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Ray Barrell, E Philip Davis, Dilruba Karim and Iana Liadze

National Institute of Economic and Social Research,
2, Dean Trench Street, London SW1P 3HE

BANK REGULATION, PROPERTY PRICES AND EARLY WARNING SYSTEMS FOR BANKING CRISES IN OECD COUNTRIES

Bank regulation, property prices and early warning systems for banking crises in OECD countries

Ray Barrell[a, *], E Philip Davis[b], Dilruba Karim[c] and Iana Liadze[d]

a NIESR, 2 Dean Trench Street, Smith Square, London SW1P 3HE, United Kingdom

b NIESR and Brunel University, Uxbridge, Middlesex, UB8 3PH, United Kingdom

c Brunel University

d NIESR

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Abstract

Early warning systems (EWS) for banking crises generally omit bank capital, bank liquidity and property prices. Most work on EWS has been for global samples dominated by emerging market crises where time series data on bank capital adequacy and property prices are typically absent. We estimate logit crisis models for OECD countries, finding strong effects from capital adequacy and liquidity ratios as well as property prices, and can exclude traditional variables. Higher capital adequacy and liquidity ratios have a marked effect on the crisis probabilities, implying long run benefits to offset some of the costs that such regulations may impose.

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Keywords: Banking crises; Systemic risk; Early warning systems; Logit estimation; Bank regulation; Capital adequacy; Liquidity regulation.

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* Corresponding author. Tel: +44 20 7222 7665 Fax: +44 20 7654 1900
E-mail addresses: rbarrell@niesr.ac.uk (R Barrell), e_philip_davis@msn.com (E P Davis), dilruba.karim@brunel.ac.uk (D Karim), iliadze@niesr.ac.uk, (I Liadze).

1. Introduction

There is a large literature on systemic banking crisis prediction via so called early warning systems (EWSs) which utilise a range of estimators from panel logit (as in Demirgüc-Kunt and Detragiache 2005, Davis and Karim 2008a) to signal extraction (Kaminsky and Reinhart 1999, Borio and Lowe 2002, Borio and Drehmann 2009) to binary recursive trees (Duttagupta and Cashin 2008, Karim 2008, Davis and Karim 2008b).

These models' success at predicting crises varies, with the logit and binary trees outperforming signal extraction in terms of type I and type II errors.[1] Nevertheless, a shared feature of these previous studies has been their reliance on cross-sections of heterogeneous economies and a common set of explanatory variables to explain banking crises. Following Demirgüc-Kunt and Detragiache (1998), these typically include macroeconomic and financial variables such as real GDP growth, terms of trade and domestic real credit growth. The reliance on such generic indicators links to the dearth of data on more specific banking sector and asset price variables for many emerging market countries, that are nevertheless included in samples in order to boost the number of infrequent banking crisis observations.

We contend that the specifications of such models are undoubtedly inadequate for two reasons. Firstly, the triggers of a crisis depend on the type of economy and the nature of the banking system. For example, in advanced economies with high levels of banking intermediation and developed financial markets, shocks to terms of trade are less important crisis triggers than, say, property price bubbles.[2] This implies that focusing on a certain class of economies and selecting explanatory variables that are relevant to their banking structures and lending behaviour could improve EWS design.

Secondly, (and related to the previous point), the regulation of developed economy banking systems is more likely to employ liquidity and capital adequacy. Financial regulators are typically monitor such ratios to restrict instability, which implies these variables are at least used implicitly as EWSs. Previous EWSs failed to incorporate balance sheet variables as explicit banking crisis predictors, perhaps because of a lack of foresight on the part of

[1] See Davis and Karim (2008a) and Karim (2008).

[2] Beltratti and Morana (2010) analyse the wider relationship between house prices and macroeconomic fluctuations, both domestically and internationally.

regulators.[3] It is also possible that EWS design never evolved in this direction because banking crises in developed economies were viewed as highly unlikely over the past decade during the "Great Moderation" when this literature has developed. Hence, despite data availability, extant research has not assessed new leading indicators of crises for their explanatory power in developed countries.

In this paper, we address these deficiencies in EWS design. We develop an EWS which demonstrates that unweighted[4] banking sector capital adequacy[5] (often known as the leverage[6] ratio) and the banking sector liquidity ratio, alongside real house price growth, are the most important crisis determinants for OECD economies. Moreover, their importance remains invariant to different robustness tests and we can use the information they convey to predict the sub-prime episode out-of-sample. Since research has hitherto not examined these variables, our results have important policy implications for financial regulators and central banks; optimising the liquidity and capital adequacy[7] ratios of banks and suppressing rapid property price growth may well mitigate future OECD crises.

We structure the paper as follows, in Section 2 we outline the panel logit methodology we have adopted, and we introduce the dataset. In Section 3 we detail the results. In Section 4 we provide some analysis of the robustness of our results. Section 5 concludes and makes some suggestions regarding policy implications. We also include Appendices on patterns of marginal effects and on correlation of our right hand side variables.

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[3] The potential importance of such balance sheet variables is shown in a study of individual bank distress in Eastern European transition economies by Männasoo and Mayes (2009) which shows that fragile funding bases (related to low liquidity) as well as high exposure to market risk in an environment of reforms and macroeconomic disturbance are typical precursors of financial distress on the part of individual banks.

[4] We do not use the risk adjusted capital adequacy ratio partly for data reasons, since data on this ratio is not available for most of the countries and periods examined. But also we note that a number of commentators such as Shin (2009) and Turner (2009) have suggested that unadjusted capital adequacy was highly relevant in the run up to the sub-prime crisis to complement the risk adjusted (Basel) measure.

[5] Jokipii and Milne (2008) note that capital adequacy of European banks has a negative co-movement with the cycle, which our work suggests exacerbates the risk of crises.

[6] Note this definition of the banking leverage ratio (i.e. capital/unadjusted assets) operates contrary to normal concepts of leverage, in the sense that a higher "leverage ratio" means lower "leverage" in an economic sense of debt-to-equity. Accordingly we prefer to use the term "unweighted capital adequacy" to avoid ambiguity.

[7] Note that although for data reasons we use the unweighted capital adequacy ratio, we expect that risk adjusted capital is also a crisis indicator. Our overall view is that both ratios need to be borne in mind in assessing crisis risk.

2. Methodology and data

Demirgüc-Kunt and Detragiache (1998) used the multivariate logit technique to relate the probabilities of systemic banking crises to a vector of explanatory variables. The banking crisis dependent variable, a binary banking crisis dummy, was defined in terms of observable stresses to a country's banking system, e.g. the ratio of non-performing loans to total banking system assets exceeds 10%[8], and it occurs in around 5 per cent of all time and country observations in that paper. Demirgüc-Kunt and Detragiache (2005) updated the banking crises list to include more years, and more crises.

