systemic risk, given the SRMs are observed to move in risky directions. This confirms the sensitivity of the Irish banking sector to asset-based shocks leading up to the GFC. However it is only the ΔCoVaR measure which flags any liquidity-related sensitivity. It seems the market is more responsive to liquidity dangers (e.g. high loans-to-deposit ratios) than the balance sheet measures are, as measured by the NPL and CRI SRMs. This finding is highly relevant for banking supervisors whose policy instruments are geared to flow from the analysis of market-based risk measures.

The Table 3.8 results relating to the CRI measure need to be treated with a degree of caution. By construction the CRI is comprised of significant trend deviations from sample averages of debt-to-GDP, Z-Score, undrawn-credit-to-equity, loans-to-deposit ratio and NPL rates. Therefore 2 of the remaining 4 UK VAR variables are correlated with the CRI and this correlation increases as those variables trend strongly away from their sample averages. In the case of Ireland 3 of the remaining 4 VAR variables are included in the CRI. In recognition of this fact we attach limited significance to the Granger-causality results relating to the CRI.

In Fig. 4b we examine the effects of SRM shocks upon the determinants. We see that an NPL shock leads to significantly lower leverage growth-rates within 2-3 quarters but this then recovers within the next 3 quarters. The other determinants are not impacted by NPL shocks. Comparing the five sub-graphs a pattern emerges in that SRM disturbances appear to impact the leverage ratio only in the case of Ireland with the remaining determinants showing little or no movement away from their equilibrium values (with the exception of the effect of SRM disturbances upon themselves). These results reinforce the utility of the SRMs as reflections of increasing systemic risk levels, rather than as channels for it.

In the case of the UK Figs. 5a and 5b show similar patterns. For instance the NPL sub-graph shows minor impacts on NPL levels subsequent to determinants shocks with no impact reaching even .05% impact in either direction at any point within the following 3 years. As per Ireland, MES is much more reflective of such shocks, causing negative MES values (i.e. higher risk) in all cases, most notably in the case of Z-Score and leverage shocks (both of which are primarily asset-related measures).

The 95% confidence interval extends to -0.5% in certain cases, which is a significant distance from the 0.02% average level recorded for the UK over the sample period (see Table 3.4). Hoggarth et al. (2005b) consider these IRFs as UK banking-sector stress tests. On this basis we argue that considerable systemic risk, as reflected via MES, was present in the UK whose banking sector was clearly exposed to the possibility of a systemic banking crisis. Bear in mind the fact that the IRFs only show the isolated impact of a one-standard-deviation disturbance to one variable, larger/more complex shocks are not reflected in these charts.

The SES measure also shows increased systemic risk in stressed scenarios where, for example, an almost £5bn increase in shortfall is observed in the wake of a shock to leverage growth-rates. This appears counter-intuitive however the stronger capital position of the banking sector takes approx. 5 quarters to be reflected in lower SES levels. Likewise, increased GDP output initially reduces SES levels but leads to riskier levels approximately 1 year later. Fig. 5b also shows the SRMs as reflecting rather than channelling risk which we believe is a useful property for any SRM to demonstrate. Unlike Ireland, it is not leverage but GDP growth which is the only determinant susceptible to SRM-related shocks. As the literature has repeatedly shown, a serious bank crisis, regardless of its source, eventually impacts the growth-rate of the wider economy.

We summarise the most important IRF impulse-response results in Table 3.9 showing the largest effect of each shock upon the VAR variables, the quarter when that effect takes place and the corresponding direction of the impacted variable. However when considering these stress-tests and Figs. 4a – 5b we must remember that we are looking at relatively small disturbances (one-standard-deviation only) and are also considering their effects in isolation via orthogonal IRFs. In reality, the Granger-causality results show us that the variables all interact with and influence each other in ways that are difficult to chart dynamically, therefore it would not be wise to draw too strong a conclusion from any IRF result taken in isolation. That said, it is reasonable to conclude that the MES variable is the most informative and responsive (see Table 3.9) in terms of understanding shock dynamics in the case of Ireland and the UK.

We may draw several notable inferences from Table 3.9. Once again we see differences in reaction to determinants shocks between Ireland and the UK. For instance a leverage shock in Ireland has a maximum risk-increasing impact of 2.01% contemporaneously upon the MES SRM, whereas a shock of similar proportion in the UK actually has a maximum impact in the opposite direction, where MES is seen to increase by 0.327% two quarters hence. We see similar examples of opposite direction behaviour in the case of SES following a leverage–related disturbance. MES appears to respond most rapidly to determinants shocks in that we see the largest shock effects taking place immediately in three out of the eight disturbances modelled. We also see that shocks to leverage generally induce the largest immediate response in the SRMs, an effect which is consistent between banking sectors. Also noteworthy is the fact that the market-based measures of systemic risk, i.e. MES, SES and ΔCoVaR appear to respond, in general, more rapidly to determinants shocks than do the balance-sheet-based risk measures such as CRI and NPL. The fact that we only have quarterly data relating to the latter does not adequately explain this result. We conclude that the market is much more sensitive to risk profile changes than bank managers or risk-management teams working inside banks. It takes several quarters before the largest effects of the determinants shocks are reflected in quarterly reports.

Table 3.9

	Ireland				UK			
	Undrawn credit to equity	Liquidity Ratio	Leverage	Debt to GDP	GDP Growth	Z-Score	Leverage	Debt to GDP
MES	1.22	1.34	-2.02	-0.57	0.521	-0.428	0.327	0.262
	1	1	0	3	0	0	2	1
SES	-9.32	666	-779	167	2118	1527	3756	1453
	2	1	5	2	4	9	0	3
NPL	0.014	0.012	-0.032	-0.027	0.02	0.145	0.015	0.008
	4	3	2	2	4	1	0	5
ΔCoVaR	0.841	-1.47	-0.85	0.719	-0.768	0.753	0.438	0.847
	5	3	0	1	0	5	6	6
CRI	0.036	-0.025	0.015	-0.027	0.13	0.14	-0.13	0.1
	4	7	5	2	1	4	7	5

Here we see the maximum effect of a one standard deviation shock to a systemic crisis determinant upon a systemic risk measure and the period (i.e. subsequent quarter) when that effect takes place, which is shown directly under the effect. The shocked determinants are listed at the top of the table with the impact upon the relevant SRM listed in Col 1. We first consider the Irish banking system then the UK in turn. Thus we see that a one standard deviation shock to undrawn credit to equity ratio results in a maximum 1.4% increase in NPL growth 4 quarters later (in Ireland)

Forecasts:

Understanding the source and nature of risks leading up to the GFC is extremely important. However, one of the most beneficial features of any new SRM will be in terms of its ability to signal future crises, or at least their potential to emerge, with reasonable accuracy. Therefore, we evaluate the SRM forecasts from short-term (one quarter ahead) as well as long-term (up to 20 quarters ahead) perspectives.[51] Whereas up until now we have relied upon pre-GFC data i.e. 1997Q1 – 2008Q2, at this point we can include actual SRM observations covering the years 2008Q3 to 2013Q4 for forecast comparison purposes. All long-term SRM forecasts run from 2008Q2 onwards whereas short-term forecasts commence in 1997Q2. In the case of the short-

[51] Because our VARs have been run based on data up to and including 2008Q2 any forecasts beyond 2008Q2 are essentially out-of-sample forecasts as far as our VARs are concerned. The fact that we have actual observations for the years 2009 – 2013 thus makes our job of evaluating these out-of-sample forecasts much easier.

term variant all "t+1" forecasts are based upon actual time "t" observations. By contrast, the long-term forecasts make use of forecasted values at time "t" to yield the forecasts for period "t+1". Naturally the latter are increasingly less reliable as the forecasting horizon extends outwards. We then plot what are ostensibly "out-of-sample" forecast values alongside actual SRM values and compare the results visually. Ideally, we would wish to see forecasts mirroring the direction and extent of the path actually followed by the SRM and, even though the time horizon extends, to see the actual SRM observed value remain within the 95% confidence interval (CI) band of our forecasts for as long as possible.

The short-term SRM forecasts for Ireland are presented in Fig. 6a and their UK counterparts in Fig. 6b. In the case of Ireland the forecasts for MES, ΔCoVaR and CRI demonstrate the properties we are looking for, although the observed CRI values for Ireland spiked high at the time of the Y2K / Euro introduction, behaviour which was not tracked by forecasts. The NPL and SES short-term forecasts (Ireland) are less satisfactory. Actual NPL growth-rates spike above 60% in 2009 whereas the forecasts predict much lower levels of NPL growth, making them unreliable at a time when they are most required. The same could be said for SES, where we see evidence of capital structure stability in the Irish banks as a result of emergency liquidity assistance (ELA). Thus we do not observe any post-GFC quarter where a systemic capital shortfall is reported although the forecasts fluctuate from positive to negative and do not track the actual SES path followed. However when actual SES levels spike upwards, the forecasts anticipate these quite well in the pre-GFC period.

The calculation for SES is described in Guntay and Kupiec (2014) equation (4) and this forms the basis for our equation (3.19). This in turn is drawn from the introduction of the SES measure in Acharya et al (2012). The calculations indicate that the max value, according to (3.19) during the years in question happens to be 0, where the expression $(\lambda * leverage_{i,t} - (1-\lambda)e^{(-18*MES_{i,t})})$

yields a negative number throughout the crisis years. Therefore a max value of 0 is reported. Thus equation (3.19) is reporting that the Irish banking system as a whole is not systemically undercapitalised at a threshold $\lambda = 8\%$. Note from Table 3.3 average capital to asset ratios are well in excess of 8%, hence it is not surprising that the measure does not report systemic capital shortfalls for those years. This could be considered a weakness of the measure in that, when the crisis hit the Irish banks, significant capital shortfalls were actually subsequently identified.

The UK short-term values are similar in certain respects to the Irish ones but there are differences worth noting. The post-crisis UK MES forecasts exaggerate the actual path followed, spiking higher than actually reported in each direction but tending to forecast more pessimistic MES levels than actually were observed from 2010 onwards. As per the Irish data, the ΔCoVaR forecasts are closest to actual values, especially in the pre-crisis period although, like MES they tend to be both a) pessimistic and b) less-reliable in the wake of the GFC. The UK NPL forecasts are unreliable during the crisis years, demonstrating significant deviations from actual values. This is also the case with the SES series, however it should be noted that both SES and NPL forecasts appear to be reasonably accurate in the period leading up to the GFC.

The long-term forecasts for Ireland are outlined in Fig. 7a and we include confidence intervals (CIs with 95% significance) upon which we base part of our commentary. Based upon our desired properties we argue that NPL and CRI perform best in that the forecasts remain within the CI bands for extended periods, although this condition is not met during the full-blown early years of the crisis where NPL growth is under-predicted and CRI growth over-predicted at this critical time. The MES forecasts are overly optimistic until mid-2011 but thereafter are reasonably accurate, whereas the ΔCoVaR predictions are too smooth and fail to anticipate the movements that see actual values move outside the CI bands in many instances. The long-term UK forecasts (Fig. 7b) show marked differences to those of Ireland. Generally all forecasts remain within CI bands for the duration of the pseudo-out-of-sample forecasting horizon. It is difficult to determine which forecast series is most accurate, however we make the case for SES on the basis that actual values never once move outside the CI boundary. The ΔCoVaR forecasts almost achieve this objective but approach a CI breach in 2008Q4 and again in 2010Q2.

In summary, there are differences between the SRM forecasts in terms of geography as well as forecast horizon. On balance we argue that ΔCoVaR and CRI yield, on the whole, the most accurate forecasts. That said, an argument can be made for SES in the case of the UK only as it performs well in both short and long-term forecasts with respect to this relatively important banking system.

SRMS as Crisis Determinants:

Acharya et al. (2012) provide a definition of a systemic crisis, this being characterised as a period during which the financial system as a whole is undercapitalised. This condition is satisfied, as is similarly described in equation (3.1) whenever:

$$Equity_t < \frac{k}{(1-k)} Debt_t \qquad \textbf{(3.24)}$$

Here, "Equity" represents the market value of the banking system's equity and "Debt" the market value of its debt. These are asset-weighted aggregates of each bank's individual debt and equity levels per geography, as sourced via DataStream. The value of k is intended to represent a systemically "safe" level of capital-to-asset ratio and we have set this at 8% in line with Basel III capital-adequacy guidelines (i.e. we do not include either the capital conservation or the counter-cyclical capital buffers as these fall under the remit of each country's financial regulator and have not yet been fully implemented).

We test for quarters during which this condition has been realised and then use the information in logistic regressions where the contribution of each SRM towards the likelihood of a systemic crisis (capital shortfall induced). The results are reported in Table 3.10. We test the Irish banking sector in isolation, then the UK banking sector and finally a pooled model wherein fixed effects (FE) are included. For each of our SRMs we examine the contribution of the contemporaneous (i.e. "current") SRM value as well as 1 and 2 quarter lags towards the likelihood of a systemic crisis.

TABLE 3.10

Dependent SRM variables	IRL			UK			Pooled (FE)		
	current	lag 1	lag 2	current	lag 1	lag 2	current	lag 1	lag 2
MES	-0.243**	-0.221**	-0.077	-0.280	0.047	-0.020	-0.098*	-0.082	-0.024
	(0.096)	(0.099)	(0.097)	(0.664)	(0.696)	(0.640)	(0.058)	(0.060)	(0.063)
SES	0.002	0.002	0.002	0.000*	0.000	0.000	0.000***	0.000***	0.000**
	(0.002)	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
NPL	-0.099	-0.125*	-0.112	0.132	0.068	0.022	-0.011	-0.031	-0.037
	(0.066)	(0.072)	(0.068)	(0.106)	(0.084)	(0.075)	(0.038)	(0.038)	(0.037)
ΔCoVaR	-0.186*	-0.255**	-0.399***	-0.065	-0.070	-0.062	-0.118**	-0.128**	-0.140***
	(0.110)	(0.119)	(0.151)	(0.067)	(0.062)	(0.056)	(0.052)	(0.051)	(0.051)
CRI	-0.005	-0.009	-0.023	0.007	0.010	0.009	0.003	0.005	0.004
	(0.020)	(0.023)	(0.035)	(0.012)	(0.011)	(0.011)	(0.009)	(0.009)	(0.009)
Constant	-4.065***	-3.985***	-3.223***	-3.926***	-3.337***	-2.839***	-	-	-
	(1.238)	(1.260)	(1.155)	(1.127)	(0.983)	(0.887)	-	-	-
Observations	43	42	41	44	43	42	87	85	83
Deg. Freedom	5	5	5	5	5	5	5	5	5
P-Stat	4.19e-05	3.38e-05	2.64e-05	0.0456	0.167	0.522	0.000530	0.00174	0.00817
Log Likelihood	-15.01	-14.26	-13.46	-11.87	-13.47	-15.13	-31.55	-32.27	-33.43

Here we see which of the SRMs are significantly associated with the probability that the banking sector as a whole is undercapitalised. This is driven by the Acharya et al. (2010) condition that equity is less than (k/1-k) * Debt, where k is a minimum level of capita required, set at 12.5%. We see estimates for the current quarter, 1 quarter lag and 2 quarter lags for each of the SRMs for the Irish banking sector alone, then the UK banking sector and finally a pooled model with fixed effects for inherent jurisdictional differences. Statistical significance is denoted by ***, **, * at the 1%, 5%, 10% levels respectively. Standard Errors reported in parentheses below the coefficients.

