Department of Economics Finance & Accounting

Working Paper N265-15

The Determinants of Systemic Banking Crises

A Regulatory Perspective

Michael Wosser
Department of Economics, Finance and Accounting
Maynooth University,
Maynooth,
Co. Kildare,
Ireland
June 2015

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. Neither does distance from the minimum standard, in either direction, matter. However the compound annual growth rate of Tier-1 capital is shown to be significantly associated with overall financial-services stability. Certain aspects of the regulatory environment are 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.

Key Words: Systemic Banking Crises; Determinants; Basel III Accord; Regulations; Regulatory Framework; Stability; Early Warning System

JEL Classification: G21 G28

1. Introduction

At a cost in wealth terms of up to $22 trillion the Global Financial Crisis (GFC) of 2008 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: the flow of vast sums of cheap international capital, financial liberalisation, the creation of derivative instruments (e.g. Asset-Backed-Securities), large-scale sub-prime lending to individuals who were likely to default, too complicated / interwoven financial technologies and the growth of organisations which became too-big-to-fail, etc. (see Bruno and Shin (2013), Lane and McQuade (2014), Brunnermeier (2008) and Connor et al. (2010)). 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 Claessens et al. (2010) and Crotty (2009)). The sudden collapse of important organisations 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, known as the Basel III Accord (see Wellink (2009)).[1] Minimum Tier-1 Capital levels, that is high-quality unencumbered shareholder equity plus retained earnings, were raised to 8.5% (of total risk-weighted assets). New liquidity measures were established to ensure banks could meet all of their known payment obligations within specific time-frames. For example a liquidity standard entailing a 12 month outlook, i.e. the Net Stable Funding Ratio (NSFR), was introduced. The stated purpose of these measures is to bolster the resilience of banks to large economic shocks, the crucial assumption

[1]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.

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.[2]

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 Wellink (2009) and Bank for International Settlements (2010)). However these enhancements have not been universally welcomed. Flannery (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 render 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 bank clients 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.

---

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

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? [3]

To answer these questions we form a sample panel comprising 75 emerging and developed economies covering the period 1998 to 2011 (see Tables 1 and 2). The panel'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 (2008) 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 important contributions to the literature. We provide empirical evidence supporting those in favour of enhanced standards by showing how the growth of Tier-1 capital significantly reduces the odds of systemic 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), deviations from the new minimum standard (in either direction), stricter enforcement of capital adequacy standards and the NSFR 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

[3] 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.

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 findings, together with the results of earlier research 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 presents a review of the most important and relevant prior literature. In section 3 we describe the logit model in more detail before presenting an overview of our data in section 4. The order in which the research was conducted together with the associated rationale is outlined in section 5. The results are presented in detail in section 6. A description of our robustness checks is provided in section 7 and section 8 concludes.

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 (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 risk, 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 1).

These risks 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 occur in countries where there are explicit deposit-insurance schemes. More recently, (see Demirgüç-Kunt and Detragiache (2002)), 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.[4] 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. (2005)), 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)).[5]

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 reassert the vulnerability of banks on a micro-prudential level to low GDP growth rates and high real interest rates. As Appendix 1 of Eichler and Sobański (2012) makes clear past studies share a common shortcoming in that none of the sample datasets adequately cover the period up to and including the GFC and few examine either regulatory or liquidity concerns, both of which are now inextricably linked with the GFC-synonymous term "credit crunch".

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

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.

Other important contributions include Kaminsky and Reinhart (1999) and Davis and Karim (2008). Using a signals approach model 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.

3. Methodology

To test whether a regulatory measure represents a systemic banking crisis determinant we make use of a pooled logit model. Here 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:

maxarg($\boldsymbol{\beta}$): $$LnL = \sum_{t=1}^{T} \sum_{i=1}^{N} \mathrm{P}(i,t) \ln[F((X_{i,t} + Z_{i,t})\beta')] + [1 - P(i,t)] \ln[1 - F((X_{i,t} + Z_{i,t})\beta')]$$

Here $\mathbf{Z}_{i,t}$ represents the various regulatory variables we wish to analyse whereas $\mathbf{X}_{i,t}$ represents a control cluster of ex-ante known significant systemic crisis determinants (see section 4 below for details). $\boldsymbol{\beta}$ is a vector of K unknown coefficients and F(($\mathbf{Z}_{i,t}$ + $\mathbf{X}_{i,t}$)$\boldsymbol{\beta}$) is the cumulative density function evaluated at ($\mathbf{Z}_{i,t}$+$\mathbf{X}_{i,t}$)$\boldsymbol{\beta}$.

In this model F is logistic and is evaluated as: $$\frac{e^{(z+x)\beta}}{1+e^{(z+x)\beta}}$$

T represents the number of years covered by the panel and N the number of countries. For each of the K-vector of coefficients $\boldsymbol{\beta}$ estimated it is important to realise that each individual coefficient "β_i" 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 $\mathbf{X_{i,t}}$ (or $\mathbf{Z_{i,t}}$) variables as per OLS regressions. Rather each β_i measures the effect of a unit change in one of the $\mathbf{X_{i,t}}$ variables upon the log odds ratio of country "i" experiencing a systemic banking crisis in period "t". That is β_i measures the effect of a unit change in an explanatory variable upon log ((probability of a crisis) / 1 – (probability of a crisis)). As a result the increase in crisis probability depends upon the contemporaneous values of the variables comprising vectors **Z** and **X**.

Davis and Karim (2008) provide an assessment of several alternative analytical methodologies but emphasise the importance of the pooled logit model in the systemic banking crisis determinants literature. The sign of coefficient β_i illustrates whether that variable-of-interest contributes positively or negatively to the odds of a systemic crisis and the p-value for each β_i indicates whether or not the corresponding factor is statistically significant at 1%, 5% and 10% levels. Each regression is estimated with cluster-controlled standard errors to account for any heteroskedastic errors that might result from having panel data clustered by country.