Such crisis dummies generate several problems. Firstly, the start and end dates are ambiguous. It could be a while after the onset of crisis before the crisis criteria are observably met, and the criteria themselves are static, revealing nothing about when the crisis terminates. Since the end dates are to some extent subjectively chosen there are potential endogeneity problems with estimation; ongoing crises will affect the explanatory variables. To mitigate this, in our core results we terminate our estimation before the sub-prime episode. Secondly, the timing of the crises is crude in the sense that for annual dummies, a crisis starting in December 2000 would generate a value of 1 in 2000 and zero in 2001. However we are concerned with predicting the *switch* between crisis and non-crisis states and accordingly we assume one year crisis duration. For the example given, we accept our dummy takes a value of 1 in 2000 and zero thereafter, although we will later relax this assumption and show our results remain robust.

Our dataset includes 14 systemic and non systemic crises in 14 OECD countries. We take information concerning systemic banking crises from the IMF Financial Crisis Episodes database which covers the period of 1970-2007.[9] We collect non-systemic crises from the World Bank database of banking crises over the period of 1974-2002.[10] The sample covers[11]: Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, Netherlands, Norway, Sweden, Spain, UK and the US over the period 1980-2007. Table 1 presents the matrix of crises, with bold observations indicating systemic crises. The frequency of crises in our data set is 3.2 per cent which is marginally below the 5 per cent in Demirgüc-Kunt and Detragiache (2005), but is well within acceptable bounds for the style of analysis.

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[8] Their actual criteria are: the proportion of non-performing loans to total banking system assets exceeded 10%, or the public bailout cost exceeded 2% of GDP, or systemic crisis caused large scale bank nationalisation, or extensive bank runs were visible and if not, emergency government intervention was visible.
[9] See Laeven and Valencia (2007)
[10] See Caprio and Klingebiel (2003)
[11] Choice of the countries is limited by the availability of the data for our time period.

Table 1: List of systemic and non-systemic crises

	BG	CN	DK	FN	FR	GE	IT	JP	NL	NW	SP	SD	UK	US
1980	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1981	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1982	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1983	0	1	0	0	0	0	0	0	0	0	0	0	0	0
1984	0	0	0	0	0	0	0	0	0	0	0	0	1	0
1985	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1986	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1987	0	0	1	0	0	0	0	0	0	0	0	0	0	0
1988	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**
1989	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1990	0	0	0	0	0	0	1	0	0	**1**	0	0	0	0
1991	0	0	0	**1**	0	0	0	**1**	0	0	0	**1**	1	0
1992	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1993	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1994	0	0	0	0	1	0	0	0	0	0	0	0	0	0
1995	0	0	0	0	0	0	0	0	0	0	0	0	1	0
1996	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1997	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1998	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1999	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2000	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2001	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2002	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2003	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2004	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2005	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2006	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2007	0	0	0	0	0	0	0	0	0	0	0	0	**1**	**1**

Note:BG-Belgium, CN-Canada, DK-Denmark, FN-Finland, FR-France, GE-Germany, IT-Italy, JP-Japan, NL-Netherlands, NW-Norway, SP-Spain, SD-Sweden, UK-United Kingdom, US-USA.

Our variables cover the years 1980 – 2007, but we partition the sample into 1980 – 2006 for in-sample estimation whilst we use 2007 data for out-of-sample prediction. For bank-regulatory target variables, given the cross country dataset, we use the unweighted capital adequacy (leverage[12]) ratio and not an estimate of risk-adjusted capital adequacy for the estimation. The unweighted capital adequacy ratio is the ratio of capital and reserves for all banks to the end of year total assets as shown by the balance sheet. Our corresponding measure of bank liquidity is the ratio of the sum of cash and balances with central banks and securities for all banks over the end of year total assets as shown by the balance sheet. We

[12] See footnote 3.

construct unweighted capital adequacy and liquidity ratios using data from the OECD income statement and balance sheet database for all countries apart from the UK. We obtain any missing OECD database observations, as well as the data for 2006 and 2007, from individual Central Banks and the BankScope[13] database. The OECD database does not supply figures for the UK. For that country, we define the unweighted capital adequacy ratio as for other countries and construct it using Bank of England aggregate data. We also construct UK liquidity ratios using Financial Services Authority (FSA) data, where liquidity is defined as the ratio of liquid assets[14] over total assets. Finally house prices are obtained from the NIESR NiGEM database.

As regards the explanatory variables employed, Demirgüc-Kunt and Detragiache (2005), who had 77 crises in their sample, found that they were correlated with macroeconomic, banking sector and institutional indicators. Crises occurred in periods of low GDP growth, high interest rates and high inflation, as well as large fiscal deficits. On the monetary side, they found the ratio of broad money to foreign exchange reserves and the credit to the private sector/GDP ratio, as well as lagged credit growth to be significant. Institutionally, countries with low GDP per capita are more prone to crises, as are those with deposit insurance. All these results were broadly in line with their 1998 paper which featured 31 crises, except that depreciation and the terms of trade had ceased to be significant.

In order to align our study with previous work, we include the explanatory variables used by Demirgüc-Kunt and Detragiache (2005) and Davis and Karim (2008a) (see Box 1). We construct these variables using the IMF's International Financial Statistics (IFS) database and World Bank Development (WDI) data. We do not include some typical variables because they are clearly irrelevant to OECD countries, for example, GDP per capita is broadly comparable across OECD countries, while virtually all OECD countries have some form of deposit insurance scheme. Meanwhile credit/GDP (as opposed to credit growth) may reflect the nature of the financial system in OECD countries (i.e. bank versus market dominated) rather than risk of crisis.

[13] For the liquidity measure, we calculate the ratio of liquid assets to total assets for the top 200 banks in a country in question.

[14] These are the sum of cash, gold bullion and coin, central government and central bank loans, advances and bills held and central government and central bank investments (i.e. securities).