The coefficients reported in Table 3.10 represent the maximum likelihood estimates of the vector β as per equation (1.9) above (see Chapter 1). We observe that the current quarter MES is significant in the Irish (at the 5% level of significance) and pooled model (at the 10% level) but not in the case of the UK. This is also true for ΔCoVaR where the lag values are also statistically significant. Neither NPL nor CRI are statistically significant contributors at any lag. However SES is significant in the case of the UK (current quarter) and pooled model (current plus both lags), even though the coefficients are almost zero. In general the signs of the coefficients are as expected, for instance the negative coefficient for MES indicates that as the shortfall decreases (i.e. MES tends towards positive values) the likelihood of a crisis is lower. However NPL reports unexpected signs in the case of Ireland and also where the data from the two countries are pooled. An increase in NPL is associated with lower crisis likelihood (though not at statistically significant levels). The UK NPL coefficients have the positive sign we anticipate.

The statistical significance of the coefficients only provides a partial guide as to the "best" SRM from this perspective. We also need to consider the marginal effects of the SRMs, i.e. the impact of a unit increase in one SRM upon crisis probability, where the largest marginal effects have, in essence, an economic relevance even though they may not be statistically significant. This information is provided in Table 3.11.

TABLE 3.11

SRM Marginal Effect	IRL			UK			Pooled (FE)		
	current	lag 1	lag 2	current	lag 1	lag 2	current	lag 1	lag 2
MES	-0.060	-0.053	-0.019	-0.019	0.004	-0.002	-0.012	-0.012	-0.004
SES	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
NPL	-0.025	-0.030	-0.027	0.009	0.006	0.002	-0.001	-0.004	-0.007
ΔCoVaR	-0.046	-0.062	-0.096	-0.004	-0.006	-0.006	-0.014	-0.018	-0.025
CRI	-0.001	-0.002	-0.006	0.000	0.001	0.001	0.000	0.001	0.001

Marginal Effects for the logistic regressions presented in Table 3.9. These show the impact on the probability of a crisis given a 1-unit increase in the dependent variable.

Now MES is shown to have the largest marginal effect both in the case of the UK and Ireland individually where, in the case of Ireland, a 1 percentage increase in MES is associated with a 6% increase in the probability of a crisis, as signalled by (3.24). This figure falls to 2% in the case of the UK although we would argue that this is still at a concern-generating level. At the pooled level the most significant variable across all lags is ΔCoVaR which reports a 1.4% increase in crisis probability given a 1% tail shift of the current-period conditional value-at-risk of the financial services sector. According to these marginal effects results both CRI and SES are relatively unimportant.

3.6. Robustness Checks

We include several robustness checks to ensure that the most important results and conclusions remain valid. These include: 1) modelling the VARs with various lag lengths, 2) changing the recursive ordering of the VARs, 3) running VAR regressions without including the exogenous variables identified initially, 4) progressively increasing the forecasting horizon from 1 quarter up to 20 quarters and 5) running logistic regressions at the individual bank level where the dependent variable is triggered if bank "i" received emergency liquidity assistance (ELA) support during a quarter.

The Granger-causality results are sensitive to the lag order of the VARs, however our primary focus is not so much upon which determinants Granger-cause an SRM per se, but the extent to which the SRM interacts with and is Granger-caused *in general* by systemic crisis determinants. In that sense, our conclusions remain robust to lag length. It should also be noted that there is a trade-off between the lag order, identified as optimal via information criterion such as model AIC score, and the inclusion of exogenous variables. For example, in the case of Ireland, we include short-term interest rates and international capital flows as exogenous variables in the VARs, but their inclusion limits the lag order to 3. The inclusion of more than 3 lags alongside exogenous variables results in unstable VARs. If the exogenous variables are omitted and the lag order increased the effect of any omitted variable is captured via each VAR equation's error term. We then observe changes to the Granger-causality output, however not at the overall level we are concerned with. On balance, we prefer to control for the exogenous variables at lower lag orders because this approach reduces the likelihood of covariance between our systemic crisis determinants and the error terms, a violation of OLS which has the potential to result in biased as well as inconsistent coefficient estimates.

The forecasting conclusions we have drawn are robust to changes in the forecasting horizon. The bank-level logistic regressions report minor differences in the marginal effects of each determinant. In this paper our main focus is at the banking-sector level, thus we prefer to report as per Tables 3.10 and 3.11 rather than at the micro-level. We note that the latter could be analysed and presented in a follow-up paper.

3.7. Conclusions

In a general sense our results show that the nature and characteristics of systemic risk varies from country to country. We detail the variation across multiple contributing risk factors and therefore contend that the profiling of systemic risk must reflect such heterogeneity at the country level. More specifically the time-varying risk profiles in Ireland and the UK are shown to be markedly different both pre and post-GFC, a fact that is reflected in the utility and accuracy of the SRMs across the two geographies. When we consider the various SRMs evaluated in this paper we note the relative advantages of each. MES is shown to most closely track and reflect changes in known systemic crisis determinants (see Section 3.5) and is also the most responsive to large determinants shocks. Furthermore MES is a significant contributor towards the likelihood of a systemic crisis emerging in Ireland due to capital-adequacy shortfalls. However ΔCoVaR performs best as a forecasting measure and also has the most significant marginal effect in terms of systemic crisis emergence in pooled models.

Adrian and Brunnermeier (2011) also demonstrate that forward lags of ΔCoVaR may be significantly explained at the institutional level by current-period balance-sheet metrics such as institutional size, maturity mismatch, liquidity mismatch and leverage.

Such a property could be extremely useful if it holds more generally for each banking sector as it would enhance ΔCoVaR's utility as an early-warning indicator.[52] We note that this hypothesis could form the basis for a research paper which could also capture the systemic-risk-related banking sector linkages with the most systemically-important insurance institutions and/or large corporations. We find that SES performs best as a forecasting tool in the relatively more important UK banking sector only, a result which future research may also show to prevail in the world's largest banking systems generally.

Guntay and Kupiec (2014) find that recently recommended SRMs rarely agree upon which institutions are the most systemically risky, with different lists and rankings of institutions in evidence depending upon which SRM has been employed. We find support for this conclusion at the geographical level and contend that the adoption of only one SRM as *the* global standard would be foolhardy if future crises are to be averted. Instead multiple SRMs should be assessed at the country level because each has a purpose and a value of its own. Thus where one measure may prove to have limited value in country "A" it may be of great significance in country "B".

That said, efforts to establish a single measure of systemic bank risk should continue, even though such a measure may prove both elusive and contentious. If this globally-valid SRM is ever established it could prove to be the most authoritative early-warning signal of systemic stress in general. But at present such a measure has not yet been found, at least so far as MES, SES and ΔCoVaR are concerned. Consequently, deciding which SRM is "best" depends not only upon the user's purpose (e.g. policy-setting / investment / risk-monitoring) but also upon the geography and time-frame in question.

[52] Adrian and Brunnermeier (2011) sample only US banks.

In spite of the failure of the new SRMs to consistently report risk across institutions and geographies we believe their benefits outweigh any shortcomings. These new SRMs perform better as pre-crisis signals (e.g. CRI), in forecasts based upon current and lagged aggregate balance sheet metrics and they also contribute far more individually and collectively towards systemic crisis emergence than does NPL (see Table 3.11 above). We have also established that the criticism of Benoit et al. (2013), who find the SRMs to be single-factor based, to be somewhat overstated given the richness of our Granger-causality / IRF results. We have provided evidence of such via the SRMs interaction with and response to various risk-related shocks. However, they appear to contribute little extra, in systemic crisis determinants Granger-causality terms, over and above a traditional measure such as NPL.

Our results highlight the importance of good-quality balance sheet data reported on a quarterly basis. Whilst recognising that such reporting is onerous from the banks' perspective, nevertheless we argue that banks should be forced to report critical time series data each quarter, on the premise that systemic risk does not appear suddenly but may accumulate over time and emanate from multiple different sources. Academics and analysts will require access to such information sources, including off-balance-sheet items such as unreported asset holdings, SPV commitments and the ratio of undrawn committed facilities as a proportion of shareholder equity. When such reporting standards are in force we will be better placed to refine and extend our results globally and to provide a deeper assessment of any new SRM which may emerge in the interim.

Finally, with the exception of the forecasting sub-section, our analysis has been confined to the pre-GFC period. Apart from the future research mentioned above another useful follow-up would be an examination of the properties and behaviour of the SRMs during crises years in various countries throughout the world. However, this will also require more extensive quarterly data on banking systems to be made available than currently exists, especially in the case of emerging economies.

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Figures

Fig. 1 Composite Risk Indices – Irish Banks

This figure illustrates the composite risk index scores for the leading Irish banks, including the CRI in levels as well as their respective trends. The scatter plot shows quarters on the x-axis and the CRI score on the y-axis with the commencement date of the systemic crisis (as per Laeven and Valencia (2013) represented by the vertical line in each individual graphic. The two pillar banks (Allied Irish Bank and Bank of Ireland) show very similar trends as does Permanent TSB from approx. 2001 Q3 onwards (though it commences with a very high level). Anglo's composite risk index increases from 2005 onwards and never recovers up until the point it is liquidated.

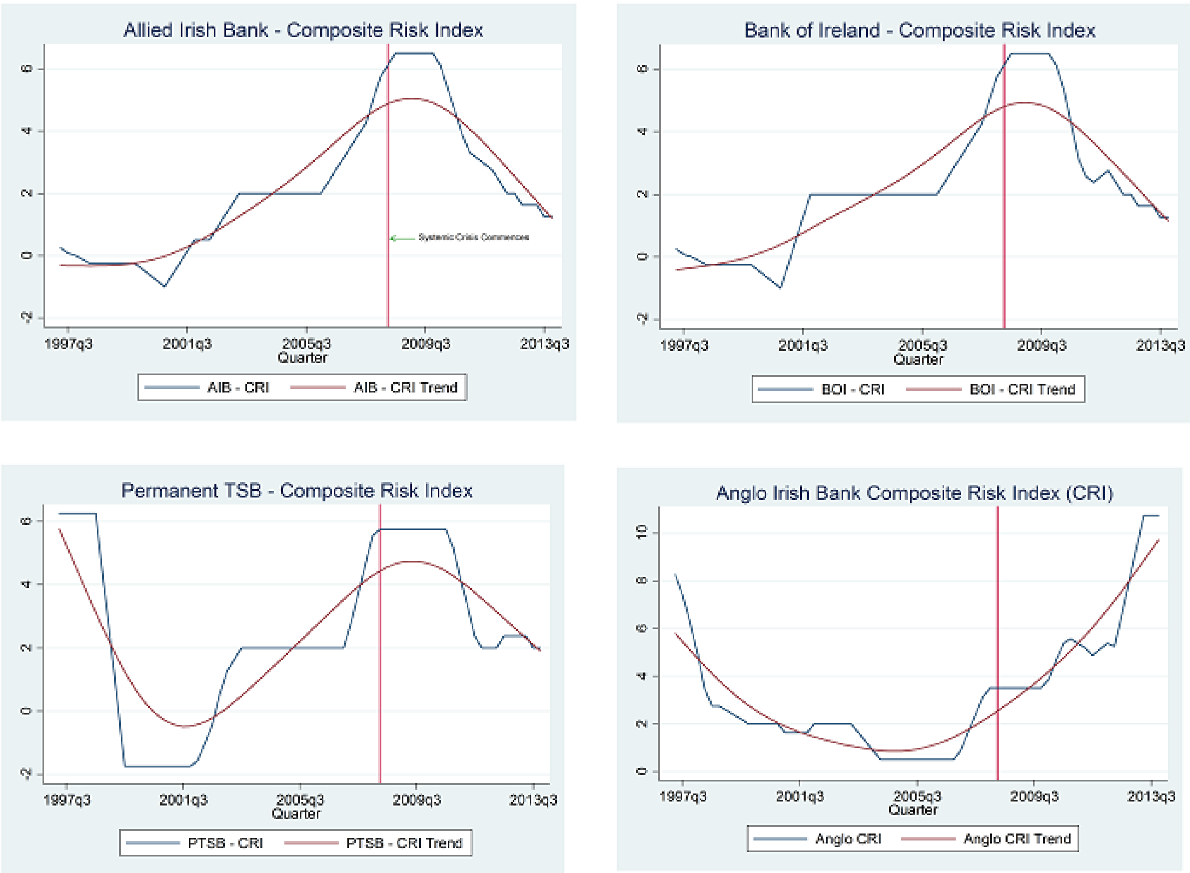


Fig. 2 Composite Risk Indices – UK Banks

This figure illustrates the composite risk index scores for the leading UK banks, including the CRI in levels as well as their respective trends. The scatter plot shows quarters on the x-axis and the CRI score on the y-axis with the commencement date of the systemic crisis (as per Laeven and Valencia (2013) represented by the vertical line in each individual graphic.

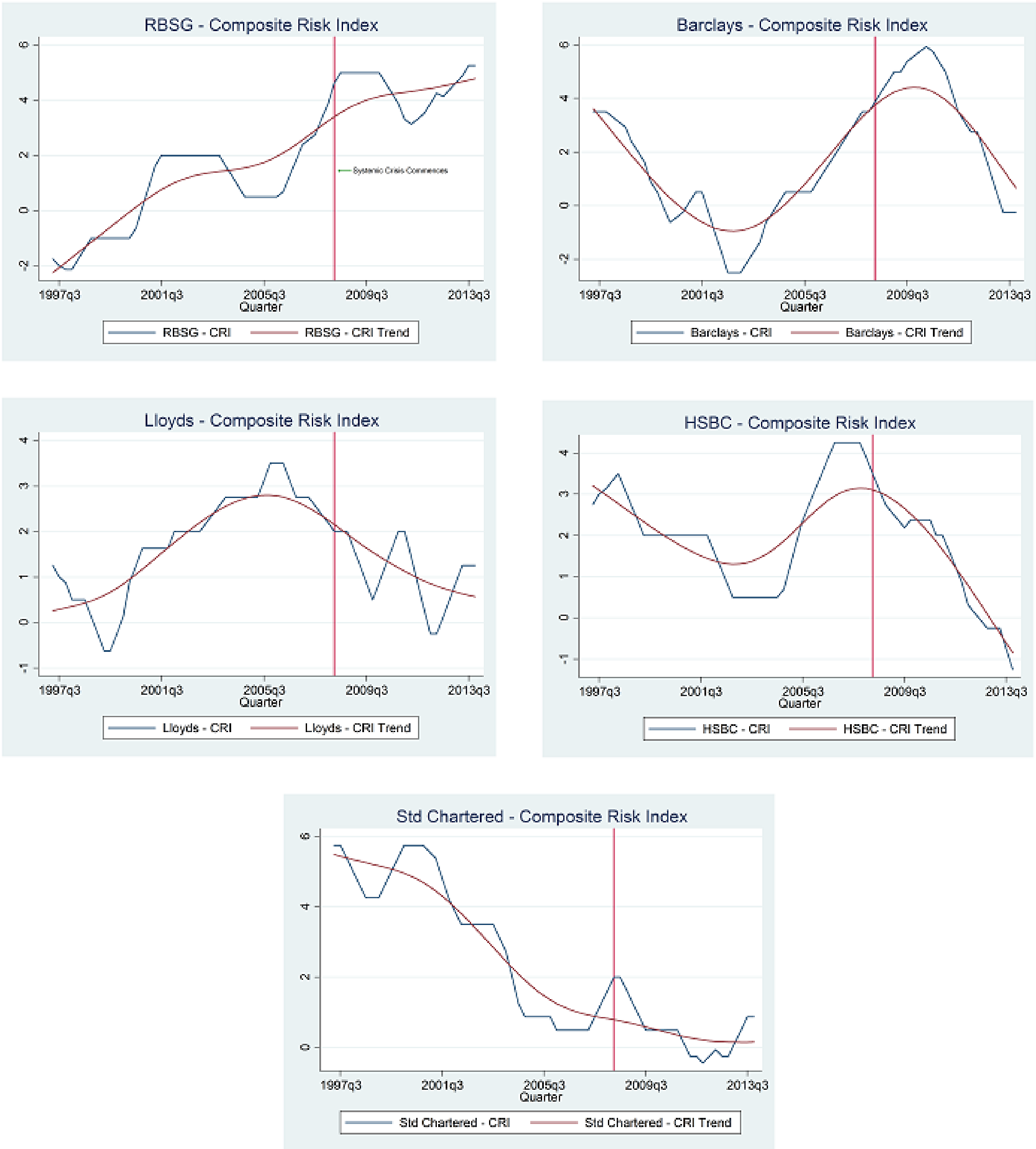


Fig. 3 Systemic Risk Measures – Comparison between Irish and UK Banks

This figure illustrates and contrasts the SRMs between the Irish and UK banking sectors. Left hand side graphs represent the Irish banks and right hand side the UK. There are graphs for each of non-performing loans (NPL), Marginal Expected Shortfall (MES), Systemic Expected Shortfall (SES), Delta CoVaR (ΔCoVaR) and Composite Risk Index (CRI). The differences in scale, timing and direction of risk levels are clearly visible between the two countries. For example the scale of the NPL levels is ten times that of the UK and the fact that NPL is a post-crisis measure rather than a pre-crisis signal is clearly evident.

