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What should we do about (Macro) Pru?
Macro Prudential Policy and Credit.

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What should we do about (Macro) Pru?

Macro Prudential Policy and Credit[1].

Ray Barrell and Dilruba Karim, Brunel University.

Abstract: Credit growth is widely used as an indicator of potential financial stress, and it plays a role in the new Basel III framework. However, it is not clear how good an indicator it is in markets that have been financially liberalised. We take a sample of 14 OECD countries and 14 Latin American and East Asian countries and investigate early warning systems for crises in the post Bretton Woods period. We show that there is a limited role for credit in an early warning system, and hence little reason for the Basel III structure. We argue that the choice of model for predicting crises depends upon both statistical criteria and on the use to which the model is to be put.

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Introduction

Many commentators on the financial crises experienced in the OECD since 2007 have attributed them to excessive credit growth, and the Basel Committee has suggested that capital buffers should respond to credit growth in order to reduce future crisis probabilities. Policy makers have recognised that they face three problems, the possibility of output not being at equilibrium, the possibility that inflation is not on target, and the possibility that there may be a financial crisis in the near future. These are related problems, but they do not coincide. It is common to discuss the allocation of instruments to problems, with fiscal policy being assigned to output, monetary policy being assigned to inflation, and macro-prudential policy to crisis prevention. Single assignment is only optimal if the problems are largely independent, which they may not be.

In this paper we first look at current regulations concerning the countercyclical buffer, and then we discuss early warning systems in general before turning to the determinants of crises. It is only once the determinants of crises are properly understood that the question of authorities' ability to influence either the determinants or therefore the probability of crisis becomes interesting. Current regulations affect credit supply without conclusive evidence that credit causes crises. This paper investigates the role of credit in crises that occurred in the OECD and in Latin America and East Asia. Unlike previous work on these regions, we include policy variables that have an established crisis reducing effect. Our analysis reveals the link between credit and crises is contingent on the extent of financial liberalisation and hence credit growth is not the prime crisis trigger in the OECD.

It may never be possible to avert idiosyncratic crises since the costs of prevention, which would require adjustment of a complete set of crisis determinants, would be exorbitantly high. Instead, identifying a core set of variables that explain a broad set of events gives policy makers a realistic menu of instruments they can deploy against crises. Although variables outside the core set may explain a few additional crises, utilising them as instruments for financial stability will be inefficient. Early Warning Systems using many predictors may be useful to monitor fragilities but a parsimonious subset must be selected such that crisis identification is not compromised by the cost of intervention against false alarms.

We look at models that include the credit to GDP gap, the ratio of credit to GDP and the growth of this ratio as alternative specification of the credit problem. We have to choose between models, and after our analysis of these three approaches we develop diagnostic tools to choose between them. We identify the parsimonious model by sequential elimination and we use Receiver Operating Characteristic (ROC) curve analysis to investigate the costs and benefits of each step since this takes into account the trade-off between correct crisis prediction and false alarms. We also use ROC analysis to help us choose between competing models of the determination of crisis probabilities. Our analysis inevitably yields separate models for the OECD and Latin America and Asia combined and reveals that the causes of crises in the latter group are more diverse than in the OECD and that the justification of countercyclical buffers needs more work.

Regulation and the Countercyclical Buffer

There were clearly many flaws in the regulatory structure before the crisis in 2007, with perhaps the most severe being a reliance on the market to regulate capital adequacy and liquidity. The non-systemic approach followed by the regulators meant authorities believed banks could, if they faced liquidity problems, turn to wholesale markets. This involved a common fallacy of composition, in that if every single entity looked safe it was assumed the system was itself safe. However by the summer of 2007, the UK the banking system was holding less liquidity in aggregate than the supposed floor of 3 per cent per bank, and when banks had to turn to the market for liquidity it was clear that little was available. Hence it was unlikely that wholesale markets could deal with a shift in the demand for liquidity on the part of all banks simultaneously. Compositional fallacies of this sort are common in economics, and we suspect one is being constructed in relation to credit growth.

The financial crisis of 2007 and 2008 has led to a wave of regulatory discussions that have culminated in the proposals from the Basel Committee as well the Vickers Committee report on Banking Regulation. It is now generally agreed that increasing core capital reduces the probability of a crisis occurring, and this underpins the regulatory toolkit. Work by Barrell et al (2009) and Barrell et al (2010) was the first to demonstrate that there is a statistically important role for (unweighted) capital in defending against the probability of a crisis occurring, and these findings were widely aired by the policy community in the debate over reform.

The new regulations (see Table 1) will raise common equity from the previous minimum of 1 per cent of risk weighted assets to at least 4.5 per cent, and loss absorbing equity (Tier 1) as a whole to 6 per cent. A conservation buffer of 2.5 per cent of risk weighted assets must also be built up with common equity; if this is exhausted in a crisis, the bank will be wound up. The maximum proportion of subordinated debt (Tier 2) is to be substantially reduced from 4 per cent to 2 per cent of risk weighted assets. A minimum ratio of capital to total (risk unadjusted) assets of 3 per cent must be held which will reduce banks' ability to undertake regulatory arbitrage to boost their leverage without changing measured risk weighted capital ratios. There is provision for a countercyclical capital buffer of up to 2.5 per cent of risk weighted assets, which is to be imposed at the discretion of the regulators.