Box 1: List of variables (with variable key)	
Variables used in previous studies: Demirgüc-Kunt and Detragiache (2005); Davis and Karim (2008).	1. Real GDP Growth (%) (YG)
	2. Real Interest Rate (%) (RIR)
	3. Inflation (%) (INFL)
	4. Fiscal Surplus/ GDP (%) (BB)
	5. M2/ Foreign Exchange Reserves (%) (M2RES)
	6. Real Domestic Credit Growth (%) (DCG)
Variables introduced in this study.	7. Liquidity ratio (%) (LIQ)
	8. Unweighted capital adequacy ratio (%) (LEV)
	9. Real Property Price Growth (%) (RHPG)

Turning next to our estimator, we use the cumulative logistic distribution which relates the probability that the dummy takes a value of one to the logit of the vector of n explanatory variables:

$$\Pr ob(Y_{it} = 1) = F(\beta X_{it}) = \frac{e^{\beta' X_{it}}}{1 + e^{\beta' X_{it}}} \qquad (1)$$

where Y_{it} is the banking crisis dummy for country i at time t, β is the vector of coefficients, X_{it} is the vector of explanatory variables and $F(\beta\ X_{it})$ is the cumulative logistic distribution. The log likelihood function which we use to obtain actual parameter estimates is:

$$Log_e\ L = \sum_{i=1}^{n} \sum_{t=1}^{T} \left[\left(Y_{it} \log_e F(\beta' X_{it}) \right) + (1 - Y_{it}) \log_e \left(1 - F(\beta' X_{it}) \right) \right] \qquad (2)$$

Although we can easily interpret the signs on the coefficients as representing an increasing or decreasing effect on crisis probability, the values are not as intuitive to interpret. Equation (2) shows the coefficients on X_{it} are not constant marginal effects of the variable on banking crisis probability since the variable's effect is conditional on the values of all other explanatory variables at time t. Rather, the coefficient $ß_i$ represents the effect of X_i when all other variables are held at their sample mean values. Whilst this makes the detection of non-linear variable interactions difficult, (the logit link function is linear), the logistic EWS has the benefit of being easily replicable by policy makers concerned with potential systemic risk in their countries.

3. Results

In order to obtain our final model specification, we use a general to specific approach, starting with all the variables listed in Box 1, using the sample 1980-2006 to leave the sub-prime crisis for forecasting. At each stage, we omit the variable that was least significant in the previous stages. In order to capture developments in the economy prior to the crisis and to avoid endogenous effects of crises on the explanatory variables we lag all variables by one period, apart from real house price growth which has 3 lags. We allow house price growth to have a longer lag because it is an indicator of potential lending problems that frequently develop as a consequence of a house price bubble. Besides being essential to obtain a true "early warning"[15], lagging variables is also econometrically sound since the driving variables also respond to a crisis and hence are jointly determined in the current period.

Table 2: The general to specific approach

LIQ(-1)	-0.118 (-3.55)	-0.124 (-3.55)	-0.137 (-3.64)	-0.135 (-3.55)	-0.135 (-3.45)	-0.144 (-3.39)	-0.147 (-3.25)
LEV(-1)	-0.333 (-2.85)	-0.239 (-1.90)	-0.315 (-2.24)	-0.247 (-1.64)	-0.271 (-1.67)	-0.280 (-1.72)	-0.273 (-1.62)
RHPG(-3)	0.113 (2.8)	0.113 (2.87)	0.104 (2.67)	0.100 (2.59)	0.104 (2.67)	0.108 (2.76)	0.110 (2.67)
DCG(-1)	-	-0.099 (-1.82)	-0.10 (-1.97)	-0.10 (-1.86)	-0.10 (-1.99)	-0.13 (-1.98)	-0.13 (-1.98)
RIR(-1)	-	-	0.084 (1.37)	0.085 (1.40)	0.165 (1.41)	0.173 (1.46)	0.166 (1.30)
M2RES(-1)	-	-	-	-0.00 (-1.0)	-0.00 (-1.0)	-0.00 (-1.1)	-0.00 (-1.1)
INFL(-1)	-	-	-	-	-0.13 (-0.8)	-0.14 (-0.8)	-0.13 (-0.7)
YG(-1)	-	-	-	-	-	0.116 (0.65)	0.125 (0.66)
BB(-1)	-	-	-	-	-	-	-0.013 (-0.1)

Note: estimation period 1980-2006; t-statistics in parentheses; LIQ-liquidity ratio, LEV- unweighted capital adequacy ratio, YG-real GDP growth, RPHG-real house price inflation, BB-budget balance to GDP ratio, DCG-domestic credit growth, M2RES-M2 to reserves ratio, RIR-real interest rates, DEP-depreciation, INFL-inflation.

As expected in the context of the OECD, all of the "traditional" variables prove insignificant, despite experimentation with different lag lengths. For example, domestic credit growth is

[15] It is notable that some of the work in this area uses current levels and not lags and so is only providing "Contemporaneous Confirmation Indicators" of crises.

insignificant with a negative sign.[16] We list the specific variable deletions and their corresponding t-statistics in Table 2. We test for joint elimination of insignificant variables and the F statistic is insignificant at 0.318.

We also apply our final specification to data for 1980 – 2007 (see Table 3) to ensure our conclusions are not affected by the sub-prime episode. Given that they were not majorly affected , we accepted equation 3 as our final EWS.

Table 3: Comparing the effects of sample period on estimation results

	Estimation period	
	1980-2006	1980-2007
LIQ(-1)	-0.118 (-3.55)	-0.13 (-4.1)
LEV(-1)	-0.333 (-2.85)	-0.261 (-2.51)
RHPG(-3)	0.113 (2.8)	0.106 (2.79)
Note: t statistics in brackets		

$$\log\left[\frac{p(\text{crisis})}{1-p(\text{crisis})}\right] = -\ 0.333\ \text{LEV}(-1) - 0.118\ \text{LIQ}(-1) + 0.113\ \text{RHPG}(-3) \qquad (3)$$

$$(-2.85) \qquad (-3.55) \qquad (2.8)$$

where p(crisis) is the probability of crisis occurrence and t-statistics are given below each coefficient.

The results in Table 2 clearly show that increased unweighted capital adequacy and liquidity ratios in the banking sector have a beneficial impact of reducing crisis probability.[17] Those banking systems with healthy levels of capital one year prior to the crisis are less likely to collapse, as are those that held relatively high levels of cash and securities on their balance

[16] Although domestic credit growth is significant if included as a contemporaneous variable, including it would be contrary to our aim of providing an Early Warning System, also it has a negative sign which implies scarcity of available credit once the crisis materialises.

[17] The corresponding Wald test statistic which tests for the joint insignificance of all other explanatory variables listed in Box1 proves that apart from unweighted capital adequacy ratios, liquidity and real house price growth all other variables were insignificant. The actual probability (under the F distribution) was 31%.

sheets. On the other hand, higher real house price growth three years prior to the crisis suggests a prolonged period of risky mortgage lending by banks will unambiguously increase the chances of borrower default and thus a crisis.