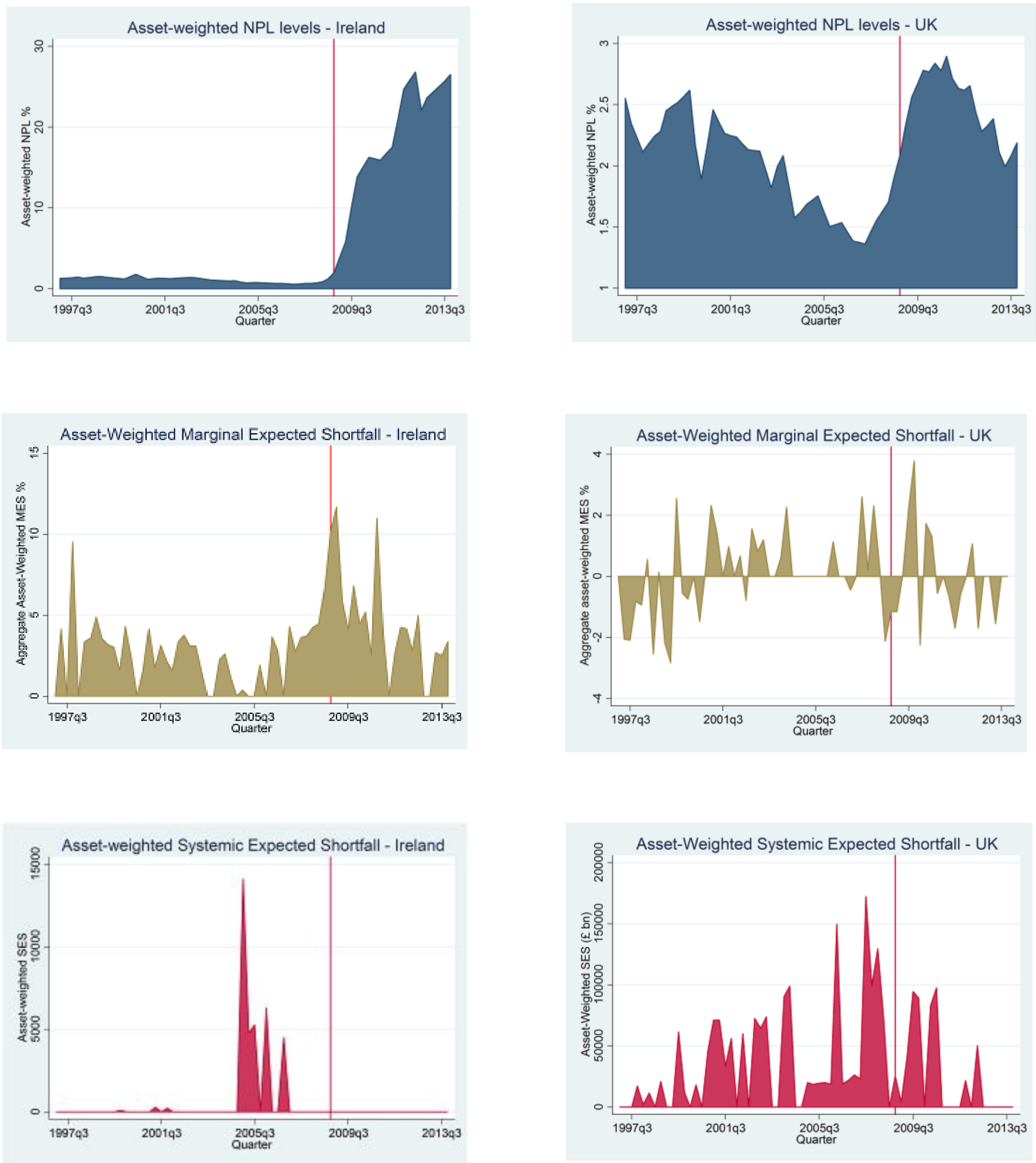


Fig. 3 (Contd.) Systemic Risk Measures – Comparison between Irish and UK Banks

This figure illustrates and contrasts the SRMs between the Irish and UK banking sectors. Left hand side graphs represent the Irish banks and right hand side the UK. There are graphs for each of non-performing loans (NPL), Marginal Expected Shortfall (MES), Systemic Expected Shortfall (SES), Delta CoVaR (ΔCoVaR) and Composite Risk Index (CRI). The differences in scale, timing and direction of risk levels are clearly visible between the two countries. For example the scale of the NPL levels is ten times that of the UK and the fact that NPL is a post-crisis measure rather than a pre-crisis signal is clearly evident.

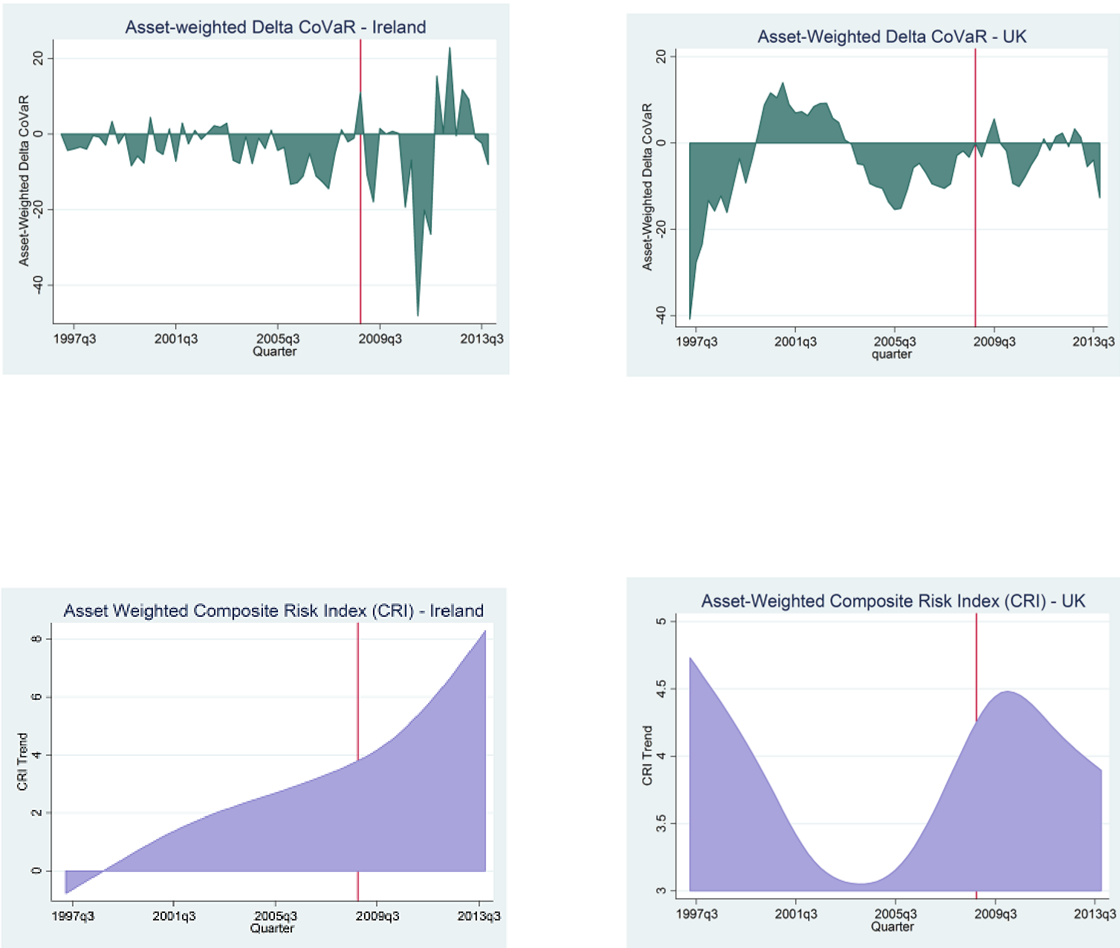


Fig. 4a Response of SRMs to Crisis Determinants Impulses – Ireland

This figure shows how the systemic risk measures respond to systemic crisis determinants shocks to the Irish banking sector. We include an IRF for each of NPL, MES, SES, ΔCoVaR and CRI.

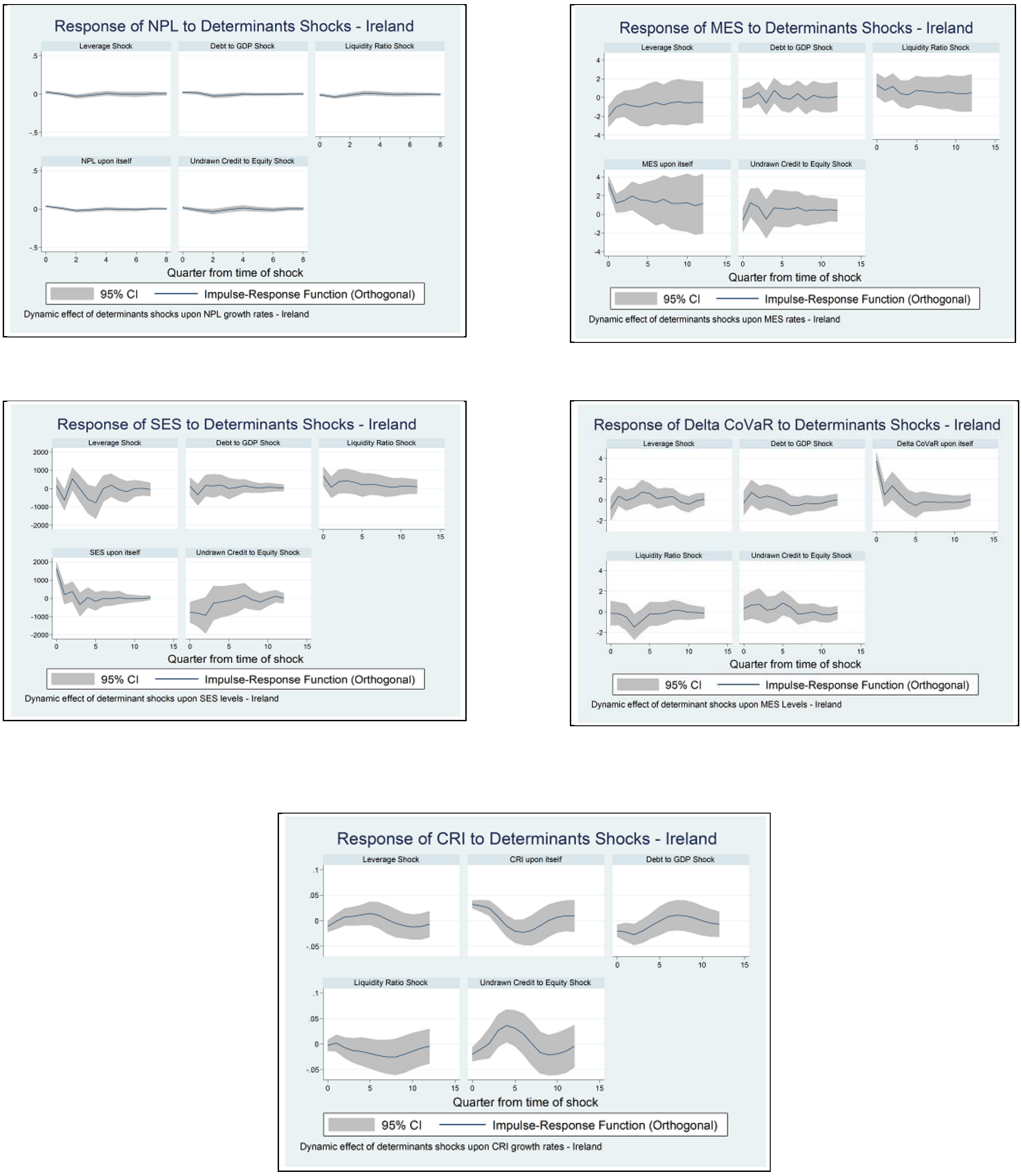
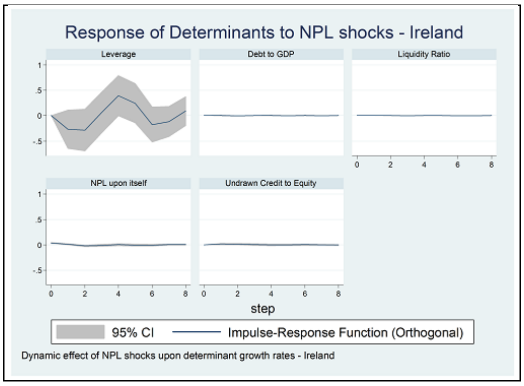
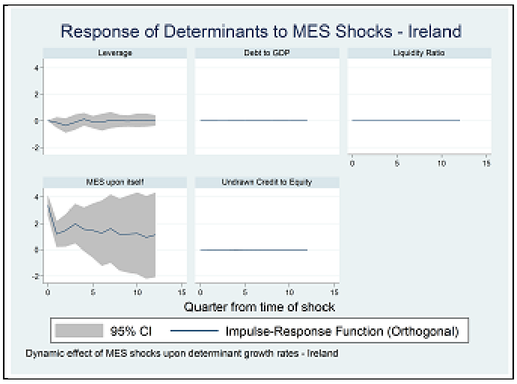
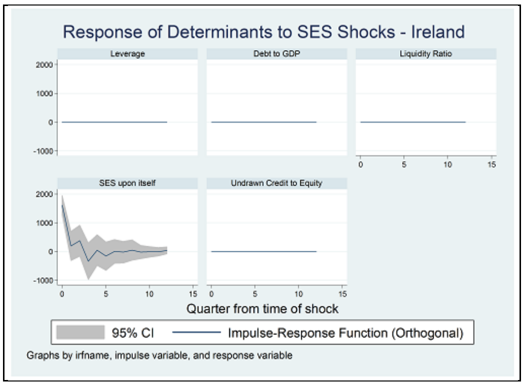


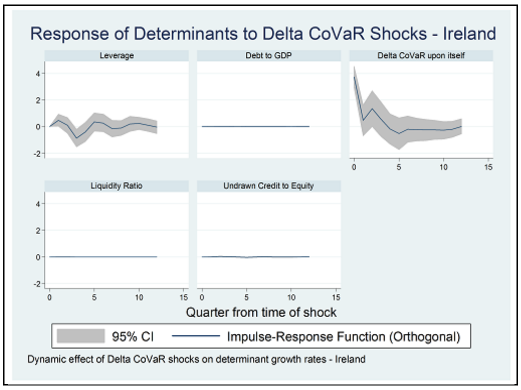
Fig. 4b Response of Crisis Determinants to SRM Impulses – Ireland

This figure shows how shocks to the systemic risk measures impact the systemic crisis determinants of the Irish banking sector. We include an IRF response for each of NPL, MES, SES, ΔCoVaR and CRI.