4. Data

A panel of data 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 country, crisis start / end-dates as well as crisis descriptions are provided.[6] 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

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

8.5% of risk-weighted assets.[7] 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 the intra-country regulatory framework, our data sourced via the Barth et al. (2013) regulatory survey dataset. This 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.[8]

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. High quality capital is unencumbered capital such as shareholder equity and cash / highly-liquid 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%.[9] 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 regulatory standard. In future, in order to remain compliant banks must ensure that cash-flow remains positive at all times in the upcoming 12 months, regardless of time-of-calculation or seasonal / business cycle fluctuations. This means that banks must always have enough cash or readily-convertible assets to fulfil all payment obligations falling due in the

---

[7] 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.

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

[9] This measure includes 6% capital reserves to risk-weighted assets plus a further 2.5% of reserves known as a capital conservation buffer. Local regulators can require up to 2.5% of additional reserves or capital which are not included in the 8.5% quoted here.

next 12 months. Banks have only recently started to report this ratio in their annual reports so to examine the measure over the period 1998-2011 requires the use of a proxy variable. We use the ratio of liquid assets to deposits plus short-term funds for this purpose and also anticipate significantly negative regression coefficients.

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. There are two issues at stake. First we wish to determine whether deviations from this minimum are significantly associated with crises. We also examine whether the deviation or "delta" is significant as a result of a) over-provisioning or b) under provisioning Tier-1 capital. The latter is controlled by use of a dummy variable in the regressions. 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 financing, and might impact GDP growth rates which earlier literature has shown to be significantly associated with systemic crises.

The capital regulation index measures how stringent the capital adequacy requirements are and the degree 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 bank 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 (range 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 curtailed 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 1 and 2 below. Table 1 lists countries that experienced a systemic crisis at some stage during the 1998-2011 period covered by the panel whereas Table 2 lists those countries that never experienced a systemic crisis throughout those 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.

TABLE 1

This table gives an overview of several key sample variables for countries that experienced a systemic crisis during the sample time-frame (1998-2011). In addition to the crisis years per country are statistics relating to Tier 1 Regulatory Capital, the Net Stable Funding Ratio (NSFR) and distance to minimum Tier 1 standards. Key regulatory framework elements including overall bank capital monitoring and enforcement, restrictions on securities trading activities and overall trading restrictions are also presented. 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.Tier 1 delta measures distance from minimum Basel III standards (8.5%). The regulatory framework variables are measured as indices and are drawn from Barth, Caprio and Levine's (2013) regulatory survey database.

		Tier 1 Capital			NSFR			Tier 1 Delta			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																	

TABLE 2

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) and distance to minimum Tier 1 standards. Key regulatory framework elements including overall bank capital monitoring and enforcement, restrictions on securities trading activities and overall trading restrictions are also presented. 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.Tier 1 delta measures distance from minimum Basel III standards (8.5%). The regulatory framework variables are measured as indices and are drawn from Barth, Caprio and Levine's (2013) regulatory survey database.

	Tier 1 Capital %			NSFR			Tier 1 Delta			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																	

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 3 below. Here, summary statistics by key variable 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 slightly higher at 13.45% during those years. 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).

TABLE 3

This table presents further summary statistics of the key variables examined in this paper. The statistics are drawn from the entire panel 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 years 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.

	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	10	6.19	3	10	6.19	1	10
Securities Trading Restrictions Index	1.72	1	4	1.49	1	3	1.75	1	4
Overall Trading Restrictions Index	6.60	3	12	6.27	3	10	6.65	3	12

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 1 – 3 are suggestive of some of the key findings we report in the results section, further discussion of which is deferred for the present.

The variables listed in Table 3 represent the **Z** vector of key factors as described in section 3 above. 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. 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 is insolvent whenever its asset values decline below that of its liabilities. Generally this requires a winding-up process or a forced sale 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. 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. These risks 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) 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 constitute an important source of bank income, representing the difference between what banks charge borrowers and pay to lenders / depositors, many of whom are other banks. These inter-bank deposits represent an important source of short-term funding, for which the lending institution is paid fees and interest. Therefore an unexpected increase in real interest rates can have negative consequences for bank income / earnings and may also reduce the ability of certain borrowers (including banks themselves) to meet loan repayment commitments. 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 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. (2005)). 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 suggests banks may 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 variables, including source, description and rationale for inclusion is provided in Table 10 below.

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. [10]

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 crises to total observations (approx. 5%). For each regression the corresponding predicted crisis probabilities are determined.[11] 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, but without over-predicting crises. Likewise the model should also 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.

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"

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

[11] The Stata analytical software package is used for the purpose. Predictions are made via the "*Predict*" command.

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 Table 10.

6. Results

In Table 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 systemic 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 1-3 and is now confirmed. In the "Summary Results" section of Table 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 makes crises harder 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 various countries, each of whom is free to adopt their own risk-weighting methodologies under the Basel Accord.

Table 5 presents the corresponding results. Now Tier-1 capital is significant in all regressions, except the final pair and also has the negative sign theory suggests. By aggregating high quality capital over an extended period we observe significantly lower systemic banking crisis probabilities. This result supports 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. Further comparison between Tables 4 and 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 score for regression 1 of Table 4 is 213.2 whereas its Table 5 counterpart is 116.6, representing a significantly better fit. 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.[12]

Next, deviations from the minimum required Tier-1 capital ratio of 8.5% are considered, the results of which are presented in Table 6.

As per the Table 4 results, Table 6 shows that deviations from Tier-1 capital, measured in either direction, are not significantly associated with systemic crises. The negative coefficients suggest that as the gap to the minimum Tier-1 capital standard increases, the less likely a country is to experience a crisis. However the coefficient on the over-provisioning dummy variable implies that when a country's banking sector is over-capitalised according to minimum Tier-1 capital standards then this is associated with a higher systemic-crisis probabilities. This outcome is compatible with Flannery (2009) and with the BIS Macroeconomic Assessment Group's report (2011) that meeting the minimum Base III capital reserves has the potential to dampen GDP growth by as much as 0.22% over several years compared with the older Basel II standards. Once again these findings are compatible with our summary data conclusions (see Tables 1 – 3).