We calculate two correlation matrices, one for the levels of the variables and another for the chosen lags (see Appendix 2) in order to evaluate the interactions between variables in our testing process. We find no statistically significant evidence of high correlations between right-hand-side variables such as could bias the results. For example, there are no correlations of over 0.22 for DCG or DCG(-2) that could explain the sign and significance of that credit growth variable. Indeed, when taking the relevant lags there are no correlations over 0.35 other than the real interest rate and inflation, and most are below 0.2.

We note that there are additional variables that recent research suggests could be included if data were available for our OECD 1980-2007 sample. One example is bank concentration, which Beck et al (2006) show to be correlated with banking crises (more concentrated systems are less vulnerable[18]). Beck et al (2006) study 69 countries, including OECD countries, middle and low income ones,[19] but it is not clear that these would necessarily form an internally consistent group, as we discuss above. Furthermore, due to shortcomings in Bankscope data[20] the authors inserted the 3-firm concentration variable as a period average constant in their regressions. When we do include the same average level of concentration in our preferred equation for the OECD countries considered here, along the lines of Beck et al (2006), the variable is insignificant.

The supervision variables used by Beck et al (2006) are also constant over their dataset. We test similarly as for concentration, including their supervision variables[21] one by one in our preferred equation for the OECD countries. For each of the supervision variables they found

[18] On the other hand, using aggregate balance sheet data, Uhdea and Heimeshoff (2009), show that more concentrated banking systems in the EU may be more vulnerable to financial instability.
[19] Accordingly, we have already shown that our sample is significantly different from Beck et al (2006).
[20] The data for the late 1980s and early 1990s in Bankscope are highly incomplete, suggesting an overestimation of concentration over this period. Furthermore, even using the extended dataset from Bankscope presented in the World Bank Financial Structure Database, (see Beck and Demirgüc-Kunt 2009) data only start in 1988 in most OECD countries in our sample, and in 1993 in Sweden and the US. These combined difficulties explain the use of an average measure in Beck et al (2006).
[21] We obtained the data from the World Bank website where the Beck et al (2006) dataset is provided, see http://econ.worldbank.org/WBSITE/EXTERNAL/EXTDEC/EXTRESEARCH/0,,contentMDK:20699045~pagePK:64214825~piPK:64214943~theSitePK:469382,00.html.

significant (namely, fraction of bank entry applications denied, activity restrictions, banking freedom, economic freedom and governance (KKZ composite)), none are significant in our preferred equation. Hence our estimation suggests that these variables play no significant role in driving OECD crises, at least as currently specified, but they may have a role in structuring the determinants of non-OECD crises, an issue we do not address here.

Meanwhile, financial liberalisation is present for all the crisis periods, according to data from Demirgüc-Kunt and Detragiache (1997), Mehrez and Kauffmann (1999) and Canals (1997) so when we include it, the logit suffers “complete separation” and the variable, like deposit insurance, is unusable.

Since previous work has not quantified the impacts of unweighted capital adequacy ratios, liquidity and house price growth on the log-odds of crisis, it is worth investigating their individual marginal effects on crises, because simply observing the coefficients in equation 3 cannot produce a meaningful ranking of variable importance. Table 4 shows the marginal contribution of each variable to crisis probability for the entire 1980 – 2006 estimation period. Since the marginal effect of each variable is contingent on the values taken by all other variables, it is customary to compute marginals whilst holding all other variables at their sample mean values.

Table 4. Marginal effect of a 1 point rise in the variable on crisis probability

	LIQ	LEV	RHPG
BG	-0.17	-0.49	0.17
CN	-0.22	-0.61	0.21
DK	-0.05	-0.14	0.05
FN	-0.23	-0.65	0.22
FR	-0.78	-2.17	0.74
GE	-0.23	-0.65	0.22
IT	-0.17	-0.46	0.16
JP	-0.38	-1.05	0.36
NL	-0.56	-1.57	0.53
NW	-0.33	-0.91	0.31
SD	-0.12	-0.34	0.12
SP	-0.08	-0.24	0.08
UK	-1.19	-3.32	1.13
US	-0.08	-0.22	0.07

Note: percentage points. Country definitions in note to Table 1

Of the three leading indicators, the unweighted capital adequacy ratio consistently causes the highest marginal reduction in banking crisis likelihood, irrespective of the country in question. The highest impact occurs in the UK and France because their mean unweighted capital adequacy ratio measures were lower than the remaining sample. The implication is that a one point rise in the unweighted capital adequacy ratio alone could reduce crisis probability by at least 0.14 % (Denmark) and by as much as 3.32% (UK). The next highest marginal impact occurs via improved liquidity. If, in aggregate, banks simply increased their holdings of cash and short-term securities by one point, with no attention to other variables, the reduction in crisis probability would be at least 0.08% (USA) and could be as high as 1.19% (UK). Again the effect in the UK is highest due to the lowest sample mean liquidity, whilst in the US it is lowest due to the converse. It is worth noting that the apparently high liquidity held in the US was overestimated in the sense that the measure ignored the liquidity risk attached to sub-prime securitised assets and that once this materialised, actual liquidity in the US banking sector evaporated. The sub-prime episode has highlighted the importance of off-balance sheet items affecting crisis probabilities, an issue that requires further work.

Even with no deterioration in the health of bank balance sheets, a point rise in real house price growth is sufficient to raise the probability of a crisis by at least 0.07% (US) and by as much as 0.74% (France). This general result conforms to the traditional banking crisis literature on leading indicators of crises including Borio and Drehmann (2009) and recent findings by Reinhart and Rogoff (2008) who note the sub-prime episode was no different from previous OECD cases which were characterised by house price booms in the run up to crises. Whereas Reinhart and Rogoff (2008) simply identify property prices as a leading indicator, we are able to quantify their impact and the impact of unweighted capital adequacy ratios and liquidity in the run-up to the sub-prime episode. For more detailed discussion see Appendix 1.