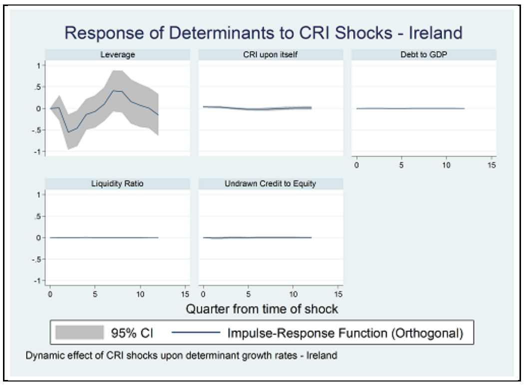
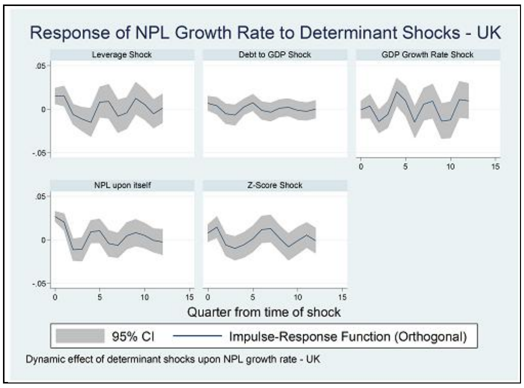
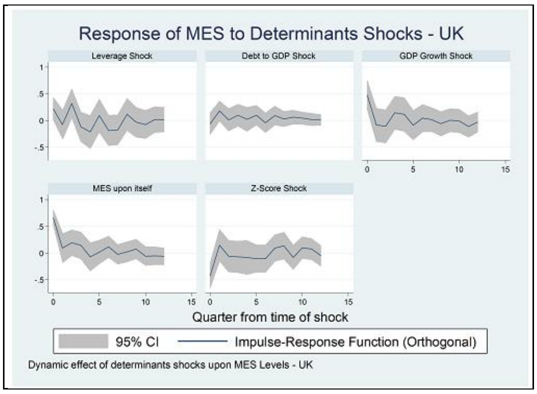
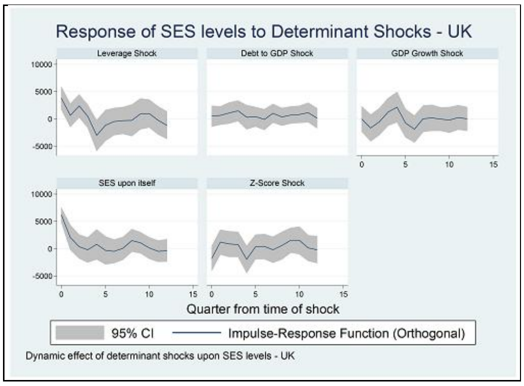


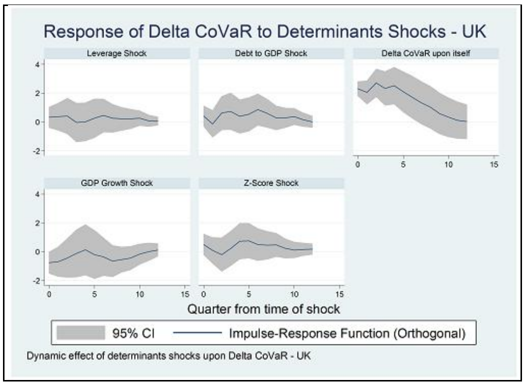
Fig. 5a Response of SRMs to Determinants Shocks – UK

This figure shows how shocks to the systemic crisis determinants impact the systemic risk measures as measured in the case of the UK banking sector. We include an IRF response for each of NPL, MES, SES, ΔCoVaR and CRI.









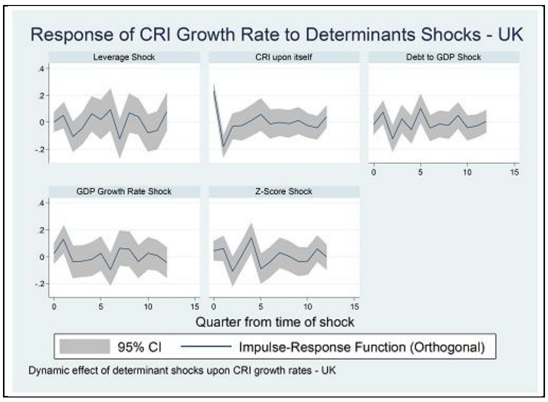


Fig. 5b Response of Crisis Determinants to SRM Impulses – UK

This figure shows how shocks to the systemic risk measures impact the systemic crisis determinants of the Irish banking sector. We include an IRF response for each of NPL, MES, SES, ΔCoVaR and CRI.

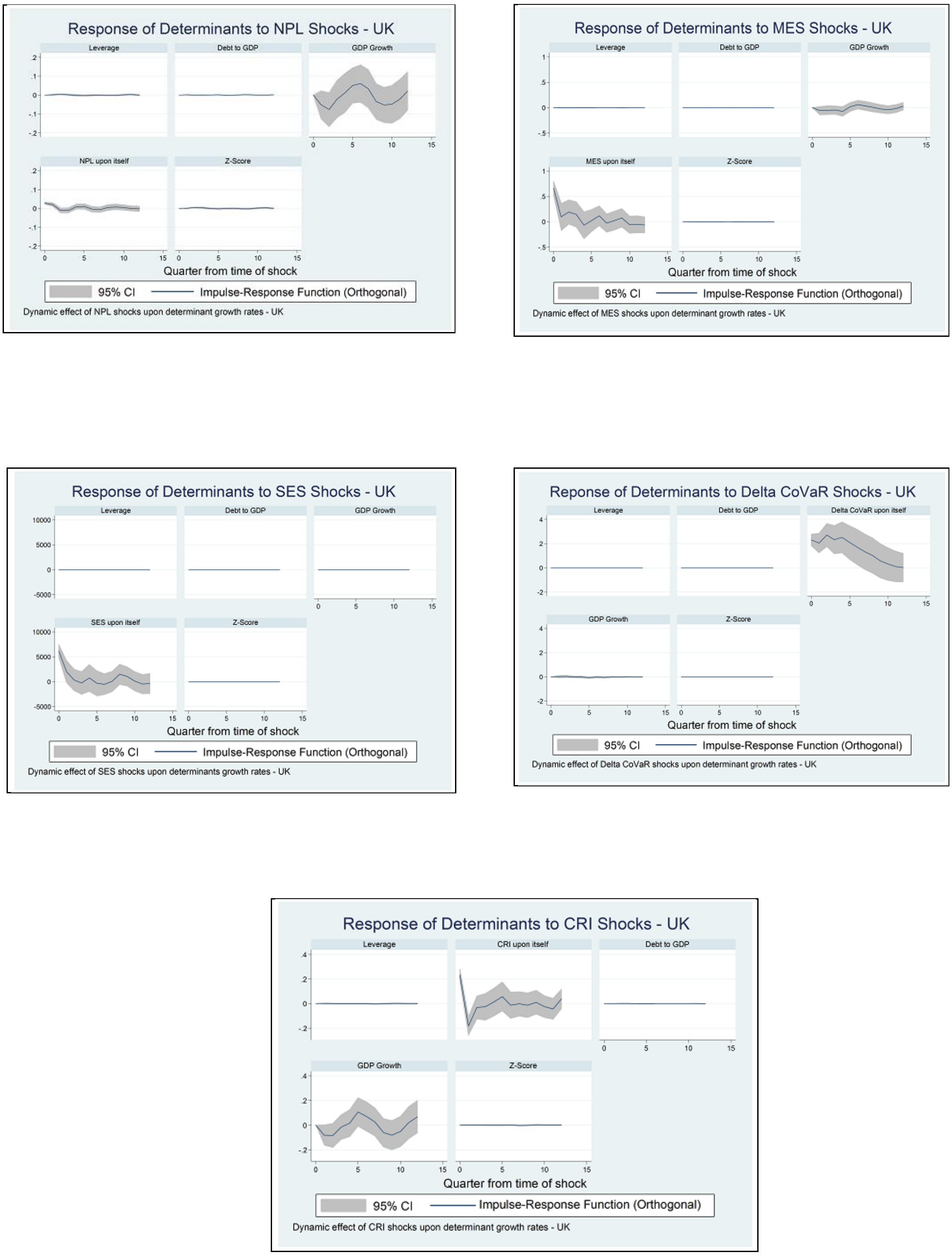
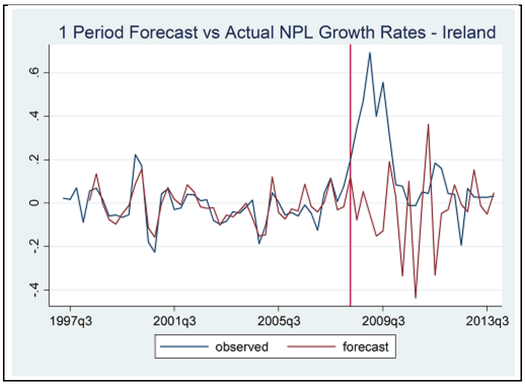
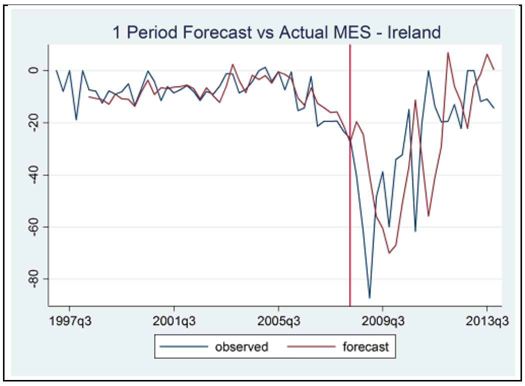
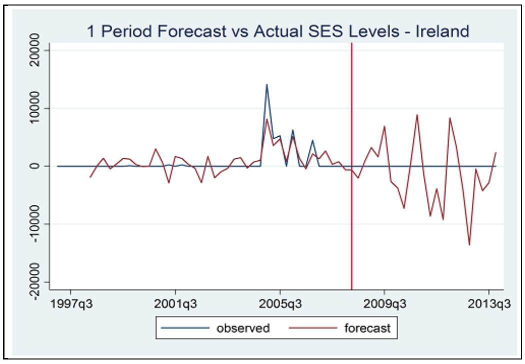


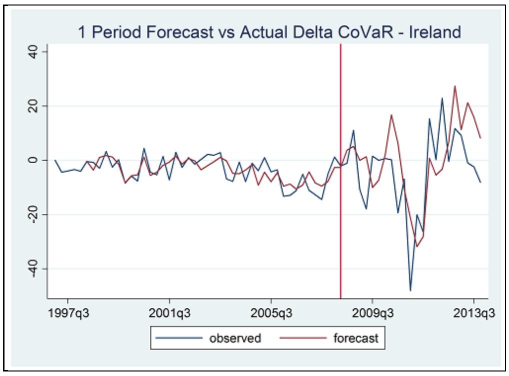
Fig. 6a Single Period SRM Forecasts - Ireland

This figure shows the one period ahead SRM forecasts for Ireland, compared with actual values realised. Forecasts for time "t+1" are based upon actual observations known at time "t" so that a forecast does not rely upon any past forecast, making it more accurate than longer-term forecasts, at least in theory.









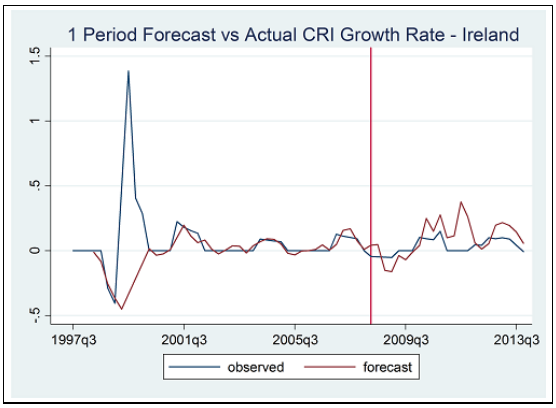
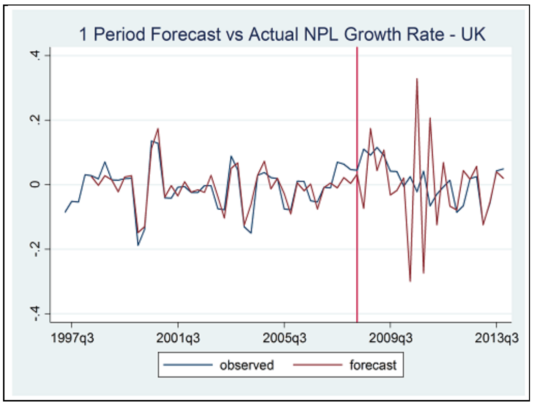
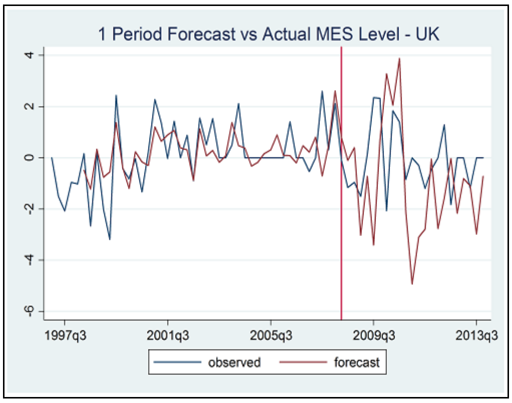
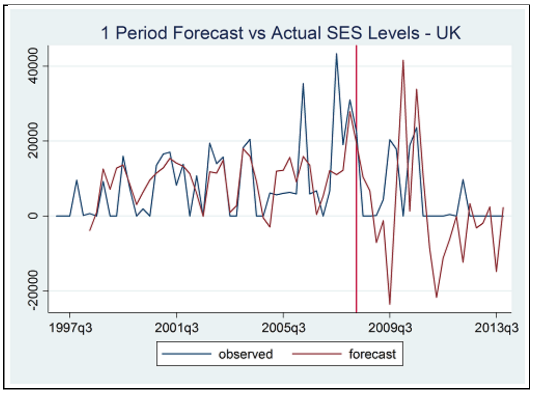


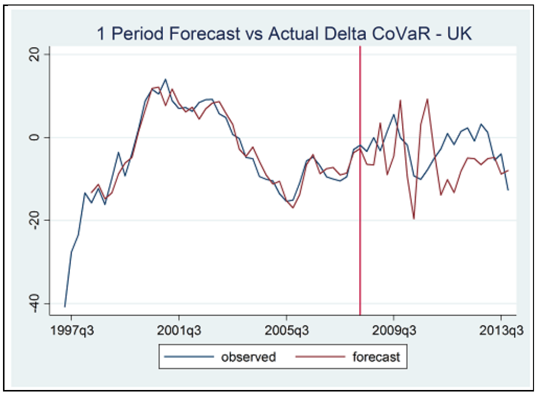
Fig. 6b Single Period SRM Forecasts - UK

This figure shows the one period ahead SRM forecasts for the UK, compared with actual values realised. Forecasts for time "t+1" are based upon actual observations known at time "t" so that a forecast does not rely upon any past forecast, making it more accurate than longer-term forecasts, at least in theory.