In Table 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 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. Furthermore, this specification is clearly over-predicting crises as evidenced by the 90% and 100% crisis

[12] If compounding takes place over N years then N-1 observations per country are removed from the sample. Thus 2 observations per country are lost as a result of compounding over 3 years as described.

prediction success rates associated with the final pair of regressions coupled with the large reduction in accurate no-crisis predictions.

In contrast with Tier-1 capital (see Table 4), the inclusion of the NSFR proxy makes systemic crises marginally easier to predict as evidenced by the slightly improved percentage of total correct in-sample predictions. However when one considers the pairs of regressions of Table 7 independently from Table 4 the inclusion of the NSFR proxy makes crises more difficult to predict. Also, although it represents an improvement over Tier-1 capital, the NSFR proxy is not as effective at improving prediction success rates as the Tier-1 capital growth measure. 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 4 and comprise the remainder of the **Z**-vector of key variables. The results are presented in Table 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 1 and 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 8 regressions. Nevertheless the findings re-confirm the results of Tables 1-4 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 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 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 1-4. 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 no corresponding increase in 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 resulting degree of asymmetric risk-related reporting has distorted the regulatory-compliance landscape. 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, controlling for the regulatory indices as before.

In contrast with Tier-1 capital, the simpler capital-to-assets ratio is significant in two regressions, i.e. regressions 7 and 8, a result which reinforces the view that simpler regulations can be as effective as their more complicated counterparts.

Using 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 52% 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 harder to gain a license to operate in a country that country is more susceptible to crises, regardless of the distribution of 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 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 and those who have examined systemic crises in the past.

The 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.[13] 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 offset, in that we commence our search for the best-predicting model by considering the well–

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

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 4 for a brief description of the variables that help to determine the CAMELS scores.

Regressions 1-4 of Table 9 illustrate our CAMELS-related variables 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. 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. We do not report all of these regressions because of space restrictions, but we include the most informative ones. 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 and short-term funding ratio are added to the variables in regression 1. This is illustrated by regression 5. Note that only one macroeconomic factor has been included.[14] The remaining variables fall within the remit of regulators and so can be fine-tuned to help deflect embryonic crises. This model correctly predicts the in-

[14] 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.

sample crises in 91.18% of cases but also achieves a successful no-crisis prediction rate of 84.23%. As such, that 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 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 that 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, 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. (2005).

7. Robustness checks

The results relating to the various pooled logit regressions are presented in the Tables 4 – 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 set of economic factors over the panel' time-span.

A fixed-effects model can be utilised if we believe 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 resulting 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 11 presents a comparison between pooled logistic, fixed-effects and random-effects specifications.

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 unreliable.

A final robustness check involves the removal of crisis episodes via the elimination of countries from the panel. Doing so ensures that the results are not driven by factor behaviour peculiar to one specific country. Starting with regression 7 of Table 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 12. 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.

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 when countries significantly grow Tier-1 capital levels over a 3 year period, systemic banking crises appear to be significantly less likely. This finding bolsters support for proponents of increased capital and/or reserves-based regulatory changes.

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 do deviations from minimum Tier-1 capital standards appear to matter, regardless of whether the delta results from under or over-provisioning. Rather, echoing Goodhart (2008), it is the growth of Tier-1 capital that is important. The introduction of a liquidity measure such as the Net Stable Funding Ratio does not contribute towards more resilient banking systems. Likewise only a relatively small subset of the regulatory architecture is relevant vis-à-vis sectoral stability. This includes 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 degree.

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). Weak support for Haldane's (2012) view that simpler heuristics-based measures are equally as effective as the more complicated Basel III standards is provided.

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.

TABLE 4

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 data is described in the paper 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, Demirgüç-Kunt, Feyen, Beck and 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. Robust standard errors clustered by country in parentheses below the coefficients

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Tier 1 Capital - Level	-0.042		0.007		-0.012		-0.001		-0.002		-0.064	
	(0.039)		(0.057)		(0.061)		(0.065)		(0.069)		(0.136)	
GDP Growth Rate	-0.208***	-0.210***	-0.179**	-0.180**	-0.183**	-0.182**	-0.167**	-0.166**	-0.148*	-0.148*	-0.205***	-0.189***
	(0.057)	(0.060)	(0.077)	(0.074)	(0.079)	(0.077)	(0.081)	(0.078)	(0.083)	(0.079)	(0.075)	(0.070)
Real Interest Rate	0.073***	0.072***	0.041	0.041	0.050	0.050	0.074*	0.074*	0.082*	0.082*	-0.038	-0.049
	(0.023)	(0.023)	(0.046)	(0.046)	(0.047)	(0.048)	(0.045)	(0.045)	(0.044)	(0.044)	(0.121)	(0.125)
Inflation	0.074***	0.071***	0.054*	0.054*	0.063**	0.062**	0.079***	0.078***	0.086***	0.086***	0.227*	0.210
	(0.015)	(0.015)	(0.028)	(0.028)	(0.029)	(0.029)	(0.026)	(0.026)	(0.026)	(0.026)	(0.135)	(0.131)
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
	(0.005)	(0.005)	(0.007)	(0.007)	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.010)	(0.009)
Private Credit Growth Rate			-0.015**	-0.015**	-0.017**	-0.017**	-0.029***	-0.029***	-0.027***	-0.027***	-0.020**	-0.020**
			(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
No Deposit Insurance Dummy					-0.776	-0.747	-1.389**	-1.386**	-1.591**	-1.588**	-1.626	-1.559
					(0.587)	(0.553)	(0.662)	(0.629)	(0.699)	(0.679)	(1.108)	(1.092)
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 %									0.005	0.005	-0.003	-0.003
									(0.005)	(0.005)	(0.006)	(0.005)
House Price Index											-0.075	-0.068
											(0.051)	(0.046)
Constant	-4.076***	-4.507***	-4.929***	-4.847***	-4.481***	-4.649***	-4.936***	-4.956***	-5.505***	-5.532***	-2.967	-3.862***
	(0.720)	(0.627)	(1.165)	(0.891)	(1.260)	(0.960)	(1.242)	(0.854)	(1.306)	(0.806)	(2.676)	(1.482)
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 Score	-103.6	-104.3	-68.96	-68.97	-67.48	-67.50	-60.67	-60.67	-60.32	-60.32	-43.16	-43.27