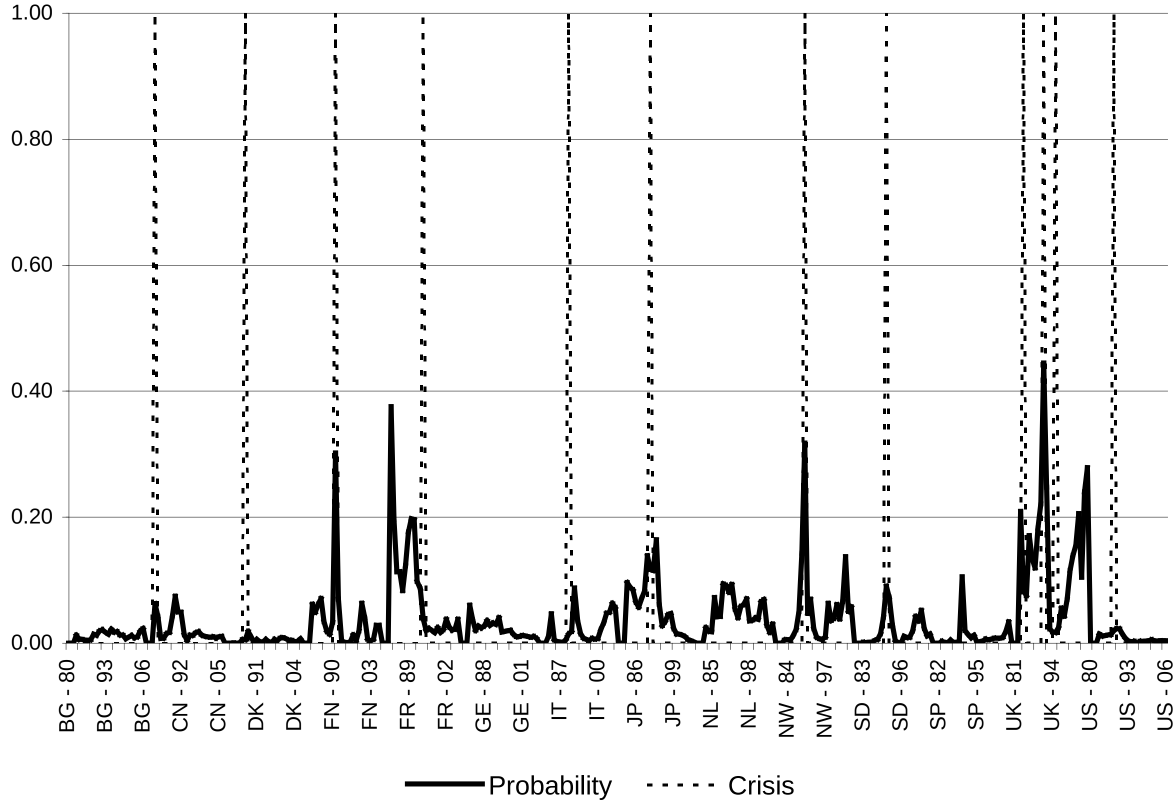
Given the results described above, we now turn to see which crises were picked up by our EWS. Figure 1 below shows the actual in-sample crisis probabilities against the EWS fitted values. If we use the in-sample probability of crisis as a cut-off threshold[22] to identify which crises are called, for our sample we obtain a cut-off threshold of 0.032 (3.2%). Based on this threshold, our model is able to correctly identify 8 out of the 12 crises in the estimation period, equivalent to a 66% success rate, implying that we would outperform a random naïve model which would only call crises on 50% of occasions. The corresponding type II error rate is 29%, but encouragingly, many of these so-called false alarms actually occur close to the crisis onset, implying the EWS predictions are at least able to distinguish between episodes of financial stability and instability and in many cases can identify actual crisis onset.[23] Table 5

[22] This follows the approach of Demirgüc-Kunt and Detragiache (1998) and Kaminsky and Reinhart (1999).

[23] Demirgüc-Kunt and Detragiache (2005) for their most preferred equation had a type II error of 32% and a type I error of 39%, with an overall success rate of 69% at a threshold of

gives details of the in-sample predictive performances for each country and the relation of any false alarms to the timing of crises, and shows the false call rate to be 25% when we include the crisis aftermath. We observe high call rates for France, Japan, Netherlands[24], Norway and the UK, all of which either experienced crises or had major crises in the post estimation period. The highest call rate is in the UK, but it also has the highest crisis frequency, with four crises recorded in IMF and World Bank sources. The high call rate in Japan reflects the nature of the dummy we use to indicate crises, as it catches the start of a crisis but does not reflect the length of the crisis. Six of the calls in Japan were in the years following the start of the crisis and reflect the depth and length of the event. The call rate is low in the US, reflecting the unusual nature of the crisis experienced in 2007. It however spread to other countries through the banking system and hence our indicators picked up effects elsewhere (see Barrell et al 2010).

Figure 1: Probability of crises according to the logit model



Note: Country definitions in note to Table 1

0.05. Our corresponding results at 0.05 threshold instead of the 0.032 quoted here are for a type II error of 22% and a type I error of 42%, with an overall success rate of 77%. Hence our work stands up well in comparison.

[24] Although the Netherlands did not experience a banking crisis till 2007, there were certainly concerns over asset price developments in the late 1990s, also expressed in official circles (De Nederlandsche Bank 2000), that help justify the estimated crisis probability in that period.

Table 5: In-sample prediction

	Total Calls	Crises	Aftermath of the Crises	False Calls	Timing of False Calls relative to Crisis Onset
BG	0	0	0	0	
CN	6	1	1	4	next year
DK	0	0	0	0	
FN	10	1	1	8	next year
FR	14	1	0	13	
GE	5	0	0	5	
IT	8	0	2	6	2nd and 3rd years
JP	15	1	6	8	Next 7 years, with a break on the 4th year
NL	18	0	0	18	
NW	14	1	2	11	next 2 years
SD	6	1	1	4	next year
SP	2	0	0	2	
UK	20	2	0	18	
US	0	0	0	0	
total	*118*	*8*	*13*	*97*	

Note: Country definitions in notes to Table 1

Based on these results, we contend that an EWS based on liquidity ratios, unweighted capital adequacy ratios and real house price growth can significantly improve policy makers' abilities to avert crises in the OECD. To verify our claim, we next turn to out-of-sample prediction to see if our EWS is able to detect the sub-prime episode in any of the OECD economies. We base our results on two crises definitions given in Borio and Drehmann (2009). According to Definition 1, a crisis occurs in "countries where the government had to inject capital in more than one large bank and/ or more than one large bank failed". By the end of January 2009 this definition classified the US, the UK, Belgium, France, Germany and the Netherlands as in crises in our sample. Definition 2, which is less stringent, states countries experienced a crisis when "countries undertook at least two of the following policy operations: issue wholesale guarantees, buy assets, inject capital into at least one large bank, or announce a large scale recapitalisation programme". Under this definition, all the countries previously listed experienced crises but in addition, Canada, Denmark, Italy, Spain and Sweden also fell into the crisis list in our sample.