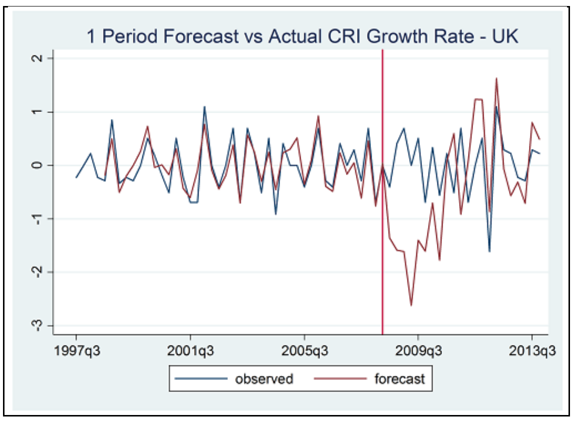
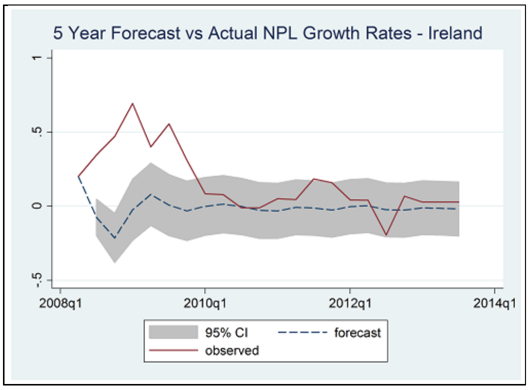
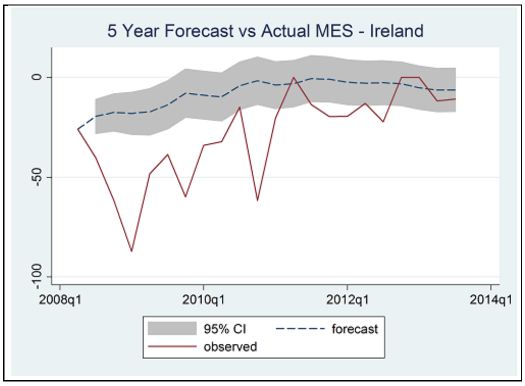
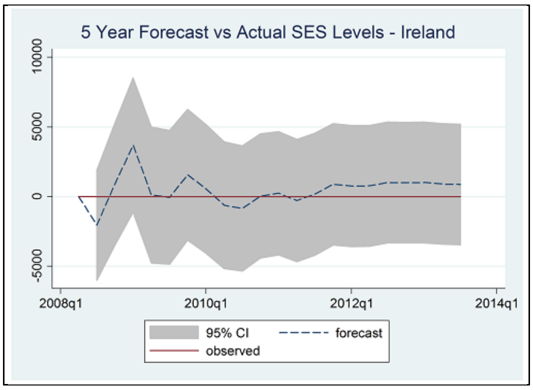


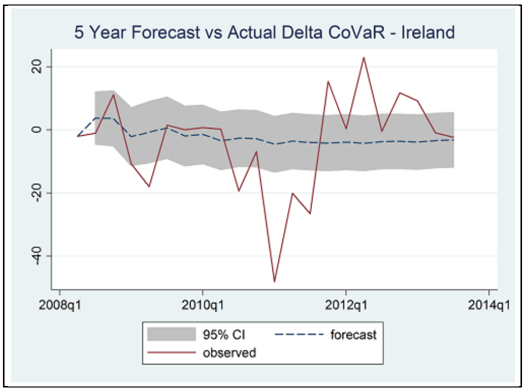
Fig. 7a 5 Year SRM Forecasts - Ireland

Here the five year forecasts for each of the Irish SRMs are presented as of 2008 Q2. Forecasts for time "t+1" are based upon actual observations as of 2008 Q2, but upon time "t" forecasts thereafter. Thus forecasts become less accurate the longer the forecast horizon. Confidence Intervals are depicted at the 95% level of significance and actual observations from covering the period 2008 Q3 - 2013 Q4 are also shown for evaluation of the forecasting accuracy per SRM.









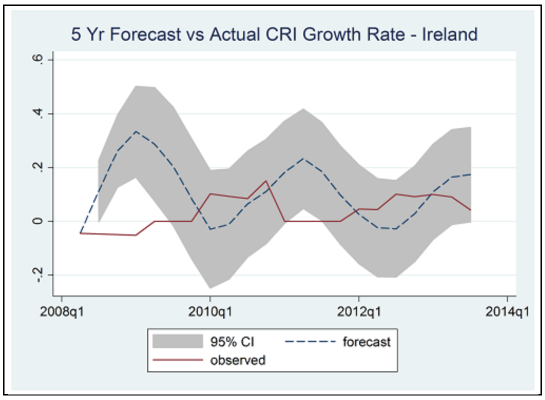
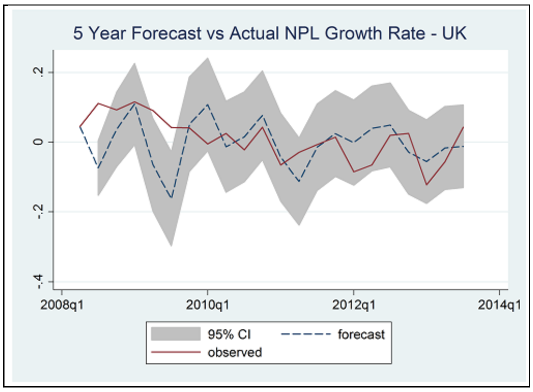
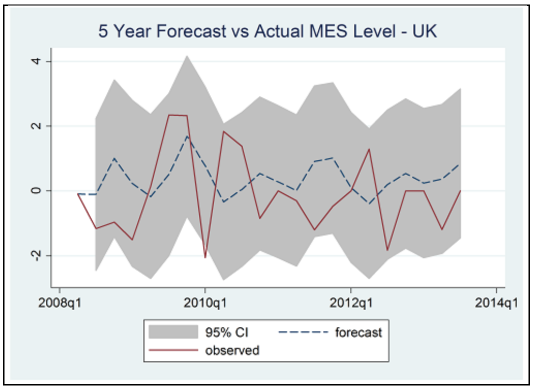
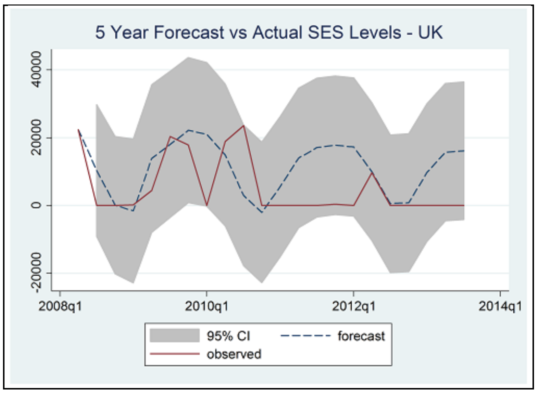


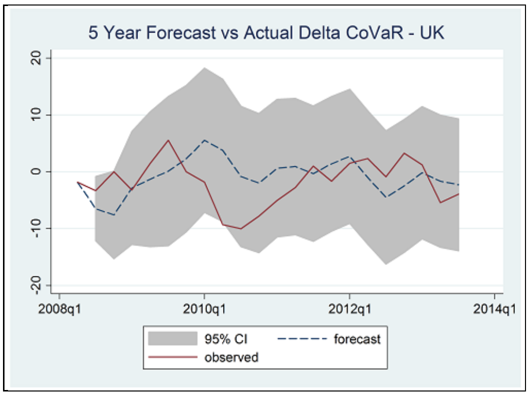
Fig. 7b 5 Year SRM Forecasts - UK

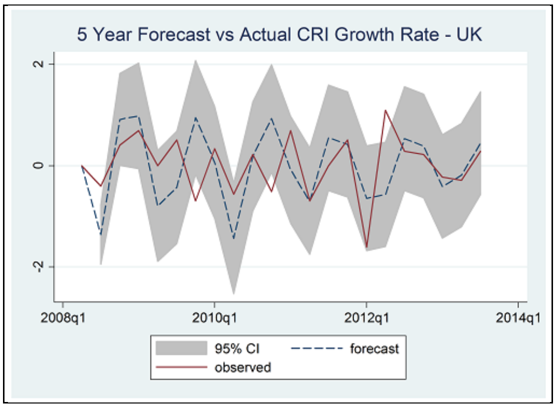
Here the five year forecasts for each of the UK SRMs are presented as of 2008 Q2. Forecasts for time "t+1" are based upon actual observations as of 2008 Q2, but upon time "t" forecasts thereafter. Thus forecasts become less accurate the longer the forecast horizon. Confidence Intervals are depicted at the 95% level of significance and actual observations from covering the period 2008 Q3 - 2013 Q4 are also shown for evaluation of the forecasting accuracy per SRM.











Appendices

Appendix 1 – Description of Variables in Panel A

Variable	Variable Type	Description and Source
Dependent Variable – Crisis	Binary	Takes the value of 1 if a country experiences a systemic banking crisis in a particular year and 0 otherwise. This definition of a systemic crisis follows Demirgüç-Kunt and Detragiache's (1998) definition as described in their paper.
GDP Growth-rate	Continuous	Year on year growth-rate of real (inflation adjusted) GDP. Source is the International Monetary Fund (IMF) International Financial Statistics (IFS) database. Values are percentages and typically fall in the range 0 – 100 (i.e. 9% appears as 9 and not 0.09). The IFS code for this variable is NGDP_R. Calculate the GDP growth-rate by using the following formula GDP Growth-rate $i,_{t+1}$ = ((NGDP_R $i,_{t+1}$– NGDP_R $i,_{t}$) / NGDP_R $i,_{t}$)*100 where "i" represents a country and "t" a year.
Terms-of-trade Change	Continuous	Changes in the terms-of-trade. Source data comes from the World Bank's World Development Indicator (WDI) database. The indicator code is TT.PRI.MRCH.XD.WD with description "Net Barter Terms-of-trade Index" which is referred to in the following equation as NBTOTI. The formula used to calculate this field is:- Terms-of-trade Change $_{i,t+1}$ = (NBTOTI $_{i,t+1}$- NBTOTI $_{i,t}$) / NBTOTI i,t) * 100.
Depreciation of Currency	Continuous	Year on year rate of change of the national currency to the US $ exchange rate (for USA use the Nominal Effective Exchange Rate as reported in the IFS database and as directed by Demirgüç-Kunt and Detragiache (1998). The data is held in the IMF's IFS database with code NUSD and with description "National Currency per US Dollar". Formula used to calculate the figure is :- Depreciation of Currency $_{i,t+1}$ = ((NUSD $i,_{t+1}$– NUSD $i,_{t}$) / NUSD $i,_{t}$)*100.
Real-interest Rate %	Continuous	The real-interest rate (inflation adjusted interest rate). Comes from the World Bank's WDI database with variable code FR.INR.RINR which is described as Real-interest Rate %. An interest rate of, e.g. 2.5% is stored as 2.5 and not as .024.
Inflation	Continuous	Level of inflation in percentage terms experienced by country "i" in year "t". The data source is the IMF's IFS database with code NGDP_D which has the corresponding description "Gross Domestic Product, Deflator". Different values of this field are stored for different country / year combinations. I select only values that have the additional specification of "Percent Change over Corresponding Period of Previous Year". Panel B uses an alternative source of inflation data where the source is the World Bank's WDI database. The IFS values in panel A are used to replicate Demirgüç-Kunt and Detragiache (1998) as faithfully as possible, whereas in panel B the WDI data is more tractable and for that reason is preferred.

Appendix 1 – Description of Variables in Panel A

Variable	Variable Type	Description and Source
Surplus Govt Budget to GDP %	Continuous	Represents the Government Current Account balance as a % of GDP. The data source is the World Bank's WDI database. The data code for this variable is BN.CAB.XOKA.GD.ZS which has the description "Current Account Balance (% of GDP) as a description. Values are percentages such that a figure of, e.g. 8% is stored as 8 and not as 0.08.
M2 Money to Forex Reserves %	Continuous	The ratio of a country's M2 (broad money supply) to its Foreign Exchange Reserves position. M2 money comes from the WDI database, with code FM.LBL.MQMY.CN which is described as "Money and quasi money (M2) (current Local Currency Units)". This is converted to US $ using the prevailing rate of exchange (see Depreciation of Currency variable for data source). The Foreign Exchange Reserves are sourced via the IFS database with field code RAXGFX, described as "Foreign Exchange Reserves". Several variants of this field are held, the one selected for the denominator in this ratio has the further description "US Dollars". The ratio is then easily calculated.
Private-credit-to-GDP %	Continuous	Level of private credit afforded by banks as a proportion of GDP. Data is in local currency for both numerator and denominator and comes from the IFS database. The relevant IFS code is 32D__ with description "Claims on Private Sector". GDP is also from the IFS and is as described above. If data is not available for a particular year and country combination an alternative data source is the Financial Development and Structures Database (see Cihák, Demirgüç-Kunt, Feyen and Levine 2013)), field code "pcrdbgdp".
Ratio of bank liquid reserves to bank assets	Continuous	This ratio measures the level of bank liquid reserves (e.g. cash or assets easily converted to cash) as a percentage of total assets of the bank. Data is sourced via the World Bank's WDI database. The code for the requisite field is FD.RES.LIQU.AS.ZS described as "Bank liquid reserves to bank assets ratio (%)". In 1998 this field was calculated using several IFS variables – this WDI value used here is more accessible.
Private Credit Growth-rate	Continuous	This variable measures the growth-rate in the levels of indebtedness of the private sector of an economy from the previous year to the current year. The data in panel A comes from three separate sources. In order of priority these are 1) Financial Development and Structures Database (see Cihák et al. (2013)), field code is "pcrdbgdp" 2) World Bank's WDI Database data on private credit growth-rates (access code FM.AST.DOMS.CN and 3) IMF's IFS database with code 22D described as "claims on private sector" .
Real GDP per-capita	Continuous	Measures the average level of wealth per person in a country in a given year in US$. The data is sourced via the World Bank's WDI database with variable code NY.GDP.PCAP.KD described as "GDP per-capita (Constant US$)".
Deposit-insurance	Binary	Takes the value of 1 if country "i" has an **explicit** (i.e. has procured via an insurance policy) deposit-insurance scheme in place for banking sector deposits in year "t" and 0 otherwise. The data for this variable comes from two sources which are, in order of priority 1) Deposit-insurance around the world database