TABLE 5

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 data is described in Table 7 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, Demirgüç-Kunt, Feyen, Beck and 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 during crises. Statistical significance is denoted by ***, **,* for the 1%, 5% and 10% levels respectively. Robust standard errors clustered by country in parentheses below the coefficients.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
3 Year CAGR of Tier 1 Capital %	-0.0288***		-0.0308***		-0.0304**		-0.0231*		-0.0228*		-0.0362	
	(0.0111)		(0.0118)		(0.0122)		(0.0118)		(0.0120)		(0.0825)	
GDP Growth Rate	-0.3000***	-0.2734***	-0.2756***	-0.2507***	-0.2702***	-0.2471***	-0.2495***	-0.2336***	-0.2378***	-0.2208***	-0.1818**	-0.1745**
	(0.0816)	(0.0870)	(0.0707)	(0.0788)	(0.0727)	(0.0850)	(0.0697)	(0.0823)	(0.0677)	(0.0802)	(0.0745)	(0.0728)
Real Interest Rate	-0.0516	-0.0056	-0.0543	-0.0011	-0.0537	0.0126	-0.0035	0.0521	0.0027	0.0584	-0.0335	-0.0428
	(0.0604)	(0.0840)	(0.0601)	(0.0791)	(0.0681)	(0.0875)	(0.0630)	(0.0703)	(0.0615)	(0.0690)	(0.1250)	(0.1283)
Inflation	0.0421	0.0654	0.0213	0.0502	0.0306	0.0624	0.0691	0.0907*	0.0727	0.0940*	0.2185*	0.2107*
	(0.0633)	(0.0548)	(0.0799)	(0.0636)	(0.0786)	(0.0636)	(0.0585)	(0.0546)	(0.0601)	(0.0558)	(0.1262)	(0.1253)
Private Credit to GDP %	0.0143**	0.0141**	0.0130*	0.0132*	0.0132	0.0135*	0.0131*	0.0132*	0.0128*	0.0129*	0.0109	0.0102
	(0.0067)	(0.0067)	(0.0072)	(0.0071)	(0.0081)	(0.0082)	(0.0074)	(0.0076)	(0.0077)	(0.0078)	(0.0094)	(0.0094)
Private Credit Growth Rate			-0.0132	-0.0121	-0.0138*	-0.0134*	-0.0251***	-0.0259***	-0.0241***	-0.0248***	-0.0180**	-0.0185**
			(0.0081)	(0.0080)	(0.0078)	(0.0079)	(0.0084)	(0.0084)	(0.0087)	(0.0087)	(0.0084)	(0.0084)
No Deposit Insurance Dummy					-0.6376	-0.6650	-1.3467*	-1.4377*	-1.5022*	-1.6031*	-1.5682	-1.6077
					(0.6000)	(0.6029)	(0.7444)	(0.7576)	(0.8424)	(0.8373)	(1.0710)	(1.0455)
M2 Money to Forex Reserves %							0.0039***	0.0043***	0.0039***	0.0043***	0.0042**	0.0045***
							(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0017)	(0.0015)
Bank Credit to Bank Deposit %									0.0026	0.0029	-0.0024	-0.0025
									(0.0053)	(0.0053)	(0.0047)	(0.0049)
House Price Index											-0.0777	-0.0663
											(0.0534)	(0.0455)
Constant	-3.8966***	-4.0818***	-3.8268***	-4.0661***	-3.6932***	-3.9893***	-4.1749***	-4.4340***	-4.4935***	-4.7882***	-3.7164**	-3.6737**
	(0.9574)	(0.9714)	(1.0191)	(1.0129)	(1.0837)	(1.1038)	(0.9516)	(1.0025)	(0.9226)	(0.9653)	(1.4508)	(1.4456)
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	0.0002	0.0013	0.0001	0.0004	0.0004	0.0031	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Log Likelihood Score	-55.31	-57.12	-53.91	-55.90	-53.17	-54.93	-47.88	-48.78	-47.80	-48.67	-41.43	-41.58