Using the same cut-off threshold as before (the predicted probability exceeds the sample average of 3.2 per cent), we derive out-of-sample predictions for all the countries in our sample for the years 2007 and 2008. If we call a crisis in any country we then check the Borio and Drehmann (2009) definition to see if a crisis had actually materialised there or not. We provide the results in Table 6, which indicates any crises called by our EWS in columns 1 and 2 and the corresponding crisis occurrence according to the definitions. As can be seen, our

EWS is able to call 4 out of 6 crises according to definition 1, and 6 out of 10 crises according to definition 2, with false calls in only two countries. Given that we are able to call 66% of crises in-sample, our model has not lost any of its predictive power out-of-sample. This is the ultimate test of any EWS, since generally they have better in-sample performance than out-of-sample predictive ability. On the basis of these results, we argue that our EWS specification would be a valuable tool for any OECD policy maker wishing to avert future crises. Moreover, we now go on to show our specification is extremely robust and can therefore be used with confidence.

Table 6: Out of sample predictions

	2007	2008	definition1	definition2
BG	X	X	X	X
CN	-	-		-
DK	-	-		
FN	-	X		
FR	X	X	X	X
GE	-	-	-	-
IT	X	-		X
JP	-	-		
NL	X	-	X	X
NW	X	X		
SD	-	-		-
SP	X	X		X
UK	X	X	X	X
US	-	-	-	-

Note: Country definitions in note to Table 1

4. Robustness tests

Our conclusions do not change when we thoroughly test our coefficients for robustness. To examine the possibility that variable behaviour in an individual economy drives our results, we re-estimate the logit equation by dropping the systemic crises economies individually. This results in the deletion of UK, US, Norway and Finland and Japan one by one, yet in each case, all our coefficients retain their significance, sign and order of magnitude. To ensure a further degree of robustness, we also re-estimate the logit function after dropping the US and Japan together, since it could be argued that our results are driven by the non-European crises. Again, the separation of crises by region made no difference to the impacts of liquidity ratios, unweighted capital adequacy ratios or real house price growth on crisis probability, demonstrating the importance of these variables in all OECD banking crises. The results of the country elimination tests are given in Tables 7.

Table 7. Results for country elimination tests

	Final panel	UK not includ ed	US not included	Japan not included	US and Japan not included	Norway not included	Finland not included	Sweden not included
LIQ(-1)	-0.118 (-3.55)	-0.143 (-2.99)	-0.125 (-3.55)	-0.111 (-3.28)	-0.119 (-3.29)	-0.124 (-3.59)	-0.121 (-3.5)	-0.115 (-3.41)
LEV(-1)	-0.333 (-2.85)	-0.3 (-1.78)	-0.339 (-2.79)	-0.344 (-2.94)	-0.349 (-2.86)	-0.282 (-2.38)	-0.293 (-2.43)	-0.343 (-2.87)
RHPG(-3)	0.113 (2.8)	0.152 (3.44)	0.119 (2.82)	0.111 (2.74)	0.118 (2.76)	0.089 (2.04)	0.083 (1.84)	0.107 (2.58)

Note: t statistics in brackets

Next, we turn to crisis dates, in recognition of the fact that timing the onset of a crisis relies on some degree of subjective judgement, and it could therefore be suggested that our results are dependent on the specific crisis dates we happened to choose. If several different crisis definitions generate the same start date for a given crisis, we would conclude that subjectivity does not distort the timing of the crisis. If however, the same crisis is timed differently according to different definitions, we might worry that subjectivity has biased our coefficients. Accordingly, we turn to the recent work of Reinhart and Rogoff (2008) who examined the causes of OECD crises and compared our crisis dates to theirs. Their crisis dates differ for Japan and the US as they date them as 1992 and 1984 respectively. For additional robustness, we redefine the crisis dummy for Japan (crisis in 1992) and the US (crisis in 1984) but find this makes no difference to our results, as can be seen in Table 8.

Table 8. Effect of alternative crisis dates on variable significance

	Final version	Japanes e crisis at 1992	US crisis at 1984
LIQ(-1)	-0.118 (-3.55)	-0.119 (-3.56)	-0.12 (-3.58)
LEV(-1)	-0.333 (-2.85)	-0.332 (-2.85)	-0.317 (-2.73)
RHPG(-3)	0.113 (2.8)	0.113 (2.8)	0.104 (2.56)

Note: t statistics in brackets

Another criticism of our crisis dummy could be that the one year duration could affect our results. Assuming the dummy takes a value of one only for the year in which the crisis starts, and zero otherwise could mean that we are relating post-crisis explanatory variables to supposed non-crisis periods when the economy in question could still be in a crisis. We adopt the following procedure to identify which variables contribute to the switch between non-crisis and crisis states, rather than to identify which variables prolong the crisis: We test whether relaxing the assumption that crises last for one year changes our results. By looking at our crisis definitions and identifying the duration of each crisis, we can drop all observations for the years in which the crisis persisted. This reduces the number of false calls and also removes data that would 'call' a new crisis whilst an existing one continued. This allows us to verify the sensitivity of our results to crises durations and avoids endogeneity between the crisis itself and the explanatory variables in the post-crisis period. Our results continue to be robust; even when we drop post-crisis observations, the significance of our coefficients does not change as Table 9 shows.

Table 9. Impact of the elimination of continuing-crisis observations on variable significance

	Final version	Japanese crisis at 1992	US crisis at 1984
LIQ(-1)	-0.118 (-3.55)	-0.119 (-3.56)	-0.12 (-3.58)
LEV(-1)	-0.333 (-2.85)	-0.332 (-2.85)	-0.317 (-2.73)
RHPG(-3)	0.113 (2.8)	0.113 (2.8)	0.104 (2.56)

Note: t statistics in brackets

As a further robustness check we test to see whether parameters estimated up to the early 2000's remain stable when data on the sub-prime crisis are included. To that end we add three new variables with data on liquidity and capital adequacy ratios and the real house price variables containing observations starting from year 2001[25], including crisis year are added to the final specification. If there is a break in the impact of any of the variables at the end of our sample than we expect non-trivial changes in the size as well as significance of the explanatory variables and at least some of the added variables to be significant. Test results that we present in Table 10 illustrate that none of the added variables are significant and estimated parameters and their significance remain broadly unchanged, indicating robustness against sub-crime crisis period.

[25] As real house prices enter the equation with a three year lag, in order to get model prediction for 2004, we need 2001 observations.