Table 1 Capital requirements and buffers (all numbers in per cent)

	Common equity (after deductions)	Tier 1 capital	Total capital
Minimum	4.5	6.0	8.0
Conservation buffer	2.5		
Minimum + conservation buffer	7.0	8.5	10.5
Countercyclical buffer range	0-2.5		

Our main focus of discussion is the construction of the countercyclical buffer. The financial system has always been procyclical, with easy availability of credit boosting growth in the upturn and credit crunches often aggravating the downturn, and this feature was present notably in the subprime crisis. One underlying factor behind procyclicality is that provisions for loan losses are generally based on immediate risk of loss so capital cushions are not built up in advance of recessions. Saurina (2011) outlines experience of one of the first systematic macro prudential policies, which long predate the subprime crisis, namely the dynamic provisioning system applied in Spain since 2000. This built up a buffer of provisioning during economic boom periods, to be drawn on in periods of mounting loan losses which often occur in recessions. This system, he argues, has markedly enhanced the robustness of Spanish banks and of the system as a whole, although recent developments suggest it did not extend to the Caixa's, where lending quality was hard to monitor because of their integration with regional and local political structures. However, the buffer was released for output related countercyclical reasons in 2010-11 and when it was needed for macro=prudential countercyclical reason in 2011-12 it was already spent, and as a result the Spanish bank solvency crisis was worse than it would otherwise have been.

Whilst the tightening of capital standards is justified by empirical studies such as Barrell et al (2010), the countercyclical buffer as currently designed does not have such conclusive empirical backing. The problem lies in its construction which is contingent on the ratio of credit to GDP. The proposed 'indicator' variable for building (and running down) the buffer is the excess (or gap) of the ratio of credit to GDP compared to an Hodrick Prescott filtered trend. Concerns over the buffer are discussed in Repullo and Saurina (2012) who point out that the credit to GDP 'gap' is negatively related to GDP growth as credit tends to 'follow' GDP and hence it is likely to act in a perverse way in enhancing stability. They argue that the buffer will exacerbate the procyclicality of bank regulation, and that it would be better to have more forward looking provisioning. We argue that if the buffer were to reduce the probability of financial crises, then it could still be justified, and in some markets with significant financial rationing it may do so, but there is no evidence to support the contention that it will reduce the probability of crises in the OECD.

Although there are theoretical reasons as to why excessive credit growth can generate systemic instability, there is no conclusive evidence that credit variables raise banking crisis probabilities directly. The Signal Extraction Methodology (SEM) used by Borio and Drehmann (2009) and Borio et al (2010) to justify the buffer takes a large group of countries and looks for associations between single (or composite) indicators and the occurrence of crises. Optimal indicators are chosen by minimising variants of loss functions which are dependent on the noise-to-signal ratio (NTSR), which is a simplified version of the Receiver Operating Characteristics (ROC) analysis we use below.

For countercyclical provisioning against credit to be valid, SEM models based on credit should at least match the performance of logit models used in Barrell et al (2010) which excluded credit. However Barrell et al (ibid) could correctly call 75% of crises in the subprime period using a model estimated on data up until 2003 as compared 29% by the BIS study, with only 2% false calls in Barrell et al (2010) against 38% in the BIS study[2]. This superiority also translates to the type II error rate. At best, the model using the credit-to-GDP can identify 57% of crises out-of-sample but more than one in three times the signal will be a false alarm. In contrast, an OECD model which excludes credit can correctly predict 75% of crises out-of-sample with comparatively negligible cost: only 6% of signals will be false alarms.

Besides our own estimates, other papers also do not find conclusive evidence for the role of credit growth in generating financial instability. Mendoza and Terrones (2008) found that credit booms often link to banking crises in emerging market economies but less often in OECD countries. In a study of the Euro area and the US, Kaufmann and Valderrama (2007) note that "The mutually reinforcing effects of lending and asset prices contributing to the build-up of financial imbalances during boom periods is not confirmed in our model" for the Euro area[3]. Boyd et al (2001) investigate the behaviour of credit/ GDP ratios in 22 economies that experienced a single banking crisis and find unusual credit growth in only 6 of them whilst in 10 out of 21 economies rapid credit growth was not always followed by a crisis.

Aside from the methodology, the heterogeneous sample in the BIS proposal is potentially problematic since the same upper and lower buffer thresholds are applied to the OECD countries and to Latin American countries such as Brazil, Argentina and Mexico and Asian countries such as Indonesia. These banking systems operate very differently with OECD countries being financially liberalised, whilst the others are not. Hence different factors may affect the possibility of having a crisis. The research behind counter cyclical buffer proposal also includes Islamic banking systems (Saudi Arabia) alongside fundamentally different non-Islamic banking systems. One objective of this paper is to show that the determinants of banking crises differ between the OECD and emerging economies.

Early Warning Systems for Financial Crises

The literature has developed a number of distinctive multivariate Early Warning Systems (EWS) for banking crises, including logit (Demirguc Kunt and Detragiache, 1998; 2005) and the binary recursive tree as discussed in Davis and Karim (2008). The signal extraction approach (Kaminsky and Reinhart, 1999) differs by being univariate. Davis and Karim (2008) show logit to be the best of the three estimators whilst Hardy and Pasarbasioglu (1999) and Beck et. al. (2006) also demonstrate the merits of logit models. Accordingly we will adopt the logit approach to assess the role of credit and will use a binary banking crisis variable (1 for crisis, zero otherwise) based on the dating of Caprio et. al. (2003) and Laeven and Valencia (2010).

There are many potential and competing explanations for financial crises, and hence it is essential to estimate the effect of credit growth on banking crisis probabilities alongside a set of crisis determinants traditionally deemed important in the literature. This literature comprises two strands: the first class of logit crisis models estimated by Demirguc-Kunt and

[2] Even if we allow for the most generous (3 year) horizon, this model calls 18% more crises correctly.
[3] Although reinforcement occurs to an extent in the US market based banking system.