TABLE 6

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 data is described in Table 7 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, Demirgüç-Kunt, Feyen, Beck and Levine (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. Robust standard errors clustered by country are in parentheses below the coefficients.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Tier-1 Capital - Delta from 8.5% minimum	-0.0659		-0.0016		-0.0081		0.0356		0.0423		-0.0991	
	(0.0745)		(0.0825)		(0.0832)		(0.0749)		(0.0754)		(0.1789)	
Tier-1 Delta Positive Dummy	0.7523		0.9733		0.7768		-0.1229		-0.3087			
	(1.0962)		(1.3912)		(1.4813)		(1.4713)		(1.4452)			
GDP Growth Rate	-0.2079***	-0.2009***	-0.1681**	-0.1589**	-0.1702**	-0.1634**	-0.1462*	-0.1486**	-0.1307*	-0.1360*	-0.2110***	-0.1894***
	(0.0578)	(0.0575)	(0.0720)	(0.0683)	(0.0740)	(0.0717)	(0.0748)	(0.0719)	(0.0752)	(0.0722)	(0.0777)	(0.0698)
Real Interest Rate	0.0759***	0.0752***	0.0618**	0.0619**	0.0726**	0.0718**	0.0877***	0.0891***	0.0927***	0.0941***	-0.0299	-0.0488
	(0.0190)	(0.0194)	(0.0282)	(0.0293)	(0.0297)	(0.0312)	(0.0307)	(0.0303)	(0.0312)	(0.0302)	(0.1189)	(0.1247)
Inflation	0.0817***	0.0768***	0.0716***	0.0682***	0.0792***	0.0769***	0.0862***	0.0897***	0.0903***	0.0945***	0.2317*	0.2096
	(0.0156)	(0.0139)	(0.0223)	(0.0190)	(0.0237)	(0.0215)	(0.0236)	(0.0201)	(0.0227)	(0.0196)	(0.1365)	(0.1310)
Private Credit to GDP %	0.0146***	0.0153***	0.0158**	0.0165**	0.0158**	0.0163**	0.0154**	0.0151**	0.0150**	0.0146**	0.0100	0.0109
	(0.0050)	(0.0049)	(0.0067)	(0.0067)	(0.0075)	(0.0075)	(0.0065)	(0.0064)	(0.0067)	(0.0067)	(0.0097)	(0.0093)
Private Credit Growth Rate			-0.0158**	-0.0166**	-0.0174**	-0.0180***	-0.0302***	-0.0300***	-0.0288***	-0.0285***	-0.0188**	-0.0202**
			(0.0070)	(0.0069)	(0.0071)	(0.0070)	(0.0075)	(0.0071)	(0.0074)	(0.0072)	(0.0083)	(0.0083)
No Deposit Insurance Dummy					-0.7044	-0.7775	-1.3569**	-1.4017**	-1.5043**	-1.5288**	-1.5153	-1.5593
					(0.5743)	(0.5372)	(0.6460)	(0.5869)	(0.6821)	(0.6065)	(1.0970)	(1.0916)
M2 Money to Forex Reserves %							0.0044***	0.0044***	0.0043***	0.0042***	0.0047***	0.0047***
							(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0016)	(0.0015)
Bank Credit to Bank Deposit %									0.0038	0.0035	-0.0035	-0.0028
									(0.0053)	(0.0051)	(0.0059)	(0.0054)
House Price Index											-0.0791	-0.0677
											(0.0537)	(0.0456)
Constant	-4.9047***	-4.5129***	-5.8513***	-5.0183***	-5.4789***	-4.8131***	-5.1008***	-5.0445***	-5.3943***	-5.4464***	-3.3122*	-3.8619***
	(0.9316)	(0.5965)	(1.3613)	(0.8105)	(1.4555)	(0.8754)	(1.3904)	(0.7603)	(1.3152)	(0.7754)	(1.9686)	(1.4820)
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	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Log Likelihood Score	-108.2	-108.8	-73.84	-74.31	-72.31	-72.52	-65.12	-65.28	-64.92	-65.09	-42.96	-43.27

TABLE 7

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 data is described in the paper 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, Demirgüç-Kunt, Feyen, Beck and 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. Robust standard errors clustered by country in parentheses below the coefficients.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Liquid Assets to Deposits + Short Term Funds	0.0048		0.0127		0.0124		0.0128		0.0133		0.0270**	
	(0.0074)		(0.0090)		(0.0101)		(0.0107)		(0.0112)		(0.0134)	
GDP Growth Rate	-0.2105***	-0.2101***	-0.1736**	-0.1756**	-0.1759**	-0.1778**	-0.1614**	-0.1612**	-0.1408*	-0.1413*	-0.1551**	-0.1894***
	(0.0488)	(0.0493)	(0.0697)	(0.0743)	(0.0734)	(0.0783)	(0.0743)	(0.0782)	(0.0760)	(0.0793)	(0.0685)	(0.0698)
Real Interest Rate	0.0488***	0.0488***	0.0414**	0.0406**	0.0463**	0.0456**	0.0610**	0.0599**	0.0670**	0.0659**	-0.0036	-0.0488
	(0.0186)	(0.0186)	(0.0194)	(0.0202)	(0.0225)	(0.0227)	(0.0287)	(0.0280)	(0.0303)	(0.0294)	(0.1439)	(0.1247)
Inflation	0.0332***	0.0329***	0.0476*	0.0491*	0.0503*	0.0532*	0.0553	0.0597*	0.0617*	0.0666**	0.2464*	0.2096
	(0.0090)	(0.0092)	(0.0278)	(0.0257)	(0.0304)	(0.0276)	(0.0368)	(0.0316)	(0.0372)	(0.0319)	(0.1390)	(0.1310)
Private Credit to GDP %	0.0130***	0.0127***	0.0173***	0.0168***	0.0162**	0.0160**	0.0146**	0.0145**	0.0135**	0.0135**	0.0136	0.0109
	(0.0042)	(0.0042)	(0.0062)	(0.0065)	(0.0067)	(0.0072)	(0.0057)	(0.0061)	(0.0062)	(0.0066)	(0.0093)	(0.0093)
Private Credit Growth Rate			-0.0169**	-0.0156**	-0.0180**	-0.0168**	-0.0298***	-0.0283***	-0.0276***	-0.0261***	-0.0232***	-0.0202**
			(0.0074)	(0.0075)	(0.0073)	(0.0075)	(0.0076)	(0.0076)	(0.0077)	(0.0076)	(0.0081)	(0.0083)
No Deposit Insurance Dummy					-0.6636	-0.7301	-1.2768*	-1.2966**	-1.4818**	-1.5051**	-1.6815	-1.5593
					(0.5652)	(0.5503)	(0.6617)	(0.6361)	(0.7075)	(0.6870)	(1.1057)	(1.0916)
M2 Money to Forex Reserves %							0.0041***	0.0041***	0.0040***	0.0040***	0.0050***	0.0047***
							(0.0014)	(0.0013)	(0.0014)	(0.0013)	(0.0016)	(0.0015)
Bank Credit to Bank Deposit %									0.0053	0.0053	-0.0019	-0.0028
									(0.0050)	(0.0052)	(0.0053)	(0.0054)
House Price Index											-0.0853	-0.0677
											(0.0524)	(0.0456)
Constant	-4.1454***	-3.9427***	-5.4924***	-4.9482***	-5.1549***	-4.6349***	-5.2835***	-4.7835***	-5.8796***	-5.3593***	-5.6834***	-3.8619***
	(0.6091)	(0.4958)	(0.8573)	(0.7542)	(0.9173)	(0.8137)	(0.8326)	(0.7090)	(0.8536)	(0.6653)	(1.9817)	(1.4820)
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	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Log Likelihood Score	-113.8	-113.9	-69.50	-70.08	-67.94	-68.47	-61.42	-61.89	-60.98	-61.47	-41.50	-43.27