Appendix 1 – Description of Variables in Panel A

Variable	Variable Type	Description and Source
Dummy Variable		by Demirgüç-Kunt et al. (2005) and 2) Bank Regulation and Supervision Database (see Barth et al. (2013)). The first dataset formalises the data supplied by Demirgüç-Kunt and Detragiache (1998) and extends the data to 2003. The second dataset covers the period from 1999 to 2011 over which period the data for 4 regulatory surveys, which included questions on deposit-insurance schemes in situ in 180 countries, are provided.
Capital-to-asset (Leverage) Ratio	Continuous	A ratio used to measure how leveraged a bank is, in that the bank's assets (the bulk of which are loans they have extended) are financed via capital. This ratio is a measure of the proportion of the asset base of the bank that has been financed by capital (owners' equity, retained earnings etc.) versus how much of the financing for the assets that has come from debt. Here assets are not risk weighted in any way however some academics believe this simpler measure of the loss absorbing ability of a bank's capital is more informative and less prone to manipulation than the more complicated Tier – 1 Capital ratio. Panel A has a timeframe extending from 1980 to 2010, as such the only viable source for leverage ratio data extending back that far is the World Economic Outlook's Financial Development database, field code "GFDD.SI.03".
House Price Index Growth-rate	Continuous	Representing the growth in house prices (in % terms) year over year in a country. The purpose of this variable is to help capture the risk to the banking system of real-estate prices over-heating / property bubbles. Data for this variable is quite scarce and limited primarily to the OECD countries although additional data has been provided by the Bank for International Settlements in recent years. This is why the number of observations in the table drops off whenever this variable is included. I use the BIS data as the primary source of data, supplemented where possible via data provided by the OECD.
Alternative Dependent Variable – crisis dummy variable #2	Binary	The source for this data is Laeven and Valencia's (2013) dataset that accompanies their 2012 IMF Working Paper entitled "Systemic Banking Crises Database: An Update". The dataset provides worksheets for Crises Years, including the country name, start date of a systemic banking crisis, fiscal cost of the crisis, whether support was provided by the sovereign and other useful data. The definition of a systemic banking crisis is more rigorous than that outlined by Demirgüç-Kunt and Detragiache (1998). Two conditions have to be simultaneously met "1. Significant signs of financial distress in the banking system (as indicated by significant bank runs, losses in the banking system, and/or bank liquidations)" and "2) Significant banking policy intervention measures in response to significant losses in the banking system".

Appendix 2 – Description of Variables in Panel B

(Note, only those variables not already described in Appendix 1 are described here)

Variable	Variable Type	Description and Source
Bank Credit to Bank Deposit %	Continuous	This ratio essentially measures the extent of loan levels as a proportion of the banks deposit base. (An alternative view is how many times on average a euro of deposit money has been loaned out.) Data comes from the Financial Development and Structures Database (see Cihák et al. (2013)), field code "bcbd – Bank Credit to Bank Deposits (%)".
Bank Z Score	Continuous	A measure of risk incorporating earnings and capital-adequacy into one value. The term is defined as Bank Z Score $_t$ = (Return on Assets $_t$ + Capital Asset Ratio $_t$) / (Standard Deviation of Return on Assets). The value returned is sometimes described as a "Distance-to-default" measure, thus larger values imply further distance-to-default and consequently a less risky bank profile. The denominator incorporates the return on assets over a period of time (depending upon availability of data). Data for this variable comes from two sources, the primary source is the WEO Financial Development Database (code = GFDD.SI.01 "Bank Z-score"), supplemented where possible by data aggregated to country level from individual bank level data held in Bankscope. The country level Bank Z score is aggregated based upon asset weights.
Bank Concentration	Continuous	Measures proportion of total assets in a banking system held by the 3 largest banks. Data is sourced via the Financial Development and Structures database (see Cihák et al. (2013)), field code "concentration".
Net-interest-margin	Continuous	The difference between what a bank earns as loan interest income and what it pays to depositors (both individual and institutional). It is a useful indirect measure of earnings but also acts as a proxy for interest rate risk as banks may have lent on fixed rates or have tied loan products to LIBOR or central bank lending rates (e.g. "tracker" mortgages). Source data from Financial Development and Structures database (see Cihák et al. (2013)) field code "netintmargin".
Non-performing loans to Total Loans %	Continuous	The percentage of total loans in the banking sector that are at risk of being written-off, usually defined as loan repayments have not been made for 90 days or more. Source data from World Economic Outlooks Financial Development Database, field code GFDD.SI.02.
Non-resident loans to GDP %	Continuous	A measure of competition in the banking sector and degree to which financial liberalisation has progressed. Also a proxy for the potential exposure of the banking system to a reversal of capital flows as non-resident banks leave stressed markets. Source data from Financial Structures and Development Database (see Cihák et al. (2013)) field code "nrbloan".

Appendix 3 – Description of Panel C Variables

Variable	Variable Type	Description and Source
Dependent Variable	Binary	Takes the value "1" if country "We" has experienced a systemic banking crisis in year "t" and "0" otherwise. Laeven and Valencia describe a banking crisis as being a "systemic" episode if two conditions are met. These are: - 1) Significant signs of financial distress in the banking system (as indicated by significant bank runs, losses in the banking system, and / or bank liquidations) and 2) Significant banking policy intervention measures in response to significant losses in the banking system. The authors go on to describe six policy intervention measures and describe condition 2) as being satisfied if three or more of those measures have been used (see Laeven and Valencia (2013) for more details.
Tier-1 capital	Continuous	Tier-1 capital is as defined by the Banking Committee for Bank Stability (BCBS) the unit within the Bank for International Settlements (BIS) with responsibility for bank regulatory policy for the Group of leading twenty global economies (G20). The definition for Tier 1 is that it represents a ratio of high quality capital (loss absorbing capital such as common shareholder equity, cash or cash-like reserves and any other unencumbered debt used to finance banking assets divided by risk weighted assets. The risk weightings are complex and guidelines are supplied by BCBS but banks can and have interpreted guidelines to manipulate apparent compliance to minimum required levels. For that reason some analysts and researchers prefer the simpler leverage ratio (total capital divided by total assets) as a measure for how leveraged the bank is against its capital base. Tier 1 data comes from the Financial Development and Structures database (see Čihák, Demirgüç-Kunt, Feyen, Beck and Levine (2013)) with panel gaps filled, where data exists, from the Bankscope database. Typically data for this variable is not available for countries prior to 1998.
GDP Growth-rate	Continuous	Year to year growth-rate of real (inflation adjusted) GDP. Source is the International Monetary Fund (IMF) International Financial Statistics (IFS) database. Values are percentages and typically fall in the range 0 – 100 (i.e. 9% appears as 9 and not 0.09). The IFS code for this variable is NGDP_R. Calculate the GDP growth-rate by using the following formula GDP Growth-rate $i_{,t+1}$ = ((NGDP_R $i_{,t+1}$– NGDP_R $i_{,t}$) / NGDP_R $i_{,t}$)*100 where "We" represents a country and "t" a year.
Real-interest Rate	Continuous	The real-interest rate (inflation adjusted interest rate). Comes from the World Bank's WDI database with variable code FR.INR.RINR which is described as Real-interest Rate %. An interest rate of, e.g. 2.5% is stored as 2.5 and not as .024.
Inflation	Continuous	Level of inflation in percentage terms experienced by country "We" in year "t". The data source is the IMF's IFS database with code

Appendix 3 – Description of Panel C Variables

Variable	Variable Type	Description and Source
		NGDP_D which has the corresponding description "Gross Domestic Product, Deflator". Different values of this field are stored for different country / year combinations. I select only values that have the additional specification of "Percent Change over Corresponding Period of Previous Year".
Private-credit-to-GDP %	Continuous	Level of private credit afforded by banks as a proportion of GDP. Data is in local currency for both numerator and denominator and comes from the IFS database. The relevant IFS code is 32D__ with description "Claims on Private Sector". GDP is also from the IFS and is as described above. If data is not available for a particular year and country combination an alternative data source is the Financial Structures Database. That database contains a variable "pcrdbgdp" which is described as "Private Credit by Deposit Money Banks to GDP (%).
Private Credit Growth-rate	Continuous	This variable measures the growth-rate in the levels of indebtedness of the private sector of an economy from the previous year to the current year. The variable is sourced from either 1) the Financial Development and Structures database (see Čihák, Demirgüç-Kunt, Feyen, Beck and Levine (2013)) or 2) World Bank's WDI Database data on private credit growth-rates (access code FM.AST.DOMS.CN or 3) IMF's IFS database with code 22D described as "claims on private sector" . The growth-rate has to be calculated in some cases in the same way as GDP growth-rate is calculated (see above)
No Deposit-insurance Dummy Variable	Binary	Takes the value of 1 if country "We" has no explicit (i.e. procured via an insurance policy) deposit-insurance scheme in place for banking sector deposits in year "t" and 0 otherwise. The data for this variable comes from the Bank Regulation and Supervision Database by Barth, Caprio and Levine (2013). This dataset covers the period from 1999 to 2011 over which period the data for 4 regulatory surveys, which included questions on deposit-insurance schemes in situ in 180 countries, are provided.
M2 Money to Forex Reserves %	Continuous	The ratio of a country's M2 (broad money supply) to its Foreign Exchange Reserves position. M2 money comes from the WDI database, with code FM.LBL.MQMY.CN which is described as "Money and quasi money (M2) (current Local Currency Units)". This is converted to US $ using the prevailing rate of exchange (see Depreciation of Currency variable for data source). The Foreign Exchange Reserves are sourced via the IFS database with field code RAXGFX, described as "Foreign Exchange Reserves". Several variants of this field are held, the one selected for the denominator in this ratio has the further description "US Dollars". The ratio is then easily calculated.

Appendix 3 – Description of Panel C Variables

Variable	Variable Type	Description and Source
House Price Index Growth-rate	Continuous	Representing the growth in house prices (in % terms) year over year in a country. The purpose of this variable is to help capture the risk to the banking system of real-estate prices over-heating / property bubbles. Data for this variable is quite scarce and limited primarily to the OECD countries although additional data has been provided by the Bank for International Settlements in recent years. This is why the number of observations in the table drops off whenever this variable is included. I use the BIS data as the primary source of data, supplemented where possible via data provided by the OECD.
3 Year CAGR of Tier-1 capital %	Continuous	Three year compounded annual growth-rate of Tier-1 capital. Calculated as (Tier-1 capital $_{t+3}$– Tier-1 capital $_{t}$)^ $^{1/3}$ * 100. Source for data is Financial Development and Structures Database and Bankscope as described above for Tier-1 capital.
Bank Credit to Bank Deposit %	Continuous	This ratio essentially captures a risk measure that indicates the extent of loans issued by the bank as a proportion of the deposit base of the bank (an alternative view is how many times on average a euro of deposit money has been loaned out by the bank). Data comes from the Financial Structures Database (Demirgüç-Kunt, Beck and Levine 2013) with field code "bcbd – Bank Credit to Bank Deposits (%)".
Securities-trading Restrictions Index	Discrete	Measures the extent to which banks are curtailed from securities-trading activities such as underwriting, brokering or dealing in securities as well as all aspects of the mutual fund industry. Data is sourced via the Barth, Caprio and Levine database (2013) (index code is secur_act) Values range from 1 – 4 (discrete values) with higher values indicating a more restrictive regulatory environment, e.g. a value of 1 means unrestricted, a value of 4 means fully prohibited.
Overall trading restrictions index	Discrete	In addition to the securities-trading restrictions this variable measures the extent to which banks are prevented from various other activities such as insurance underwriting and real-estate investment and management activities. Data is sourced via the Barth, Caprio and Levine database (2013) (index code is act_restric(*)). Values range from 3 to 12 with higher values indicating a more restrictive regulatory regime.
New-banking-entrants Restriction Index	Discrete	This variable measures how restrictive / difficult it is for a new bank to secure a license to operate in a country. It measures the extent to which various types of legal submissions are required in order to obtain a license. Data is sourced via the Barth, Caprio and Levine database (2013) (index code is entr_bank_req). Values range

Appendix 3 – Description of Panel C Variables

Variable	Variable Type	Description and Source
		from 0 to 8 with higher values indicating a more restrictive regulatory regime. There are 8 specific documents examined including such things as organisation charts, financial projections, background of nominated directors etc. If a document is required a score of 1 for that question is added to the index value for that country. This is repeated for each of the 8 documents examined in the surveys that underpin the database. Refer to Barth, Caprio and Levine's paper for full details.
Liquid Assets to Deposits + Short-term Funds	Continuous	A liquidity measure that is closer to the definition of liquidity coverage (Liquidity Coverage Ratio and Net Stable Funding Ratios) of Basel 3 than the more simplistic Assets to Deposits ratio used in other regressions. Liquid assets are those that are cash or are easily converted to cash. The denominator comprises bank deposits but to this are added other sources of short-term funds: - the idea being that a run on deposits due to a shock is likely to impact short-term financing also and potentially threaten the liquidity position of the bank. Data is sourced via the WEO Financial Development Database (code = GFDD.SI.06 "Liquid assets to deposits and short-term funding (%))".
Tier-1 capital – Delta from 8.5% Minimum	Continuous	I subtract the minimum Basel 3 Tier-1 capital level, 8.5% from the Tier-1 capital position of the aggregate banking system Tier-1 capital position. Theory suggests that as this distance grows (in either direction) that the banking system will be more risky. Data is based upon the Tier-1 capital position described earlier.
Tier 1 Delta Positive Dummy	Binary	Takes on the value of "1" if a country's Tier-1 capital position is in excess of the minimum Basel 3 Tier-1 capital requirement. This variable is used to help explain whether or not too high a reserve is associated with systemic banking crises.
CAMEL – Capital-to-assets (Leverage) Ratio	Continuous	Refer to Capital-to-assets Ratio description. This variable is one of the measures used by security and risk analysts in the USA as part of the CAMEL rating system described in the main text above. Capital-to-asset Ratio is the "C" in the CAMEL rating system.
CAMEL – Asset Quality (NPL %)	Continuous	This variable measures the level of non-performing loans as a percentage of total bank assets. It is well known that this level rises whenever shocks appear in banking systems so theory suggests this should be positively associated with systemic crises. This variable is one of the measures used by security and risk analysts in the USA as part of the CAMEL rating system described in the main text above. Asset quality is the "A" in the CAMEL rating system. Data for this variable comes from the WEO Financial Development Database (field code is GFDD.SI.02 "Bank non-performing loans

Appendix 3 – Description of Panel C Variables

Variable	Variable Type	Description and Source
		to gross loans (%)".
CAMEL – Management Efficiency	Continuous	A measure of the effectiveness of the management team of a bank. This is one of the measures used by security and risk analysts in the USA as part of the CAMEL rating system described in the main text above. Management Efficiency is the "M" in the CAMEL rating system. A proxy for management efficiency is the proportion of bank overhead costs to total assets, where higher ratios imply management inefficiency. Data for this variable comes from the Financial Structures Database (Demirgüç-Kunt, Beck and Levine (2013).
CAMEL – Earnings (ROAA) %	Continuous	A measure of earnings is Return on Average Assets (Earnings / Average Assets for the year). This is one of the measures used by security and risk analysts in the USA as part of the CAMEL rating system described in the main text above, and is the "E" in the CAMEL rating system. Data for this variable comes from the WEO Financial Development Database (field code is GFDD.EI.05 "Return on assets (%)".
CAMEL – Liquidity Ratio	Continuous	A measure of bank loans to deposits ratio, one of the most common forms of liquidity ratios for banks.). This is one of the measures used by security and risk analysts in the USA as part of the CAMEL rating system described in the main text above, and is the "L" in the CAMEL rating system. For this variable I use the bank credit to bank deposit ratio as described above.
Bank Concentration	Continuous	Measures proportion of total assets in a banking system held by the 3 largest banks. Data is sourced via the Financial Structures database (Demirgüç-Kunt, Beck and Levine (2013)) (field code concentration "Assets of three largest banks as a share of assets of all commercial banks"). Ultimate source for the data is via the Bankscope database.