Detragiache (1998; 2005) and the second class of logit models by Barrell, Davis, Karim and Liadze (2010). The latter append new variables to the Demirguc-Kunt and Detragiache set of determinants for the OECD (1980 – 2006) and show that these "new" variables supersede the "traditional" determinants as OECD crisis predictors. We discuss the "new" variables first and then the "traditional" determinants.

The significant variables in Barrell, Davis, Karim and Liadze (2010) were unweighted bank capital adequacy[4] (bank capital/total bank assets), bank liquidity ratios (liquidity as a proportion of total bank assets) and real house price growth. The reasons for this result are twofold – originally, crisis models tended to exclude the new variables due to lack of data for global samples, and secondly, crisis determinants have been shown to differ across country groups (e.g. between Asia and Latin America, see Davis, Karim and Liadze, (2011)). In this paper (and in Barrell and Karim (2011)) we extend this analysis and include measures of capital and liquidity in the determinants of crises in these countries. However, data constraints require us to use risk weighted capital in Latin America and East Asia and hence we cannot 'pool' our two groups.

Capital adequacy and liquidity can be regarded as defences against crises, while historically low levels are commonly considered to be precursors to crises (Brunnermeier et. al., 2009). Capital is a buffer that protects banks against the variability of losses on non-performing loans which are a function of macro risks (e.g. interest rates and creditworthiness related to business cycle effects) and market risks (asset price depreciations and funding). Equally, liquidity ratios show the degree to which banks are robust to sudden demands for withdrawal by depositors or the lack of wholesale funds[5].

Crises are often the result of poor quality lending, especially in real estate markets, as is discussed in Reinhart and Rogoff (2008). Problems may emerge either in commercial or domestic property markets. Domestic property prices generally outperform commercial property prices in competing models, although the two are correlated. Unfortunately long runs of publically available commercial property prices are hard to find for most countries. In addition residential property prices are only available consistently for OECD countries hence we exclude them in this paper as we wish to maximise the comparability of results in our two pools.

Although current account data is widely available, it is not commonly employed in the empirical literature[6]. However, recent work by Jorda, Schularick and Taylor (2012) suggests national crises tend to be driven by current account imbalances and that for the post-Bretton Woods era, crisis related recessions are more strongly associated with current account

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[4] Often called "leverage". Aggregate data were obtained from the OECD Banking Income Statement and Balance Sheet data.

[5] In this paper, we use a narrow liquidity measure defined as a sum of banks' claims on general government and the central bank, while total assets comprise foreign assets, claims on general government, central bank and private sector. This measure is more legitimate (in terms of crisis prediction) than broad liquidity since the latter includes corporate securities which may actually become illiquid during a financial downturn, as in the subprime episode.

[6] Hardy and Pasarbasioglu (1999) estimated logit models of crises for both advanced and developing countries and found that the current account was not significant.

problems than normal recessions. Deficits may be accompanied by monetary inflows enabling banks to expand credit excessively and they also may accompany an overheating economy. This may both generate and reflect a high demand for credit, as well as boosting asset prices unsustainably. Current account deficits may also indicate a shortfall of national saving relative to investment and hence a need for banks to access the potentially volatile international wholesale market. Consequently, we also add the current account balance to our set of “new” crisis predictors.

To select our set of “traditional” determinants, we followed Demirguc-Kunt and Detragiache, (2005) who estimated over 1980-2002 for 94 countries with 77 crisis episodes[7]. We are selective amongst their variables in part because we want a common model for both our groups of countries. Their potential predictors included real GDP growth, the rate of growth of real domestic credit, the real short term interest rate, and inflation. We also utilise these general indicators of economic activity although we are forced to exclude real interest rates as reliable data is unavailable for Brazil, Argentina and Uruguay in our sample period because a number suffered from hyperinflations. They included the fiscal balance, the ratio of money to foreign exchange reserves, the change in the credit to GDP ratio, the dollar exchange rate and changes in the terms of trade. We utilise these variables, except for the terms of trade as this is more directly relevant to emerging markets than OECD economies[8].

Modelling Crises

Demirguc-Kunt and Detragiache (1998) first used the multivariate logit estimator to relate the probabilities of systemic banking crises to a vector of explanatory variables. Demirguc-Kunt and Detragiache (2005) updated the banking crises list to include more years, and more crises. We use the same dependent variable in our current work, updated by Laeven and Valencia (2010) in order that our analysis is comparable with most of that in the debate. The banking crisis dependent variable, a binary banking crisis dummy, is defined in terms of observable stresses to a country’s banking system. This may be indicated by the proportion of non-performing loans to total banking system assets exceeding 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

We use the cumulative logistic distribution which relates the probability that the dummy for crises takes a value of one to the logit of the vector of n explanatory variables:

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

[7] Beck et. Al. (2006) with a similar set of independent variables covered 1980-97, 69 countries and 47 episodes.

[8] For similar reasons, we also excluded Demirguc-Kunt and Detragiache’s measures of institutional quality: real GDP per capita, law enforcement and deposit insurance. Deposit insurance exists in all our OECD countries and thus the dummy would show no variation.

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 is used to obtain actual parameter estimates is given by:

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

The logistic EWS has the benefit of being easily replicable by policy makers concerned with potential systemic risk in their countries. Unlike many extant studies which use contemporaneous independent variables (e.g. Demirguc-Kunt and Detragiache, 1998; 2005), we lag all independent variables so as to obtain a valid EWS (see Barrell et. al, 2010).

We also test down from a general equation with all variables included to the simplest equation with all remaining significant variables. By definition, early warning systems rely on lagged explanatory variables so as to predict ahead and provide policymakers with opportunities for preventative action. To determine the best lag structure we applied either 1, 2 or 3 lags to all explanatory variables and ranked them on the basis of the models' AIC criteria. The 1-lag model performed the best, followed by the 2-lag model. However, a 1-lag model could not be used as an early warning system since our variables would only be reliably reported with delay and hence would not be available for forecasting purposes. Consequently we used the 2-lag model as the estimation starting point for all of our experiments on both the emerging markets and the OECD.