TABLE 8

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, Caprio and Levine'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.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
3 Year CAGR of Tier-1 Capital %	-0.0190	-0.0186	-0.0375**					
	(0.0141)	(0.0151)	(0.0175)					
Liquid Assets to Deposits plus Short Term Funds	0.00933	0.00797	-0.0148	0.00652	0.00933	0.00797	0.000617	-0.0148
	(0.0107)	(0.0109)	(0.0294)	(0.0106)	(0.0107)	(0.0109)	(0.0123)	(0.0294)
No Deposit Insurance Dummy	-0.460	-0.446	-0.381	-0.543	-0.460	-0.446	-0.480	-0.381
	(0.548)	(0.561)	(0.716)	(0.564)	(0.548)	(0.561)	(0.570)	(0.716)
Securities Trading Restriction Index	-0.729*	-0.761**	-0.527		-0.729*	-0.761**	-0.567	-0.527
	(0.375)	(0.378)	(0.510)		(0.375)	(0.378)	(0.398)	(0.510)
New Banking Entrants Restriction Index		0.280	0.224			0.280	0.314	0.224
		(0.247)	(0.261)			(0.247)	(0.207)	(0.261)
Overall Trading Restrictions Index			-0.357**				-0.220*	-0.357**
			(0.178)				(0.127)	(0.178)
Overall Capital Regulation Index			-0.0599					-0.0599
			(0.204)					(0.204)
3 Year CAGR of of Leverage Ratio (CAR) %				-0.00923	-0.0190	-0.0186	-0.0239*	-0.0375**
				(0.0146)	(0.0141)	(0.0151)	(0.0125)	(0.0175)
Constant	-2.292***	-4.304**	-0.554	-3.304***	-2.292***	-4.304**	-3.182	-0.554
	(0.796)	(2.183)	(3.291)	(0.498)	(0.796)	(2.183)	(2.081)	(3.291)
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	0.0415	0.00872	0.00552	0.289	0.0415	0.00872	0.00229	0.00552
Log Likelihood Score	-67.77	-66.96	-37.54	-70.47	-67.77	-66.96	-65.32	-37.54

TABLE 9

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 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. Robust standard errors clustered by country shown in parentheses below the coefficients.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CAMELS - Management Efficiency	0.1370*	0.0170	0.0610	0.0093	-0.0545	0.119	-0.0286	
	(0.0788)	(0.0835)	(0.0696)	(0.0835)	-0.1441	-0.2643	(0.0965)	
CAMELS - Earnings (ROAA) %	-0.4740***	-0.7661***	-0.7010***	-0.7271***	-0.9172***	-1.2030	-1.1621*	
	(0.1460)	(0.2511)	(0.2703)	(0.2611)	(0.3560)	(0.9464)	(0.6051)	
CAMELS - Liquidity Ratio	0.0114***	0.0110***	0.0111***	0.0119***	0.0105***	0.00808**	0.0104***	
	(0.0031)	(0.0036)	(0.0035)	(0.0039)	(0.0035)	(0.0039)	(0.0039)	
GDP Growth Rate					-0.1430	-0.1010	-0.1942	-0.2420***
					(0.1100)	(0.1770)	(0.2160)	(0.0772)
Private Credit Growth Rate					-0.0171*	-0.0129		-0.0229***
					(0.0088)	(0.0123)		-0.0068
Liquid Assets to Deposits + Short Term Funds					0.0120			
					(0.0109)			
CAMELS - Capital to Assets (Leverage) Ratio		0.1230		0.1180				
		(0.1110)		(0.1101)				
CAMELS - Assets Quality (NPL %)			0.0378	0.0213				
			(0.0330)	(0.0343)				
House Price Index						-0.0382		
						(0.0387)		
3 year CAGR private credit							-0.0314***	
							(0.0103)	
CAMELS - Real Interest Rate								0.0226
								(0.0179)
Inflation								0.0096
								(0.0382)
No Deposit Insurance Dummy								-0.5780
								(0.5280)
Bank Concentration								-0.0011
								(0.0089)
Constant	-4.519***	-4.828***	-4.189***	-4.973***	-4.448***	-3.582***	-0.465	-2.966***
	(0.602)	(1.128)	(0.724)	(1.190)	(1.018)	(0.925)	(1.639)	(0.796)
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	0.0000	0.0000	0.0000	0.0000	0.0001	0.0063	0.0001	0.0000
Log Likelihood Score	-111.3	-82.63	-86.38	-81.58	-51.93	-39.70	-32.29	-65.22

TABLE 10 – Panel 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.

TABLE 10 – Panel Variables

Variable	Variable Type	Description and Source
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 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 2 uses an alternative source of inflation data (see Table 12 below) where the source is the World Bank’s WDI database. The IFS values in Panel 1 are used to replicate Demirgüç-Kunt and Detragiache (1998) as faithfully as possible, whereas in Panel 2 the WDI data is more easily accessed and for that reason is preferred.
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 as described in Table 8. 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)”.

TABLE 10 – Panel Variables

Variable	Variable Type	Description and Source
		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.
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 $_{t}$)$^{\wedge\ 1/3}$ * 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

TABLE 10 – Panel Variables

Variable	Variable Type	Description and Source
		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 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 described in Table 11. 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.

TABLE 10 – Panel Variables

Variable	Variable Type	Description and Source
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 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.

TABLE 11

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 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.