Table 10. Impact from the sub-crime run-up period on variable significance

	Final version	1980-2007 estimation with break
LIQ(-1)	-0.118 (-3.55)	-0.128 (-3.4)
LEV(-1)	-0.333 (-2.85)	-0.241 (-1.94)
RHPG(-3)	0.113 (2.8)	0.106 (2.85)
LIQ(-1)^b	-	-0.029 (-0.34)
LEV(-1)^b	-	-0.045 (-0.19)
RHPG(-3)^b	-	0.006 (0.05)

Note: LIQ^b, LEV^b, RHPG^b represent liquidity, capital adequacy and real house price variables, but with data starting from 2001. Prior to this the variable values are assumed to be zero. 't' statistics in brackets

We note that some commentators have criticised the measures of banking crises used in this and other papers, since they may capture the official response rather than the crisis year itself. In our view, the one year lag (or longer) we employ for our explanatory variables should be sufficient to prevent any distortion of the results for liquidity and capital adequacy (which tend to fall when the crisis begins). However, as a further test, we took the second lag of the liquidity and capital adequacy variables prior to the crises. As shown in Table 11, this amendment does not change the results to any great extent, indicating that these variables are robust early warning indicators of crises.

Table 11. Taking the second lag of liquidity and capital adequacy

LIQ (-2)	-0.104 (-3.27)
LEV (-2)	-0.385 (-3.22)
PHG (-3)	0.119 (3.00)

Note: t statistics in brackets

Finally, a possible criticism of our work is that we use both non systemic and systemic crises in a common panel. We consider this is warranted for OECD countries given the shortage of crisis observations. But estimates can still be derived for systemic crises only, which number only 5 up to 2006, as shown in Table 1. All three of our early warning variables are highly significant for systemic as well as total crises, as shown in Table 12, again highlighting the robustness of the specification and the potentially increased importance of capital adequacy in systemic crises.

Table 12. Systemic crises only

LIQ (-1)	-0.121
	(-2.49)
LEV (-1)	-0.768
	(-3.59)
PHG (-3)	0.235
	(3.71)

Note: t statistics in brackets

5. Conclusions

In contrast to the existing literature, we estimate equations for early warning systems for banking crises in OECD countries using not only standard indicators but also measures of bank capital and liquidity adequacy and of property price growth. These have not been assessed as indicators in extant work. We find that unweighted bank capital adequacy, bank liquidity and property prices impact on banking crisis probabilities and tend to exclude more traditional variables such as GDP growth, inflation and real interest rates. Furthermore, we can use the model to detect increases in crisis probabilities out-of-sample in the run up to the sub-prime episode. Moreover, we find that the importance of capital and liquidity adequacy and house price growth remains invariant to different robustness tests.

Our results have important policy implications for financial regulators and central banks. They underline the need for high levels of capital[26] and liquidity[27] in banks. Furthermore, suppressing rapid property price growth may well mitigate future OECD crises. Given the difficulties of using monetary policy to counteract risks to financial stability and monetary stability with one instrument (e.g. use of interest rates to limit asset price bubbles in a low-inflation context), use of supervisory instruments such as capital adequacy on mortgage loans or limits on loan to value ratios on mortgage lending may be warranted.

The suspicion that bank capital adequacy and liquidity are countercyclical (as is shown for example in Babihuga (2007)) means that our results also validate measures to restrict

[26] See Van Hoose (2007) for a review of the theoretical literature on bank capital regulation.
[27] See Wagner (2007) on some of the conflicting effects liquidity regulation may have on banks.

procyclicality of the financial system, such as the regulatory policy in Spain which raises capital adequacy when credit grows rapidly. For a review of recent work and policy discussion in the field of such macroprudential regulation see Davis and Karim (2010). For example, Repullo et al (2009) recommend that in order to mitigate procyclicality there should be adjustments of capital requirements using a simple multiplier that depends on the deviation of the rate of growth of GDP from its long-run average. As discussed in Brunnermeier et al (2009), an alternative is a response of capital adequacy to debt-equity, maturity mismatch, credit growth and asset price growth, suitably weighted – a broader approach that our results underpin. Liquidity risk could be reduced by "marking to funding" and capital charges against illiquidity. It is encouraging to see that the latest regulatory response to the global banking crisis, the Turner Review (Financial Services Authority 2009) is consistent with our results, in calling for improved quality of liquidity and capital adequacy in the UK banking system, for countercyclical ratios and also a focus on a unweighted capital adequacy ratio[28] as well as risk adjusted capital adequacy. Equally, academic commentators such as Shin (2009) suggest that experience of episodes such as the Northern Rock failure suggest a need to implement or tighten regulation of bank liquidity and capital adequacy to complement the existing regulation of risk adjusted capital adequacy.

[28] To quote the recommendations of the Turner Review, "A maximum gross leverage ratio should be introduced as a backstop discipline against excessive growth in absolute balance sheet size" (ibid, page 7).

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Appendix 1: Marginal effects

We use sample mean values of the indicators to derive the marginal effects in Table 4. However, to assess their true contribution to the current crisis, we evaluate the marginals on the basis of ex-ante data in Table A1. We compute marginals using 2006 data values, because this was in advance of the 2007 sub-prime episode. Hence when we compute the 2006 marginal impacts we are actually utilising 2005 values for liquidity and unweighted capital adequacy ratios (both lagged 1) and 2003 values for real house price growth (lagged 3). Henceforth for ease of exposition we refer to these as 2006 values.

Table A1.1: Marginal effect of a 1 point rise on the probability of a crisis using 2006 data values

	LIQ	LEV	RHPG
BG	-0.27	-0.76	0.26
CN	-0.12	-0.35	0.12
DK	-0.09	-0.24	0.08
FN	-0.32	-0.91	0.31
FR	-0.43	-1.22	0.42
GE	-0.09	-0.25	0.08
IT	-0.64	-1.78	0.61
JP	-0.02	-0.06	0.02
NL	-0.35	-0.97	0.33
NW	-0.65	-1.81	0.62
SD	-0.17	-0.48	0.17
SP	-0.39	-1.08	0.37
UK	-2.38	-6.68	2.28
US	-0.05	-0.14	0.05

Note: percentage points. LIQ and LEV are at 2005 values owing to lag 1 and PHPG is at 2003 levels owing to lag 3. Country definitions in note to Table 1

If we compare Tables 4 and A1, we find there were clear changes in the marginal impacts of liquidity, unweighted capital adequacy ratios and property prices just before the sub-prime crisis relative to the sample mean. If the difference between the absolute marginal based on sample averages and the absolute marginal based on 2006 data is positive (ceteris paribus) the variable's impact on crisis probability has increased. This could arise for three reasons: either the 2005 level of liquidity or the unweighted capital adequacy ratio is lower than the sample mean level or that real house price growth has recently overshot the average. For example, in the case of liquidity, an increase in the marginal effect would imply aggregate liquidity levels in 2005 were too low and since liquidity was so scarce, a marginal improvement in capital and reserves would have a stronger crisis reducing effect than in other years. A similar story would apply to the unweighted capital adequacy ratio, whilst for real house price growth (which is for 2003 values given the 3 year lag) the converse would be true. Since the house price coefficient is positive, the higher the level of house price growth the greater the marginal impact on crisis likelihood. Thus a positive marginal change describes a situation where 2003 growth rates of house prices were higher than the sample average and consequently, any additional pressure on the housing bubble could have severe consequences for the banking system. To illustrate the changes in marginal impacts, Table A2 computes the difference between the 2006 marginal effects and the marginals based on sample means.