A priori, we made no assumptions regarding the relative importance of our crisis predictors, even though Barrell, Davis, Karim and Liadze (2010) showed the "new" determinants to be superior to the "traditional" ones. We therefore adopt a general to specific approach whereby a starting regression accommodating our full set of determinants (lagged 2) is used to iteratively delete the most insignificant variable during each subsequent round of regressions. None of our variables can be regarded as controls set there to prevent the data obscuring the role of the core variables of interest. All flow from competing hypotheses of the causes of financial crises, and we wish to test between these theories. In addition, we wish to contribute to the debate on the best defences against crises, and as such we would distinguish between taking preventive action to avoid crises, where we need to know the most significant determinants and perhaps change their settings well in advance to reduce the probability of occurrence, as compared to acting to forestall a crisis once it looks likely. These are two different 'public health' models, with the first being similar to immunisation programmes, whilst the latter is similar to diagnostic based reactions to specific symptoms, and they require different actions and hence different explanations of the problem.

Crises in OECD Economies

Our dataset includes 23 crises in OECD countries over the period 1980 to 2010. Over half the crises are from the World Bank Crisis Database covering 1974-2002, (Caprio et al 2003) as used in Barrell, Davis, Karim and Liadze (2010). For the crises episodes in 2007 and 2008 we have used the crises dates from Laeven and Valencia (2010), and we have crises in Canada in 1983, Denmark in 1987, the US in 1988, Italy and Norway in 1990, Finland, Sweden and

Japan in 1991, France in 1994, whilst in the UK there are crises in 1984, 1991 and 1995. Laeven and Valencia (2010) classified Belgium, Denmark, France, Germany, the Netherlands, Spain and Sweden in crisis by 2008 and the US and UK in 2007. The authors treat the 2008 crisis in the US and the UK as a continuation of 2007 crisis, while we treat it as separate crises since 2008 was induced by the collapse of Lehman Brothers.

We undertake three sets of experiments. The first is designed to directly test the BIS hypothesis on countercyclical buffers and uses the Hodrick Prescott filtered gap between credit and GDP using the same parameters as they do. We then look at the ratio of credit to GDP and then finally the growth in this ratio. We do not include them in the same model in order to clarify their role individually. The results of the sequential elimination process are reported in Table 2. We report on elimination until the variables included all have z statistics that are significant at the conventional 1 step 5% level. However, we should note that we have performed a sequence of tests, and we should be raising our standard in order to take account of this. Hence a probability of 0.116 for GDP growth lagged two periods in the first two models or a probability of 0.109 for the growth of credit to GDP in the third model are much worse than it would appear once the effect of sequencing is taken in to account. The remaining variables would continue to be significant even once the effects of a seven step sequence are taken in to account. It can be seen that throughout all stages of the elimination process, three variables (namely capital adequacy and liquidity ratios and the current account balance/GDP ratio) are consistently significant with limited variation in their parameters. The opposite is true for all the remaining variables, all of which were highly insignificant. It is noticeable that government budget balances as a per cent of GDP were not a factor influencing financial crisis probabilities in the period to 2008. Recent changes to the single financial market in Europe may have changed this relationship. The inflation rate is also eliminated in the process, suggesting that over the period it not raise crisis risks. In each case the credit to GDP indicator drops out, suggesting it cannot compete with capital, liquidity and the current account balance as an explanatory variable for the crises that have occurred in the OECD over the last three decades.

Although we have three different starting places for our models they all end up with the same parsimonious set. These results all show that in OECD countries, lower defences from less stringent bank regulation, along with current account imbalances were the most important factors driving the probability of a banking crisis occurring between 1980 and 2008. Although lax monetary policy and credit booms, however measured, may at times contribute to banking crises, they are not the most powerful discriminators between times of crisis onset and other periods in OECD countries. In accordance with regulators' suppositions, the coefficient on liquidity is negative so that the improved liquidity requirements of the latest round of regulations should have future crisis reducing effects in this region. Similarly attention to the current account deficit, which has steadily deteriorated in the OECD for much of our sample period, should promote future financial stability.

Table 2: OECD General to Specific Estimation, 1980 – 2008.

Panel 1 Credit to GDP Gap

	1	2	3	4	5	6	7	8
Liquidity Ratio(-2)	-0.11 (0.007)	-0.111 (0.007)	-0.115 (0.006)	-0.115 (0.006)	-0.137 (0)	-0.154 (0)	-0.155 (0)	-0.142 (0)
Capital Adequacy Ratio(-2)	-0.281 (0.004)	-0.294 (0.001)	-0.281 (0.001)	-0.272 (0.002)	-0.263 (0.002)	-0.277 (0.001)	-0.258 (0.002)	-0.193 (0.005)
Current Account Balance (% of GDP)(-2)	-0.222 (0.007)	-0.229 (0.004)	-0.243 (0.003)	-0.257 (0.001)	-0.242 (0.003)	-0.215 (0.005)	-0.216 (0.005)	-0.2 (0.008)
ΔGDP(-2)	0.179 (0.209)	0.177 (0.217)	0.147 (0.283)	0.197 (0.113)	0.22 (0.068)	0.214 (0.069)	0.185 (0.116)	
Credit to GDP Gap(-2)	3.868 (0.192)	3.718 (0.204)	3.415 (0.241)	3.69 (0.195)	3.993 (0.164)	3.685 (0.199)		
Inflation(-2)	-0.101 (0.197)	-0.1 (0.202)	-0.097 (0.215)	-0.085 (0.258)	-0.08 (0.286)			
Budget Balance (% of GDP)(-2)	0.054 (0.431)	0.058 (0.386)	0.061 (0.362)	0.073 (0.267)				
Δ Domestic Credit(-2)	0.041 (0.372)	0.04 (0.384)	0.038 (0.406)					
Exchange Rate(-2)	-0.006 (0.404)	-0.007 (0.386)						
M2 Money/ Forex Reserves(-2)	0 (0.736)							