	Pooled Logit	Fixed Effects	Random Effects
3 Year CAGR of Tier 1 Capital %	-0.0288***	0.3067	-0.0288**
	(0.0111)	(0.2398)	(0.0136)
GDP Growth Rate	-0.3000***	-0.3903	-0.3000***
	(0.0816)	(0.7342)	(0.0794)
Real Interest Rate	-0.0516	-0.3061	-0.0516
	(0.0604)	(0.3192)	(0.0687)
Inflation	0.0421	0.1296	0.0421
	(0.0633)	(0.9090)	(0.0662)
Private Credit to GDP %	0.0143**	0.3124**	0.0143***
	(0.0067)	(0.1567)	(0.0052)
Constant	-3.8966***		-3.8960***
	(0.9574)		(0.9136)
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	0.0002	0.0000	0.0001
Log Likelihood Score	-55.31	-5.258	-55.31

TABLE 12

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 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.

	Country Removed					
	Benchmark	Argentina	United States	Germany	Sweden	Russia
3 Year CAGR of Tier 1 Capital %	-0.0228*	-0.0003	-0.0255**	-0.0215*	-0.0221*	-0.0275*
	(0.0120)	(0.0276)	(0.0126)	(0.0119)	(0.0117)	(0.0150)
GDP Growth Rate	-0.2378***	-0.2146***	-0.2389***	-0.2281***	-0.2324***	-0.2493***
	(0.0677)	(0.0650)	(0.0687)	(0.0680)	(0.0671)	(0.0735)
Real Interest Rate	0.0027	-0.0562	-0.0024	0.0241	0.0049	-0.0099
	(0.0615)	(0.0769)	(0.0671)	(0.0602)	(0.0601)	(0.0723)
Inflation	0.0727	0.0679	0.0765	0.0873	0.0733	-0.0172
	(0.0601)	(0.0562)	(0.0634)	(0.0577)	(0.0586)	(0.0831)
Private Credit to GDP %	0.0128*	0.0120	0.0143*	0.0140*	0.0126	0.0131
	(0.0077)	(0.0078)	(0.0082)	(0.0080)	(0.0077)	(0.0082)
Private Credit Growth Rate	-0.0241***	-0.0216**	-0.0239***	-0.0244***	-0.0213**	-0.0296***
	(0.0087)	(0.0090)	(0.0089)	(0.0087)	(0.0095)	(0.0084)
No Deposit Insurance Dummy	-1.5022*	-1.4872*	-1.4313*	-1.5186*	-1.4167	-1.2552
	(0.8424)	(0.8570)	(0.8564)	(0.8660)	(0.8778)	(0.8699)
M2 Money to Forex Reserves	0.0039***	0.0037***	0.0034***	0.0037***	0.0037***	0.0038***
	(0.0014)	(0.0014)	(0.0012)	(0.0013)	(0.0013)	(0.0015)
Bank Credit to Bank Deposit %	0.0026	0.0031	0.0034	0.0037	0.0029	0.0004
	(0.0053)	(0.0054)	(0.0055)	(0.0055)	(0.0061)	(0.0049)
Constant	-4.4935***	-4.3561***	-4.8153***	-4.9266***	-4.4934***	-4.0863***
	(0.9226)	(0.8867)	(0.9959)	(0.9399)	(0.9094)	(1.0409)
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	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Log Likelihood Score	-47.80	-46.24	-44.48	-44.50	-47.03	-42.93

References

Acharya, Viral V. and Matthew Richardson, (2009), "The Financial Crisis of 2007-2009: Causes and Remedies", *Financial Markets, Institutions and Instruments*, Vol. 18, Iss:2, pp. 89-137

Allen, Franklin and Douglas M. Gale, (2000), "Bubbles and Crises", *The Economic Journal*, Vol. 110, Iss: 4, pp. 236-255

Allen, Franklin and Douglas M. Gale, (2003), "Competition and Financial Stability", Wharton Financial Institutions Center Working Paper No. 03-26

Avery, Robert B., Terrence M. Belton and Michael A. Goldberg, (1988), "Market Discipline in Regulating Bank Risk: New Evidence from the Capital Markets", *Journal of Money, Credit and Banking,* Vol. 20, Iss: 4, pp. 597-610

Bank for International Settlements, (2010), "Basel III: A global regulatory framework for more resilient banks and banking systems", BIS web site

Bank for International Settlements, (2011), Macroeconomic Assessment Group – Final Report: Assessing the Macroeconomic Impact of the Transition to Stronger Capital and Liquidity Requirements", BIS Web Site, ISBN 92-9131-835-3.

Barrell, Ray, E. Philip Davis, Dilruba Karim and Iana Liadze, (2010), "Bank regulation, property prices and early warning systems for banking crises in OECD countries", Journal of Banking and Finance, Vol. 34, Iss. 9, pp. 2255-2264.

Barth, James R., Gerard Caprio and Ross Levine (2004), "Bank Regulation and supervision: what works best?", *Journal of Financial Intermediation*, Vol. 13, Iss:2, pp. 205-248

Barth, James R., Gerard Caprio and Ross Levine (2013), "Bank Regulation and supervision in 180 countries from 1999 to 2011", *Journal of Financial Economic Policy,* Vol. 5 Iss: 2, pp. 111-219

Beck, Thorsten, Asli Demirgüç-Kunt and Ross Levine, (2006), "Bank concentration, competition, and crises: First results", *Journal of Banking and Finance*, Vol. 30, Iss: 5, pp. 1581-1603

Blundell-Wignall, Adrian, Paul Atkinson and Caroline Roulet, (2014), "Bank business models and the Basel system: Complexity and interconnectedness", *OECD Journal: Financial Market Trends*, Vol. 2013 Iss.2.

Brunnermeier, Markus K. (2008), "Deciphering the Liquidity and Credit Crunch 2007-2008", NBER Working Paper No. 14612.

Brunnermeier, Markus K., Andrew Crocket, Charles Goodhart, Martin Hellwig, Avinash D. Persaud and Hyun Shin (2009), "The fundamental principles of financial regulation", Geneva Report on World Economy 11, Centre for Economic Policy Research (CEPR), London, UK. ISBN 9780955700972

Bruno, Valentina, and Hyun Song Shin, (2013), "Capital Flows, Cross Border Banking and Global Liquidity", NBER Working Paper No. 18942.