Table A1.2: Change in the marginal impacts in the run up to the sub-prime crisis (2006); all variables held at values relevant to 2006

	LIQ	LEV	RHPG
BG	0.10	0.28	0.09
CN	-0.10	-0.27	-0.09
DK	0.04	0.10	0.04
FN	0.09	0.26	0.09
FR	-0.34	-0.95	-0.32
GE	-0.15	-0.41	-0.14
IT	0.47	1.32	0.45
JP	-0.35	-0.99	-0.34
NL	-0.21	-0.59	-0.20
NW	0.32	0.89	0.30
SD	0.05	0.15	0.05
SP	0.30	0.85	0.29
UK	1.20	3.35	1.14
US	-0.03	-0.08	-0.03

Country definitions in note to Table 1

Table A2 displays the combined marginal effects of all variables in the run up to crises, because all variables take on their 2006 (2005 and 2003) values. Hence, for example when we say the ability of higher unweighted capital adequacy ratios to reduce crisis probability increases ex-ante, we are taking this effect conditional on the fact that liquidity and house price growth were displaying a certain ex-ante behaviour. To isolate the pure change in the marginal effect of a variable on crisis probability, we compute the marginal effect of each variable in 2006, holding the two other variables constant at their sample mean values (Table A3).

The two tables yield interesting insights into the contribution of each variable to crises. If other variables behave as they do on average, the ability of liquidity to reduce crisis probability increases in 2006 in most countries. For example, a one point increase in liquidity in Belgium would have reduced crisis likelihood by 0.01 percentage points if unweighted capital adequacy ratios and house prices had behaved “normally”. But once we allow these two variables to take on their 2006 values, the liquidity levels in Belgium become much more important for crisis prevention; the marginal effect is now ten times higher at 0.10 percentage points. Similarly significant impacts of liquidity are observed for Denmark and Spain, with the most dramatic effect being observed in the UK. Moreover, the result is heterogeneous because in some countries such as Finland and France, once the other variables were allowed to take on their 2006 values, the marginal effect of liquidity actually fell, whilst in the US the ability of liquidity to prevent a crisis actually fell given the ex-ante dynamics of the other variables. This may be because by 2006, increased liquidity in the banking system may have further fuelled the last phase of the property price bubble.

Table A1.3: Change in the marginal impacts in the run up to the sub-prime crisis, variable in question held at 2006 or 2004 values; all other variables held at sample means

	LIQ	LEV	RHPG
BG	0.01	0.01	0.07
CN	-0.12	-0.09	0.08
DK	0.01	0.09	0.00
FN	0.23	-0.33	0.09
FR	-0.53	-0.32	0.65
GE	-0.12	-0.05	-0.04
IT	0.41	-0.18	0.13
JP	-0.29	-0.57	-0.14
NL	-0.28	0.63	-0.06
NW	0.32	-0.07	0.02
SD	-0.03	0.03	0.03
SP	0.05	0.01	0.14
UK	0.08	-0.10	1.10
US	0.01	-0.13	0.02

Country definitions in note to Table 1

The marginal impact of unweighted capital adequacy ratios in some countries is even more dramatic than liquidity. For example, in Belgium, once liquidity and house price growth took on their levels relevant to 2006, the ability of higher cash and reserves to bring down the risk of crisis rose from the "average" level of 0.01 percentage points to 0.28 percentage points. We observe similarly important increases for Finland, Italy, Norway, Spain and the UK, suggesting that intervention to improve the capital base of banks in these countries would have had beneficial effects. Conversely, the marginal impact of unweighted capital adequacy ratios on crisis probability in Canada, France, Germany and Japan actually fell in the run-up to the sub-prime episode, implying at this stage, an improvement in capital could not avert the crisis by much.

The most interesting marginal impacts are those displayed by real house price growth. In most countries, once liquidity and unweighted capital adequacy ratios were allowed to take on their 2006 values, the ability of further house price increases (in 2003) to cause crises increased.

Appendix 2: Correlation matrices for the right hand side variables

We use the Breusch Pagan (1980) test for cross section dependence to investigate the orthogonality of regressors. According to the test, the correlation coefficients are distributed as a standard normal variate where N is the cross section dimension and T is the time dimension

$$CD = (1/(N(N-1)))^{**}(1/2)^{*}(\sum_{i=1,N}\sum_{j=i+1, N-1}(T\ \rho_{ij}{}^{**2} - 1)$$

In neither case below is there any significant indication of correlation, In the first case the standard normal deviate is 0.66 and in the second it is -0.18 whereas the 95 percent two sided bound is 1.96. As we use the timing pattern in Table A5 in our work we can be certain there are no interdependences in the data set.

Table A2.1: Contemporaneous correlations

	LIQ	LEV	RHPG	M2RES	YG	BB	RIR	INFL
LEV	0.042579							
RHPG	0.022786	0.160822						
M2RES	-0.101842	-0.051601	-0.019934					
YG	0.009832	0.095600	0.480042	0.010237				
BB	-0.180464	0.207130	0.365441	-0.013358	0.247354			
RIR	-0.083565	-0.044662	-0.248618	-0.192285	-0.171030	-0.344527		
INFL	-0.000291	-0.070024	-0.224086	-0.171539	-0.213520	-0.160056	0.776156	
DCG	-0.040456	0.066859	0.212377	0.086542	0.133408	0.129208	-0.038832	-0.062544

Table A2.2: Correlations of chosen lags

	LIQ(-1)	LEV(-1)	RHPG(-3)	M2RES(-1)	YG(-1)	BB(-1)	RIR(-1)	INFL(-1)
LEV(-1)	0.037664							
RHPG(-3)	-0.090390	0.132627						
M2RES(-1)	-0.107448	-0.086365	-0.041822					
YG(-1)	-0.006521	0.096612	-0.001930	0.026441				
BB(-1)	-0.205604	0.195277	0.348927	-0.016157	0.225827			
RIR(-1)	-0.047852	0.021694	-0.036750	-0.197941	-0.095491	-0.318103		
INFL(-1)	0.005953	0.046803	0.012426	-0.187053	-0.123446	-0.150839	0.799846	
DCG(-2)	-0.040466	0.017056	0.174693	0.104046	0.013226	0.122363	0.011048	0.010902