Panel 2 Credit to GDP Ratio

Regression Number	1	2	3	4	5	6	7	8
Liquidity Ratio(-2)	-0.119 (0.005)	-0.119 (0.005)	-0.122 (0.004)	-0.139 (0.001)	-0.128 (0.001)	-0.132 (0.001)	-0.155 (0)	-0.142 (0)
Capital Adequacy Ratio(-2)	-0.326 (0.004)	-0.337 (0.002)	-0.337 (0.002)	-0.351 (0.001)	-0.28 (0.001)	-0.271 (0.001)	-0.258 (0.002)	-0.193 (0.005)
Current Account Balance (% of GDP)(-2)	-0.24 (0.004)	-0.246 (0.003)	-0.262 (0.002)	-0.238 (0.002)	-0.222 (0.004)	-0.233 (0.002)	-0.216 (0.005)	-0.2 (0.008)
ΔGDP(-2)	0.128 (0.364)	0.129 (0.366)	0.171 (0.197)	0.167 (0.196)	0.185 (0.144)	0.163 (0.179)	0.185 (0.116)	
Budget Balance (% of GDP)(-2)	0.073 (0.297)	0.077 (0.268)	0.089 (0.185)	0.084 (0.203)	0.071 (0.259)	0.073 (0.251)		
Exchange Rate(-2)	-0.01 (0.265)	-0.01 (0.275)	-0.011 (0.235)	-0.011 (0.244)	-0.005 (0.471)			
Domestic Credit/ GDP(-2)	0.543 (0.327)	0.48 (0.369)	0.589 (0.256)	0.582 (0.259)				
Inflation(-2)	-0.089 (0.243)	-0.088 (0.248)	-0.076 (0.297)					
Δ Domestic Credit(-2)	0.037 (0.442)	0.037 (0.443)						
M2 Money/ Forex Reserves(-2)	0 (0.679)							

Panel 3 Credit to GDP Growth

Regression Number	1	2	3	4	5	6	7	8
Liquidity Ratio(-2)	-0.112 (0.006)	-0.113 (0.006)	-0.11 (0.007)	-0.114 (0.006)	-0.107 (0.007)	-0.126 (0)	-0.145 (0)	-0.142 (0)
Capital Adequacy Ratio(-2)	-0.287 (0.004)	-0.289 (0.002)	-0.281 (0.002)	-0.271 (0.002)	-0.245 (0.002)	-0.236 (0.003)	-0.248 (0.001)	-0.193 (0.005)
Current Account Balance (% of GDP)(-2)	-0.226 (0.006)	-0.228 (0.004)	-0.228 (0.005)	-0.241 (0.003)	-0.23 (0.003)	-0.213 (0.006)	-0.187 (0.011)	-0.2 (0.008)
Δ Domestic Credit/ GDP(-2)	0.053 (0.347)	0.053 (0.349)	0.048 (0.299)	0.046 (0.319)	0.061 (0.144)	0.072 (0.07)	0.06 (0.109)	
Inflation(-2)	-0.06 (0.46)	-0.06 (0.463)	-0.091 (0.232)	-0.09 (0.241)	-0.093 (0.219)	-0.095 (0.212)		
Budget Balance (% of GDP)(-2)	0.064 (0.337)	0.065 (0.326)	0.063 (0.345)	0.065 (0.329)	0.067 (0.308)			
ΔGDP(-2)	0.136 (0.342)	0.136 (0.343)	0.132 (0.349)	0.109 (0.42)				
Exchange Rate(-2)	-0.005 (0.479)	-0.005 (0.474)	-0.006 (0.44)					
Δ Domestic Credit(-2)	-1.355 (0.731)	-1.372 (0.727)						
M2 Money/ Forex Reserves(-2)	0 (0.957)							

Note: *,**,*** indicate significance on 90%,95%,99% levels correspondingly
P-values in parentheses, (-2) indicates a variable is lagged by 2 years.

In each case the coefficient on capital is also negative and significant. This reflects the crisis reducing effect of standard capital defences against deteriorations in asset quality and to this extent the increased requirements in core capital ratios and the conservation buffer under Basel III should have beneficial effects. However, by definition, our capital ratios do not capture the impacts of countercyclical buffers.

Table 3: In sample performance of the OECD model

	Estimated Equation		
	Dep=0	Dep=1	Total
P(Dep=1)<=0.061	232	7	239
P(Dep=1)>0.061	123	16	139
Total	355	23	378
Correct	232	16	248
% Correct	65	70	66
% Incorrect	35	30	34

Note: The in sample proportion of crisis years (0.061) is the cut-off probability; "Dep" is the (binary) dependent variable

We check the in-sample performance of the final model, which is the same in each case, using the sample average crisis rate as a cut off. As shown in Table 3, the false call rate when there is no crisis[9] is 35% and the false call rate when there is a crisis[10] is 30%. The overall successful call rate (both crisis and no crisis called correctly) is 66%, with 16 out of the 23 (or 70 %) crisis episodes captured correctly at a cut-off point of 0.061[11]. These results stand up well against the wider literature. For example, Demirgüc-Kunt and Detragiache (2005) 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 0.05 for their most preferred equation.