Appendix 4a

List of Panel A countries included in regressions in Chapter 1 by table id and regression number. Countires included in the regressions are marked with an "x".

		Table 1.3			Table 1.4			Table 1.5						Table 1.6					Table 1.9		
Country	**Country Id**	**(1)**	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(1)**	**(2)**	**(3)**
Australia	1	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x		x
Austria	2	x			x	x	x		x	x		x	x	x	x	x	x		x	x	x
Bahrain	3	x	x		x	x		x	x	x	x	x	x								
Belgium	4	x			x	x	x		x	x		x	x	x	x	x	x	x	x	x	x
Burundi	5	x	x		x	x		x	x		x	x									
Canada	6	x			x	x	x	x	x	x	x	x	x	x	x	x	x	x	x		x
Colombia	7	x	x	x	x	x	x	x			x			x	x	x	x		x		x
Congo, Rep.	8	x	x		x	x		x	x		x	x									
Cyprus	9	x	x		x	x		x	x	x	x	x	x	x							
Denmark	10	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Ecuador	11	x	x	x	x	x	x	x			x			x	x	x	x		x		x
Egypt, Arab Rep.	12	x			x			x			x			x	x	x	x		x		x
El Salvador	13	x	x	x	x	x	x	x			x			x	x	x	x		x		x
Finland	14	x	x	x	x	x	x	x	x		x	x		x	x	x	x	x	x		x
France	15	x			x	x	x		x	x		x	x	x	x	x	x	x	x	x	x
Germany	16	x			x	x	x		x	x		x	x	x	x	x	x	x	x	x	x
Greece	17	x			x	x	x			x			x	x	x	x	x	x	x	x	x
Guatemala	18	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x		x		x
Guyana	19	x	x		x	x		x	x		x	x									
Honduras	20	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x		x		x
India	21	x	x	x	x	x	x	x	x		x	x		x	x	x	x		x		x
Indonesia	22	x	x	x	x	x	x	x	x		x	x		x	x	x	x		x		x
Ireland	23	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Israel	24	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x		x		x
Italy	25	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Jamaica	26	x	x	x	x	x	x	x	x		x	x									
Japan	27	x	x	x	x	x	x	x	x		x	x		x	x	x	x	x	x		x
Jordan	28	x	x	x	x	x	x	x			x			x	x	x	x		x		x
Kenya	29	x	x	x	x	x	x	x			x			x	x	x	x		x		x
Korea, Rep.	30	x	x	x	x	x	x	x			x			x	x	x	x		x		x
Malaysia	31	x	x	x	x	x	x	x	x		x	x		x	x	x	x		x		x
Mali	32	x	x		x	x		x			x										
Mexico	33	x	x	x	x			x			x			x	x	x	x		x		x
Nepal	34	x	x		x	x		x			x										
Netherlands	35	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
New Zealand	36	x	x	x	x	x	x	x	x	x	x	x	x								
Niger	37	x	x		x	x		x			x										
Nigeria	38	x	x	x	x	x	x	x	x		x	x		x	x	x	x		x	x	x
Norway	39	x	x	x	x	x	x	x	x		x	x		x	x	x	x	x	x		x
Papua New Guinea	40	x			x	x		x	x	x	x	x	x								
Paraguay	41	x	x	x	x	x	x	x	x		x	x		x	x	x	x		x		x
Philippines	42	x			x	x	x	x			x			x	x	x	x		x		x
Portugal	43	x			x	x	x		x	x		x	x	x	x	x	x		x	x	x
Senegal	44	x	x		x	x		x			x			x	x	x	x		x		x
Seychelles	45	x	x		x	x		x	x	x	x	x	x	x	x	x	x		x		x
Singapore	46	x			x			x	x	x	x	x	x	x	x	x	x		x		x
South Africa	47	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x		x		x
Sri Lanka	48	x	x	x	x	x	x	x			x										
Swaziland	49	x	x		x	x		x	x		x	x		x	x	x	x		x		x
Sweden	50	x			x			x	x		x	x		x	x	x	x	x	x	x	x
Switzerland	51	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Syrian Arab Republic	52	x			x	x		x		x	x		x								
Tanzania	53	x						x						x	x	x	x		x		x
Thailand	54	x	x	x	x	x	x	x			x			x	x	x	x		x		x
Togo	55	x	x	x	x	x	x	x	x		x	x									
Uganda	56	x	x	x	x	x	x	x	x		x	x		x	x	x	x		x		x
United Kingdom	57	x			x			x	x	x	x	x	x	x	x	x	x	x	x	x	x
United States	58	x			x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Uruguay	59	x			x			x			x			x	x	x	x		x	x	x
Venezuela, RB	60	x	x	x	x	x	x	x	x		x	x		x	x	x	x		x		x
Zambia	61	x	x	x	x	x	x	x	x		x	x									
Country Count		**61**	**44**	**33**	**60**	**54**	**41**	**55**	**42**	**26**	**54**	**42**	**26**	**47**	**46**	**46**	**46**	**17**	**46**	**16**	**46**

Appendix 4b

List of Panel B countries included in regressions in Chapter 1 by table id and regression number. Countires included in the regressions are marked with an "x".

		Table 1.7						Table 1.8			Table 1.10					
Country	**Country Id**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(1)**	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Argentina	1	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Australia	2	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Austria	3	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Bahrain	4	x	x	x	x				x							
Belgium	5	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Brazil	6							x	x	x						
Bulgaria	7	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Burundi	8								x							
Canada	9	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Colombia	10							x	x	x						
Congo, Rep.	11	x	x	x	x				x							
Croatia	12							x	x	x						
Cyprus	13	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Czech Republic	14							x	x	x						
Denmark	15	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Ecuador	16							x	x	x						
Egypt, Arab Rep.	17	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
El Salvador	18	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Estonia	19	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Finland	20	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
France	21	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Germany	22	x	x	x	x	x	x	x	x	x	x	x	x		x	x
Guatemala	23	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Guyana	24	x	x	x	x				x							
Honduras	25	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Hungary	26	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
India	27	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Indonesia	28							x	x	x						
Ireland	29	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Israel	30	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Italy	31	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Jamaica	32								x							
Japan	33							x	x	x						
Jordan	34	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Kenya	35	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Korea, Rep.	36	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Kuwait	37	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Latvia	38	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Lithuania	39	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Mali	40	x	x	x	x				x							
Mexico	41	x	x					x	x	x						
Nepal	42	x	x	x	x				x							
Netherlands	43	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
New Zealand	44	x	x	x	x				x							
Niger	45	x	x	x	x				x							
Nigeria	46	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Norway	47	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Papua New Guinea	48	x	x	x	x				x							
Paraguay	49	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Peru	50	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Philippines	51							x	x	x						
Portugal	52	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Romania	53	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Russian Federation	54	x	x	x	x	x	x	x	x	x	x	x	x	x	x	
Senegal	55	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Seychelles	56	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Singapore	57	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Slovak Republic	58							x	x	x						
South Africa	59	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Spain	60							x	x	x						
Sri Lanka	61	x	x	x	x				x							
Swaziland	62								x							
Sweden	63	x	x			x		x	x	x	x	x	x	x		x
Switzerland	64	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Syrian Arab Republic	65	x	x	x	x				x							
Tanzania	66	x	x	x	x			x	x	x						
Thailand	67							x	x	x						
Togo	68	x	x	x	x				x							
Turkey	69							x	x	x						
Uganda	70	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
United Kingdom	71	x	x	x	x	x	x	x	x	x	x		x	x	x	x
United States	72	x	x	x	x	x	x	x	x	x	x	x		x	x	x
Uruguay	73	x	x	x	x			x	x	x						
Venezuela, RB	74	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Zambia	75								x							
Country Count		**59**	**59**	**57**	**57**	**45**	**44**	**60**	**75**	**60**	**45**	**44**	**44**	**44**	**44**	**44**

Appendix 5a

List of Panel B countries included in regressions in Chapter 2 by table id and regression number. Countires included in the regressions are marked with an "x".

		Table 2.4						Table 2.5						Table 2.6					
Country	**Country Id**	**(1) & (2)**	**(3) & (4)**	**(5) & (6)**	**(7) & (8)**	**(9) & (10)**	**(11) & (12)**	**(1) & (2)**	**(3) & (4)**	**(5) & (6)**	**(7) & (8)**	**(9) & (10)**	**(11) & (12)**	**(1) & (2)**	**(3) & (4)**	**(5) & (6)**	**(7) & (8)**	**(9) & (10)**	**(11) & (12)**
Argentina	1	x	x	x	x	x		x	x	x	x	x		x	x	x	x	x	
Australia	2	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Austria	3	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Bahrain	4	x	x	x	x	x		x	x	x	x	x		x	x	x	x	x	
Belgium	5	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Brazil	6	x												x					
Bulgaria	7	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Burundi	8																		
Canada	9	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Colombia	10	x												x					
Congo, Rep.	11																		
Croatia	12	x												x					
Cyprus	13	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Czech Republic	14	x												x					
Denmark	15	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Ecuador	16	x												x					
Egypt, Arab Rep.	17	x	x	x	x	x		x	x	x	x	x		x	x	x	x	x	
El Salvador	18	x	x	x	x	x		x	x	x	x	x		x	x	x	x	x	
Estonia	19	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Finland	20	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
France	21	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Germany	22	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Guatemala	23	x	x	x	x	x		x	x	x	x	x		x	x	x	x	x	
Guyana	24	x	x	x	x	x		x	x	x				x	x	x	x	x	
Honduras	25	x	x	x	x	x		x	x	x	x	x		x	x	x	x	x	
Hungary	26	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
India	27	x	x	x	x	x		x	x	x	x	x		x	x	x	x	x	
Indonesia	28																		
Ireland	29	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Israel	30	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Italy	31	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Jamaica	32	x												x					
Japan	33	x												x					
Jordan	34	x	x	x	x	x		x	x	x	x	x		x	x	x	x	x	
Kenya	35	x	x	x	x	x		x	x	x	x	x		x	x	x	x	x	
Korea, Rep.	36	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Kuwait	37	x	x	x	x	x		x	x	x	x	x		x	x	x	x	x	
Latvia	38	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Lithuania	39	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Mali	40																		
Mexico	41	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Nepal	42	x	x	x	x	x		x	x	x	x	x		x	x	x	x	x	
Netherlands	43	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
New Zealand	44	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Niger	45	x	x	x	x	x		x	x	x	x	x		x	x	x	x	x	
Nigeria	46	x	x	x	x	x		x	x	x	x	x		x	x	x	x	x	
Norway	47	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Papua New Guinea	48																		
Paraguay	49	x	x	x	x	x		x	x	x	x	x		x	x	x	x	x	
Peru	50	x	x	x	x	x		x	x	x	x	x		x	x	x	x	x	
Philippines	51	x												x					
Portugal	52	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Romania	53	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Russian Federation	54	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Senegal	55	x	x	x	x	x		x	x	x	x	x		x	x	x	x	x	
Seychelles	56	x	x	x	x	x		x	x	x	x	x		x	x	x	x	x	
Singapore	57	x	x	x	x	x		x	x	x	x	x		x	x	x	x	x	
Slovak Republic	58	x												x					
South Africa	59	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Spain	60	x												x					
Sri Lanka	61	x	x	x	x	x								x	x	x	x	x	
Swaziland	62	x												x					
Sweden	63	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Switzerland	64	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Syrian Arab Republic	65																		
Tanzania	66	x	x	x	x	x		x	x	x	x	x		x	x	x	x	x	
Thailand	67	x												x					
Togo	68	x	x	x	x	x		x	x	x	x	x		x	x	x	x	x	
Turkey	69	x	x	x	x	x								x	x	x	x	x	
Uganda	70	x	x	x	x	x		x	x	x	x	x		x	x	x	x	x	
United Kingdom	71	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
United States	72	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Uruguay	73	x	x	x	x	x								x	x	x	x	x	
Venezuela, RB	74	x	x	x	x	x								x	x	x	x	x	
Zambia	75	x												x					
Country Count		**69**	**56**	**56**	**56**	**56**	**30**	**52**	**52**	**52**	**51**	**51**	**30**	**69**	**56**	**56**	**56**	**56**	**30**

Appendix 5b

Continuation of Panel B countries included in regressions in Chapter 2 by table id and regression number. Countires included in the regressions are marked with an "x".

		Table 2.7								Table 2.8								Table 2.9								Table 2.10							
Country	**Country Id**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Argentina	1	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x			x	x	x	x	x	x			x
Australia	2	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Austria	3	x	x		x	x	x	x		x	x		x	x	x	x		x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Bahrain	4	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x				x		x	x	x				x		x	x
Belgium	5	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Brazil	6									x								x	x	x	x					x	x	x	x				
Bulgaria	7	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Burundi	8									x								x								x							
Canada	9	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Colombia	10									x								x	x	x	x					x	x	x	x				
Congo, Rep.	11									x								x				x			x	x				x			x
Croatia	12									x								x	x	x	x					x	x	x	x				
Cyprus	13	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Czech Republic	14									x								x		x						x		x					
Denmark	15	x	x		x	x	x	x		x	x		x	x	x	x		x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Ecuador	16									x								x	x	x	x					x	x	x	x				
Egypt, Arab Rep.	17	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x		x	x	x	x	x	x	x		x	x
El Salvador	18	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x		x	x	x	x	x	x	x		x	x
Estonia	19	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Finland	20	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
France	21	x	x		x	x	x	x		x	x		x	x	x	x		x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Germany	22	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Guatemala	23	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x		x	x	x	x	x	x	x		x	x
Guyana	24	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x				x		x	x	x				x		x	x
Honduras	25	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x		x	x	x	x	x	x	x		x	x
Hungary	26	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
India	27	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x		x	x	x	x	x	x	x		x	x
Indonesia	28									x								x		x						x		x					
Ireland	29	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Israel	30	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Italy	31	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Jamaica	32									x								x								x							
Japan	33									x								x	x	x	x					x	x	x	x				
Jordan	34	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x		x	x	x	x	x	x	x		x	x
Kenya	35	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x		x	x	x	x	x	x	x		x	x
Korea, Rep.	36	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Kuwait	37	x	x		x	x	x	x		x	x		x	x	x	x		x	x	x	x	x		x	x	x	x	x	x	x		x	x
Latvia	38	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Lithuania	39	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Mali	40									x								x				x		x	x	x				x		x	x
Mexico	41	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Nepal	42	x	x		x	x	x			x	x		x	x	x			x				x		x	x	x				x		x	x
Netherlands	43	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
New Zealand	44	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x				x	x	x	x	x				x	x	x	x
Niger	45	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x				x		x	x	x				x		x	x
Nigeria	46	x	x		x	x	x	x		x	x		x	x	x	x		x	x	x	x	x		x	x	x	x	x	x	x		x	x
Norway	47	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Papua New Guinea	48									x								x				x		x	x	x				x		x	x
Paraguay	49	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x		x	x	x	x	x	x	x		x	x
Peru	50	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x		x	x	x	x	x	x	x		x	x
Philippines	51									x								x	x	x	x					x	x	x	x				
Portugal	52	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Romania	53	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Russian Federation	54	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Senegal	55	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x		x	x	x	x	x	x	x		x	x
Seychelles	56	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x		x	x	x	x	x	x	x		x	x
Singapore	57	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x		x	x	x	x	x	x	x		x	x
Slovak Republic	58									x								x	x	x	x					x	x	x	x				
South Africa	59	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Spain	60									x								x	x	x	x					x	x	x	x				
Sri Lanka	61									x								x				x		x	x	x				x		x	x
Swaziland	62									x								x								x							
Sweden	63	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Switzerland	64	x	x		x	x	x	x		x	x		x	x	x	x		x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Syrian Arab Republic	65									x								x				x		x	x	x				x		x	x
Tanzania	66	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x		x	x	x	x	x	x	x		x	x
Thailand	67									x								x	x	x	x					x	x	x	x				
Togo	68	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x				x		x	x	x				x		x	x
Turkey	69									x								x	x	x	x	x			x	x	x	x	x	x			x
Uganda	70	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x		x	x	x	x	x	x	x		x	x
United Kingdom	71	x	x	x	x	x	x	x	x		x	x	x	x	x	x	x																
United States	72	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Uruguay	73									x								x	x	x	x	x		x	x	x	x	x	x	x		x	x
Venezuela, RB	74									x								x	x	x	x					x	x	x	x				
Zambia	75									x								x								x							
Country Count		**52**	**52**	**45**	**52**	**52**	**52**	**51**	**45**	**74**	**52**	**45**	**52**	**52**	**52**	**51**	**45**	**74**	**57**	**59**	**57**	**58**	**29**	**55**	**58**	**74**	**57**	**59**	**57**	**58**	**29**	**55**	**58**