Calvo, Guillermo A., (1998), "Capital Flows and Capital Markets Crises: The simple economics of sudden stops", *Journal of Applied Economics*, Vol. 1, Iss: 1, pp. 35-54.

Cihák, Martin, Asli Demirgüç-Kunt, Erik Feyen and Ross Levine, (2013), "Financial Development in 205 Economies, 1960 to 2010", NBER Working Paper No. 18946.

Claessens, S., Dell'Ariccia, G., Igan, D. and Laeven, L. (2010), Cross-country experiences and policy implications from the global financial crisis. Economic Policy, 25: 267–293. doi: 10.1111/j.1468-0327.2010.00244.x

Connor, Gregory, Thomas Flavin and Brian O'Kelly, (2010), "The U.S. and Irish Credit Crises: Their Distinctive Differences and Common Features", Working Paper N214-a-10, N.U.I. Maynooth Economics and Finance Department.

Crotty, James, (2009), "Structural causes of the global financial crisis: a critical assessment of the 'new financial architecture'", *Cambridge Journal of Economics* Vol. 33, Iss. 4, pp. 563-580.

Davis, E. Philip and Dilruba Karim, (2008), "Comparing early warning systems for banking crises", *Journal of Financial Stability*, Vol. 4, Iss. 2, pp. 89-120.

Demirgüç-Kunt, Asli, and Enrica Detragiache, (1998), "The Determinants of Banking Crises in Developing and Developed Countries", *IMF Staff Papers*, Vol. 45, No. 1

Demirgüç-Kunt, Asli, and Enrica Detragiache, (2002), "Does Deposit Insurance Increase Banking System Stability? – An Empirical Investigation", *Journal of Monetary Economics,* Vol. 49, Iss. 7, pp. 1373-1406

Diamond, Douglas W., and Philip H. Dybvig, (1983), "Bank Runs, Deposit Insurance and Liquidity", *Journal of Political Economy*, Vol. 91 (June) pp. 401-19

Duttweiler, Rudolf (2010), "Comments on Consultative Document: International Framework for Liquidity Risk Measurement, Standards and Operation", Bank for International Settlements publications, Document Reference BCBS165, BIS Web Site

Eichler, Stefan and Karol Sobański, (2012), "What drives Banking Sector Fragility in the Eurozone? – Evidence from Stock Market Data", *Journal of Common Market Studies,* JCMS 2012 Vol. 50 Number 4,, pp.539-560.

Flannery, Mark J., (2009), "Stabilizing Large Financial Institutions with Contingent Capital Certificates", *University of Florida Working Paper.* Available at SSRN:http://ssrn.com/abstract=1485689.0

Goodhart, C.A.E, (1975), "Problems of monetary management: The U.K. experiences", *Papers in Monetary Economics*, Reserve Bank of Australia.

Goodhart, C.A.E, (2008), "The regulatory response to the financial crisis", *Journal of Financial Stability*, Vol. 4, Iss. 4, pp. 351-358.

Haldane, Andrew, (2012), "The Dog and the Frisbee", BIS Central Banker's Speeches, Bank for International Settlements

Hoggarth, Glenn, Patricia Jackson and Erlend Nier, (2005), "Banking crises and the design of safety nets", *Journal of Banking and Finance*, Vol. 29, Iss. 1, pp. 143-159.

Honohan, Patrick, (1999), "A model of bank contagion through lending", *International Review of Economics and Finance*, Vol. 8, Iss. 2, pp 147-163.

Johnson Simon, Peter Boone, Alasdair Breach and Eric Friedman, (2000), "Corporate governance in the Asian financial crisis", *Journal of Financial Economics,* Elsevier, Vol. 58(1-2), pp. 141-186.

Kaminsky Graciela and Carmen Reinhart (1999), "The twin crises: The Causes of Banking and Balance-of-Payments Problems", *American Economic Review*, Vol. 89. Iss: 3, pp. 473-500.

Krishnan, C.N.V, P.H. Ritchken and J.B. Thomson, (2005), "Monitoring and Controlling Bank Risk: Does Risky Debt Help?", The Journal of Finance, Vol. 60, Iss: 1, pp. 343-378.

Laeven, Luc and Fabián Valencia, (2013), "Systemic Banking Crises Database", *IMF Economic Review,* Vol. 61, pp. 225-270.

Lane, Philip R. and Peter McQuade, (2014), "Domestic Credit Growth and International Capital Flows", *The Scandinavian Journal of Economics*, Vol. 116, Iss: 1, pp. 218-252.

Melendez, Eleazar, (2013), "Financial Crisis Cost Tops $22 Trillion, GAO Says", Huffington Post article posted 14/2/2013. Available at http://www.huffingtonpost.com/2013/02/14/financial-crisis-cost-gao_n_2687553.html

Merton, R.C., (1974) "On the Pricing of Corporate Debt: The Risk Structure of Interest Rates". *Journal of Finance*, Vol. 29, No. 2, pp. 449–70.

Schaeck, Klaus, Martin Cihák and Simon Wolfe, (2009), "Are Competitive Banking, Systems More Stable", *Journal of Money, Credit and Banking*, Vol. 41, Iss. 4, pp. 711-734.

Von Hagen, Juergen and Tai-Kuang Ho, (2007), "Money Market Pressure and the Determinants of Banking Crises", *Journal of Money, Credit and Banking*, Blackwell Publishing, Vol. 39, Iss. 5, pp. 1037-1066.

Wellink, Nout, (2009) "Towards a new framework for monetary policy? Lessons from the crisis", Basel Committee on Banking Supervision Chairman's speech, Bank for International Settlements 2009

Weise, Karen, (2012), "Tallying the full cost of the financial crisis", Bloomberg Businessweek Markets and Finance article posted 14/9/2012. Available at http://www.businessweek.com/articles/2012-09-14/tallying-the-full-cost-of-the-financial-crisis.