During the subprime period there is only one genuine false call in Canada, and a failure to call Germany, where the purchase of low quality US ABS to hold on balance sheet was the source of the losses that induced the crisis. Crises are called in Belgium, Denmark, France, Italy, the Netherlands, Sweden, Spain, the UK and the US, suggesting that the explanation is sound. Looking in more detail at the in-sample performance of the model and specifically at false alarms (Type II errors), more than 30% of them occur in the three years prior to the onset of the crisis, indicating that our model, as well as identifying crises, is able to differentiate well between periods of financial stability and instability.

Crises in Developing Economies

Our data covers the years 1980 – 2010 for eight Latin American and six Asian economies: Argentina, Brazil, Chile, Mexico, Panama, Peru, Uruguay, Venezuela, Indonesia, Korea, Malaysia, Philippines, Singapore and Thailand. Whilst this country selection is dictated by data availability, it covers the major crisis incidents in both regions. Our main variables of interest, capital and liquidity, have not been used as EWS inputs in emerging markets. Of the two, capital poses the greatest problem since even for developed countries there is a lack of internationally comparable reporting prior to 1980. Barrell et. al. (2010) utilised capital adequacy ratios obtained for OECD countries but even OECD data coverage limited the sample to 14 countries for the post-1980 years. Outside the OECD, country coverage is much worse; for emerging market economies especially, international financial institutions such as the IMF or World Bank do not list capital adequacy data consistently before 1998[12].

In order to examine the role of capital in emerging market crises, we constructed a dataset for regulatory capital. Whilst regulators may not have appreciated the importance of capital ratio data during the 1980s, the banking industry itself understood the central role capital plays in bank health and thus continually surveyed this variable. We exploit this fact by utilising an industry publication, "The Banker" which has an international focus. The Banker has annually surveyed the top 1000 banks in the world since 1989 and the top 500 global banks

[9] known as the Type II error
[10] known as the Type I error
[11] Calculated as the sample mean for onset of crises i.e. 23/378. We could of course use some other cut off point for the crisis call, and this should depend on the weightings in the loss function for a false call when there is no crisis to the loss from failing to call an actual crisis. If we wished to set a cut off to call all crises then we would have around 283 false calls when there is no crisis.
[12] Capital ratios start to be systematically reported by the IMF in their Global Financial Stability Reports from 1998 onwards, possibly in response the Asian and Latin American crises which would have highlighted the lack of available data for analysis.

from 1980 – 1989. We use the Bank of International Settlements (BIS) Regulatory Capital Ratios reported by the Banker to construct our regulatory capital variable[13].

The BIS Capital Ratio is a comparable measure across banks that were required to calculate capital adequacy according to BIS rules. However coverage may be an issue because not all banks in our emerging market countries will have entered the top 1000 global bank list. Nevertheless, it is reasonable to assume that where a bank did enter the list, it would have been systemically important (in the "too-big-to-fail" sense) and thus its capital ratio would be correlated with the health of the financial system. Hence although our capital data may not contain all the variance associated with a particular banking system, it should be broadly representative of its capital soundness. From 1998 onwards, we revert to the IMF's Global Financial Stability Reports to obtain capital adequacy ratios for the entire banking system. Like The Banker, these data are risk weighted according to BIS regulatory requirements.

We use the Barrell et al (2010) definition of liquidity and the IMF's International Financial Statistics database to create the variable. This is a narrow liquidity definition because of the exclusion of claims on the private sector. During the Asian crises, capital flight would have reduced the marketability of corporate securities, rendering them illiquid. Hence a narrow liquidity measure is more representative of the liquidity position of banks during crises. The remaining variables that enter our EWS are the more traditional set of determinants as discussed previously. These data were obtained from the IMF and World Bank.

To date our crises, we rely on Demirguc-Kunt and Detragiache (2005) where a systemic crisis is recorded if one or more of the following conditions pertain in a given year: non-performing loans/ total banking system assets exceeded 10%, or public bailout costs exceeded 2% of GDP, or systemic crisis caused large scale bank nationalisation, or extensive bank runs were visible and if not, emergency government intervention occurred.

Based on these criteria, our dependent variable contains 23 systemic crisis episodes; 14 of which occurred in Latin America and 9 in Asia. A concentration of crises occurs in the early 1980s (predominantly in Latin America), the early to mid 1990s (Latin America) and the late 1990s (Asia). Only 2 crises occur after 1998 (Argentina and Uruguay) and none occur after 2002. The countries with crises were Argentina (1980, 1989, 1995, 2001), Brazil (1990, 1994), Chile (1981), Mexico (1982,1994), Panama (1988) Peru (1993), Uruguay (1981, 2002), Venezuela (1993), Indonesia (1992, 1997), South Korea (1997), Malaysia (1983, 1997) Philippines (1981, 1998), Singapore, and Thailand (1983, 1997) Once a crisis ensues it will impact on the explanatory variables either directly or due to associated policy responses.

The sample results (Table 4) are divided in to three panels. When we include the credit to GDP gap until it is excluded at the fifth stage, and is never near significance. At the end of the process we are left with a three variable model. If we include the ratio of credit to GDP, which is in panel 2, then it remains in the model, and we retain four, including the three variables in the previous model. As such this would appear to dominate the first. In the third

[13] The Banker data is not available electronically for our sample and hence manual transcription of the BIS ratios was required.

panel we include the growth of credit to GDP and we show 6 sequential variable deletions culminating in a 5 variable equation. We include all three variables from the first model, and also include an indicator of foreign exchange cover which may be relevant in credit constrained countries. Given the discussion above of the impact of a sequence of tests on significance levels it would be possible to eliminate the current account from this sample as well, making the separation of causes much clearer between the two groups of countries. However, we leave the variable in our final equation. The variable deletions themselves are of interest since they suggest changes in GDP growth, inflation, domestic credit and the exchange rate do not significantly affect crisis probabilities. The final specification is able to identify 71% of crises. This is associated with a cost of 36% false alarms so that our emerging market model marginally outperforms the OECD model in terms of crisis prediction but is fractionally worse in terms of false alarms (36% as opposed to 35%). We should note that three of the 'unforeseen' crises occurred in Argentina where the factor driving problems were often political not economic[14]. We do not replicate table 3 as the models all arrive at different solutions, and the ROC curve analysis below helps us arbitrate between them

Table 4: Latin America and Asia General to Specific Estimation, 1980 – 2008.