Appendix 6 – Original Demirgüç-Kunt and Detragiache (1998) Table 2

Table 2. Banking Crisis Determinants - Single Crisis

Dependent variable takes the value 1 if there is a crisis and 0 if there is no crisis. Time-series cross-country data are pooled over the 1980-1994 time period. Observations after the the first crisis are omitted. We estimate the probability P(t) of a financial crisis after taking the logit transformation of P(t). Standard errors are given in paranthesis.

	(1)	(2)	(3)	(4)
Macro Variables:				
GROWTH	-.067***	-.136***	-.252***	-.228***
	(.025)	(.039)	(.063)	(.059)
TOT CHANGE	-.030*	-.025	-.043*	-.045
	(.019)	(.020)	(.027)	(.032)
DEPRECIATION	.002	-.001	-.002	-.012
	(.006)	(.007)	(.008)	(.012)
RL. INTEREST	.088***	.086***	.131***	.113***
	(.024)	(.025)	(.039)	(.035)
INFLATION	.040***	.044***	.053**	.079**
	(.016)	(.018)	(.023)	(.035)
SURPLUS/GDP	.012	.024	.016	.013
	(.034)	(.036)	(.053)	(.048)
Financial Variables:				
M2/RESERVES		.012**	.014**	.018**
		(.005)	(.007)	(.009)
PRIVATE/GDP		.019*	.033**	.009
		(.012)	(.015)	(.010)
CASH/BANK		.009	.018	-.049
		(.016)	(.023)	(.039)
CREDIT GROt-2		.007	.022**	-.003
		(.012)	(.010)	(.020)
Institutional Variables:				
GDP/CAP	-.034	-.090*	-.158**	
	(.033)	(.055)	(.079)	
DEPOSIT INS.			1.415**	
			(.738)	
LAW & ORDER				-.516**
				(.238)
No. of Crisis	28	26	20	18
No. of Obs.	546	493	395	268
% total correct	74	77	79	67
% crisis correct	61	58	55	61
% no-crisis correct	75	78	81	67
model 2	31.88***	40.86***	53.79***	30.37***
AIC	204	187	131	126

*, **and *** indicate significance levels of 10, 5 and 1 percent respectively.

Appendix 7 – Additional tables with controls for 2008 effect

TABLE 1.12

	(1) (1980-1990)	(2) (1991-2000)	(3) (2001-2010)	(4) (1980-1990)	(5) (1991-2000)	(6) (2001-2010)
GDP Growth Rate	0.041	-0.212***	-0.457**	-0.082**	-0.198***	-0.275***
	(0.057)	(0.061)	(0.203)	(0.036)	(0.034)	(0.048)
Real Interest Rate	0.019	-0.006	0.052	0.018***	-0.010	0.024
	(0.012)	(0.024)	(0.089)	(0.006)	(0.008)	(0.023)
Terms of Trade Change	0.004	0.018	-0.167**	-0.010	-0.002	-0.017
	(0.017)	(0.025)	(0.083)	(0.012)	(0.010)	(0.019)
M2 Money to Forex Reserves %	-0.000	-0.002	0.006**	-0.001	-0.000	0.005***
	(0.001)	(0.008)	(0.002)	(0.004)	(0.001)	(0.001)
Year 2008 Dummy Variable			4.993***			1.431***
			(1.107)			(0.409)
Constant	-3.544***	-2.068***	-4.838***	-2.344***	-1.126***	-2.249***
	(0.353)	(0.319)	(1.017)	(0.206)	(0.149)	(0.213)
Summary Results:						
No. Observations	470	262	223	537	525	588
No. Systemic Crisis Episodes	17	18	13	44	84	55
Akaike Information Criterion (AIC Score)	141.7	120.9	43.69	284.7	413.0	283.0
Model Chi2	2.880	15.24	61.44	15.00	43.60	88.31
Total Correct In-Sample Predictions %	22.74	43.77	88.79	36.36	50.33	75.37
Correct Crisis Predictions %	88.24	55.56	84.62	77.27	61.90	69.09
Correct No-Crisis Predictions %	20.77	43.09	89.04	33.49	48.48	75.99
Degrees of Freedom	4	4	5	4	4	5
Model Significance - P Value	0.58	0.00	0.00	0.00	0.00	0.00
Log Likelihood Score	-68.37	-57.95	-18.84	-139.8	-204.0	-138.5

This table should be considered in conjunction with Table 1.5, especially regressions 3 and 6. We include a dummy variable for 2008 in these regressions which span the appropriate period containing the year 2008.

TABLE 1.13				
	(1)	(2)	(3)	(4)
Capital to Assets (Leverage) Ratio %	-0.075	-0.049	0.136	0.173
	(0.086)	(0.087)	(0.102)	(0.108)
GDP Growth Rate	-0.361***	-0.376***	-0.373***	-0.383***
	(0.081)	(0.084)	(0.095)	(0.097)
Real Interest Rate	0.094***	0.092***	0.116**	0.121**
	(0.036)	(0.036)	(0.054)	(0.054)
M2 Money to Forex Reserves %		0.004*	0.002	0.002
		(0.002)	(0.002)	(0.002)
Private Credit to GDP %			0.021***	0.022***
			(0.007)	(0.007)
Deposit Insurance Dummy Variable				0.691
				(0.740)
House Price Index Growth Rate				
Year 2008 Dummy Variable	3.216***	3.213***	3.416***	3.462***
	(0.554)	(0.582)	(0.633)	(0.642)
Constant	-2.721***	-3.008***	-6.570***	-7.373***
	(0.699)	(0.762)	(1.446)	(1.640)
Summary Results:				
No. Observations	417	400	398	387
No. Systemic Crisis Episodes	24	24	24	24
Akaike Information Criterion (AIC Score)	117.7	112.6	102.9	101.8
Model Chi2	65.30	69.47	79.86	80.67
Total Correct In-Sample Predictions %	86.15	87.04	85.26	85.35
Correct Crisis Predictions %	75	75	75	75
Correct No-Crisis Predictions %	86.82	87.79	85.90	86.02
Degrees of Freedom	4	5	6	7
Model Significance - P Value	0	0	0	0
Log Likelihood Score	-56.35	-53.28	-47.97	-46.89

This table replicates the results of Table 1.6 but here we include a 2008 dummy variable. Note this yielded a model that was completely determined in regression 5 (of Table 1.6) and no results were reported. Hence it is blank in this Table. Only M2 Money to Forex Reserves appears significantly sensitive to the 2008 dummy variable.

TABLE 1.14						
	(1)	(2)	(3)	(4)	(5)	(6)
Bank Z-Score	-0.093**	-0.101**	-0.096**	-0.091**	-0.092*	-0.099**
	(0.042)	(0.045)	(0.046)	(0.044)	(0.048)	(0.050)
Private Credit to GDP %	0.015***	0.012**	0.013**	0.010	0.009	0.014
	(0.005)	(0.006)	(0.006)	(0.007)	(0.008)	(0.011)
Private Credit Growth Rate lagged 2 years	0.005	-0.002	0.003	0.007	0.008	0.011
	(0.021)	(0.022)	(0.022)	(0.021)	(0.036)	(0.034)
Bank Concentration	-0.008	-0.010	-0.010	-0.011	-0.018	-0.016
	(0.011)	(0.011)	(0.011)	(0.011)	(0.016)	(0.017)
Bank Credit to Deposit Ratio		0.008	0.005	0.004	-0.004	-0.005
		(0.006)	(0.007)	(0.007)	(0.009)	(0.009)
Bank Deposits to Total Assets Ratio			-0.008	-0.033	0.084	0.070
			(0.037)	(0.042)	(0.094)	(0.094)
Net Interest Margin				-0.255	-0.214	-0.197
				(0.176)	(0.251)	(0.250)
Non-performing Loans to Total Loans %					0.210***	0.201***
					(0.072)	(0.072)
Non-resident Loans to Total Loans %						-0.005
						(0.007)
Year 2008 Dummy Variable	3.655***	3.563***	3.430***	3.448***	4.298***	4.247***
	(0.607)	(0.607)	(0.635)	(0.639)	(0.830)	(0.829)
Constant	-4.278***	-4.754***	-3.773	-0.208	-7.564	-6.330
	(0.877)	(0.953)	(3.015)	(3.531)	(8.574)	(8.668)
Summary Results:						
No. Observations	541	541	499	480	347	347
No. Systemic Crisis Episodes	35	35	35	35	35	35
Akaike Information Criterion (AIC Score)	100.9	99.72	96.83	94.51	74.12	74.72
Model Chi2	69.74	71.86	59.48	61.46	67.58	67.99
Total Correct In-Sample Predictions %	69.81	69.26	64.62	61.89	45.49	45.90
Correct Crisis Predictions %	88.57	85.71	88.57	88.57	94.29	94.29
Correct No-Crisis Predictions %	68.87	68.44	63.41	60.55	43.04	43.47
Degrees of Freedom	5	6	7	8	10	11
Model Significance - P Value	0	0	0	0	0	0
Log Likelihood Score	-47.43	-46.36	-44.42	-42.76	-31.06	-30.86

This table replicates the results of Table 1.7 but here we include a 2008 dummy variable. Private credit to GDP growth rate loses significance in the final 3 regressions compared with Table 1.7 and the 2008 is significant at the 1% level as would be expected. However the same variables are significant with the same signs as per Table 1.7

TABLE 2.12								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
3 Year CAGR of Tier-1 Capital %	-0.042***	-0.041***	-0.043					
	(0.014)	(0.014)	(0.034)					
Liquid Assets to Deposits plus Short Term Funds	0.017	0.016	-0.010	0.011	0.017	0.016	0.003	-0.010
	(0.014)	(0.014)	(0.031)	(0.012)	(0.014)	(0.014)	(0.016)	(0.031)
No Deposit Insurance Dummy	-0.450	-0.459	-0.682	-0.571	-0.450	-0.459	-0.594	-0.682
	(0.690)	(0.692)	(1.226)	(0.660)	(0.690)	(0.692)	(0.727)	(1.226)
Securities Trading Restriction Index	-1.012**	-1.001**	-0.278		-1.012**	-1.001**	-0.710	-0.278
	(0.501)	(0.497)	(0.869)		(0.501)	(0.497)	(0.528)	(0.869)
New Banking Entrants Restriction Index		0.104	0.257			0.104	0.178	0.257
		(0.317)	(0.454)			(0.317)	(0.374)	(0.454)
Overall Trading Restrictions Index			-0.987**				-0.438*	-0.987**
			(0.476)				(0.231)	(0.476)
Overall Capital Regulation Index			0.030					0.030
			(0.263)					(0.263)
Year 2008 Dummy Variable	4.682***	4.640***	5.482***	4.491***	4.682***	4.640***	4.863***	5.482***
	(0.789)	(0.791)	(1.338)	(0.763)	(0.789)	(0.791)	(0.839)	(1.338)
3 Year CAGR of of Leverage Ratio (CAR) %				-0.026*	-0.042***	-0.041***	-0.047***	-0.043
				(0.014)	(0.014)	(0.014)	(0.017)	(0.034)
Constant	-4.192***	-4.938*	-0.307	-5.427***	-4.192***	-4.938*	-2.842	-0.307
	-1.157	(2.639)	(4.923)	(0.874)	(1.157)	(2.639)	(3.156)	(4.923)
Summary Results:								
No. Observations	420	415	205	431	420	415	401	205
No. Systemic Crisis Episodes	36	36	36	36	36	36	36	36
Akaike Information Criterion (AIC Score)	140.5	139.9	83.08	144.9	140.5	139.9	137.6	84.08
Model Chi2	9.939	15.42	20.02	3.756	9.939	15.42	20.47	20.02
Total Correct In-Sample Predictions %	37.37	37.89	20	48.16	37.37	37.89	37.89	20
Correct Crisis Predictions %	77.78	80.56	91.67	69.44	77.78	80.56	77.78	91.67
Correct No-Crisis Predictions %	35.36	35.77	16.44	47.10	35.36	35.77	35.91	16.44
Degrees of Freedom	4	5	7	3	4	5	6	7
Model Significance - P Value	0.04	0.01	0.01	0.29	0.04	0.01	0.00	0.01
Log Likelihood Score	-67.77	-66.96	-37.54	-70.47	-67.77	-66.96	-65.32	-37.54

This table replicates the results of table 2.8 but with a dummy variable to control for the year 2008 in all regressions. Note the same regulatory framework variables remain as significant crisis determinants. However the capital growth measures which were significant in prior regressions but were less so, according to Table 2.8 are significant when 2008 is controlled for. The key findings relating to the regulatory framework still apply as the other framework variables remain insignificant.

Publications / Conferences / Seminars

Chapter 1 was presented at the Irish Society of New Economists (ISNE) Conference, Maynooth University, March 2013

Chapter 2 was presented at the UCD Economics and Finance Department's Seminar Series, UCD Campus, September 2014

Chapter 2 was presented at the Multinational Finance Society's Spring Conference, Larnaca, April 2014

Chapter 2 was presented at the Irish Economic Association Annual Conference, Dublin, June 2014

Chapter 3 was presented at the Central Bank of Ireland's Winter Seminar series, Dublin, November 2015

Chapter 1 is registered as Working Paper WPN266 – 15 in the Department of Economics, Finance and Accounting – Maynooth University's Working Paper Series

Chapter 2 is registered as Working Paper WPN265 – 15 in the Department of Economics, Finance and Accounting – Maynooth University's Working Paper Series