Panel 1 Credit to GDP Gap

	1	2	3	4	5	6	7	8
Liquidity Ratio(-2)	-0.054 (0.001)	-0.055 (0.001)	-0.049 (0.001)	-0.049 (0)	-0.048 (0)	-0.048 (0)	-0.048 (0)	-0.054 (0)
Capital Adequacy Ratio(-2)	-0.176 (0.003)	-0.175 (0.002)	-0.213 (0)	-0.226 (0)	-0.224 (0)	-0.227 (0)	-0.242 (0)	-0.249 (0)
Current Account Balance (% of GDP)(-2)	-0.095 (0.048)	-0.094 (0.042)	-0.082 (0.06)	-0.079 (0.067)	-0.08 (0.063)	-0.078 (0.068)	-0.07 (0.084)	-0.08 (0.057)
Exchange Rate(-2)	0 (0.285)	0 (0.283)	-0.001 (0.236)	-0.001 (0.217)	-0.001 (0.216)	-0.001 (0.209)	-0.001 (0.176)	
ΔGDP(-2)	-0.054 (0.306)	-0.053 (0.29)	-0.034 (0.486)	-0.034 (0.48)	-0.039 (0.412)	-0.032 (0.488)		
Credit to GDP Gap(-2)	-0.046 (0.369)	-0.046 (0.365)	-0.037 (0.435)	-0.037 (0.425)	-0.038 (0.42)			
Inflation(-2)	0 (0.555)	0 (0.553)	0 (0.544)	0 (0.559)				
M2 Money/ Forex Reserves(-2)	-0.048 (0.368)	-0.049 (0.351)	-0.024 (0.61)					
Δ Domestic Credit(-2)	0 (0.82)	0 (0.825)						
Budget Balance (% of GDP)(-2)	0.007 (0.938)							

[14] The other two unforcastables are Peru and Thailand in 1983

Panel 2 Credit to GDP Ratio

Regression Number	1	2	3	4	5	6	7
Liquidity Ratio(-2)	-0.053 (0.002)	-0.053 (0.002)	-0.047 (0.002)	-0.047 (0.002)	-0.046 (0.002)	-0.049 (0)	-0.052 (0)
Domestic Credit/ GDP(-2)	-0.019 (0.027)	-0.019 (0.017)	-0.019 (0.015)	-0.019 (0.012)	-0.019 (0.011)	-0.018 (0.012)	-0.021 (0.003)
Capital Adequacy Ratio(-2)	-0.11 (0.076)	-0.108 (0.075)	-0.13 (0.03)	-0.132 (0.027)	-0.131 (0.027)	-0.128 (0.026)	-0.12 (0.032)
Current Account Balance (% of GDP)(-2)	-0.11 (0.04)	-0.11 (0.04)	-0.099 (0.053)	-0.098 (0.05)	-0.097 (0.05)	-0.088 (0.066)	-0.097 (0.05)
Exchange Rate(-2)	0 (0.434)	0 (0.435)	0 (0.387)	0 (0.363)	0 (0.358)	0 (0.344)	
Budget Balance (% of GDP)(-2)	0.08 (0.438)	0.076 (0.444)	0.063 (0.508)	0.06 (0.512)	0.059 (0.521)		
Inflation(-2)	0 (0.635)	0 (0.629)	0 (0.619)	0 (0.585)			
ΔGDP(-2)	-0.027 (0.621)	-0.027 (0.625)	-0.006 (0.906)				
Δ Domestic Credit(-2)	0 (0.886)	0 (0.895)					
M2 Money/ Forex Reserves(-2)	0.007 (0.891)						

Panel 3 Credit to GDP Ratio

Regression Number	1	2	3	4	5	6
Capital Adequacy Ratio(-2)	-0.163 (0.005)	-0.162 (0.005)	-0.161 (0.005)	-0.166 (0.003)	-0.181 (0.001)	-0.179 (0.001)
Δ Domestic Credit/ GDP(-2)	0.06 (0.036)	0.059 (0.037)	0.061 (0.032)	0.062 (0.026)	0.06 (0.034)	0.064 (0.026)
Liquidity Ratio(-2)	-0.054 (0.004)	-0.054 (0.003)	-0.054 (0.003)	-0.055 (0.002)	-0.05 (0.003)	-0.052 (0.002)
M2 Money/ Forex Reserves(-2)	-0.167 (0.031)	-0.167 (0.03)	-0.167 (0.03)	-0.172 (0.023)	-0.164 (0.03)	-0.193 (0.011)
Current Account Balance (% of GDP)(-2)	-0.082 (0.098)	-0.082 (0.098)	-0.082 (0.101)	-0.076 (0.106)	-0.082 (0.069)	-0.091 (0.05)
Exchange Rate(-2)	0 (0.392)	0 (0.379)	0 (0.377)	0 (0.363)	0 (0.365)	
Budget Balance (% of GDP)(-2)	-0.05 (0.633)	-0.051 (0.628)	-0.052 (0.624)	-0.067 (0.485)		
ΔGDP(-2)	-0.017 (0.76)	-0.017 (0.758)	-0.019 (0.731)			
Inflation(-2)	0 (0.798)	0 (0.788)				
Δ Domestic Credit(-2)	0 (0.854)					

Note: *,**,*** indicate significance on 90%,95%,99% levels correspondingly
P-values in parentheses, (-2) indicates a variable is lagged by 2 years

The second specification suggests that the ratio of credit to GDP may be important in these countries. The final specification suggests the most important determinants of combined Latin American and Asian crises are: changes in domestic credit/ GDP, bank capital adequacy and liquidity and adds in the ratio of M2 to foreign reserves and the current account balance. An improvement in the M2 to reserves ratio, the capital and liquidity soundness of banks and the current account reduces the likelihood of systemic bank failures while an increase domestic credit relative to GDP raises the failure probability. This latter result is significant in terms of our objectives, as this variable was eliminated in the OECD sample. It suggests that curbing the growth in credit to GDP may have some benefits in emerging markets that have been financially liberalised more recently than the OECD.

Credit Constraints, Financial Liberalisation and the Policymaker's Options

The level or growth of the ratio of credit to GDP appears to be a significant determinant of crises in Latin America and East Asia, but it does not influence the probability of a crisis in OECD countries. In general we may say that OECD financial markets have been largely deregulated in the last 25 years, and hence there have been few constraints on borrowing. Barrell and Davis (2007) look at the impact of financial liberalisation on consumption and generally conclude that it was removed by the mid 1980s, and perhaps a little later in some Scandinavian countries. They give the Swedish liberalisation date as 1985 and Abaid et al (2008) show that although there was also a round of liberalisation in Finland in the mid 1980s, financial liberalisation actually peaked in 1993. Jonung (2008) notes how liberalisation in these economies fundamentally affected credit availability. The financial markets in our sample of East Asian and Latin American economies still exhibit significant credit constraints, and hence they behave differently. If perceptions of future income growth or of future assets prices change then in a market without credit constraints borrowing will increase independently of other factors. If these perceptions are shared by borrowers and lenders but are unfounded then bad lending may take place. In markets with credit constraints, borrowers and lenders are unlikely to be able to respond to these changes in perceptions. Hence it is not surprising that different determinants of financial crises emerge in these two sets of markets.

Given the estimation process, the results suggest some crises are idiosyncratic in the sense that a given variable may explain specific episodes but may not contribute to a general understanding of the causes of crises. At the penultimate stage of the elimination process, credit to GDP is marginally insignificant at conventional levels (although less so given the impact of a sequence of tests on the probability of a Type 2 error). Hence its role cannot be ignored, but it is not the best instrument to manipulate for maintaining financial stability and therefore, the consequences of the countercyclical buffer proposals may in some cases be unexpected. If credit to GDP growth is not the primary cause of some crises, then forcing banks to provision against it may tax them unnecessarily, curtail credit availability, and hurt growth.

The policymaker's objectives are similar to those of a clinician who selects a set of variables depending on whether they are concerned with forecasting if a patient will develop a disease or diagnosing it once symptoms have manifested. In the former case, the model's ability to discriminate between patient classes is important, but this metric may not yield the best diagnostic model (Cook, 2007). The latter leads to curative care which may be costly, hence the value of many different indicators should be examined to make a diagnosis. Conversely, for relatively little cost, the policymaker may wish to immunise the population against the disease. The trade-off between type I and II errors becomes important because a model which raises crisis prediction accuracy necessarily generates a higher false call rate and could elicit unnecessary costs of intervention. Hence an immunisation model should optimise the trade-off between model accuracy and the number of instruments; if the set of instruments can be reduced without compromising the informational content of a model then the toolkit becomes simpler and less costly. Immunisation models can be selected on the basis of their Receiver Operating Curve characteristics which we discuss next.

Model Selection and the use of ROC Curves

Receiver operating characteristic (ROC) curves test the "skill" of binary classifiers and hence can be used to discriminate between competing models. In the context of logit estimators, probabilistic forecasts can be classified for accuracy against a continuum of thresholds. This generates a true positive rate and true negative rate for each threshold and correspondingly a false positive and false negative rate. In the terminology of ROC analysis, the two variables of interest are: sensitivity (true positive rate) and 1 – specificity (which is equal to the false positive rate). Sensitivity is plotted on the y-axes and 1 – specificity on the x- axes, as shown in Figure 1. At a threshold of predicted probability of a crisis being 0.001 almost all crises would be correctly called, because they have a probability in excess of this low number in the model. However, almost all other periods would face a false positive call and we would see ourselves at the top right hand corner of the diagram. As the cut off threshold falls the true positive rate falls, but in a good model it falls much less rapidly than the false positive rate.

The true positive and false positive rates encapsulate the correspondence between probabilistic forecasts and actual binary events and generate a two dimensional co-ordinate in the ROC space. In turn, the mapping between these co-ordinates and the thresholds (or decision criterion), define the ROC curve. Hence ROC curves are closely associated with the "power" of a binary predictor[15].

ROC curves have been widely used in medical research and are considered to be the most comprehensive measure of diagnostic accuracy available[16]. This is because they impound all combinations of sensitivity and specificity that the diagnostic test can provide as the decision criterion varies (Metz, 2006). Since false positive and false positive errors have very different costs in clinical terms, evaluating a predictor based solely on true positive rates can be inefficient. Similarly, in the context of early warning systems for crisis prediction, these two errors will have different social consequences; an EWS that has a high level of sensitivity at

[15] In practice, the ROC curve is rarely "smooth" as drawn in Figure 1 since the relationship between the true positive and false negative rates to the threshold is not necessarily monotonic over the range of thresholds.
[16] For a recent example of ROC curve usage in the context of crises, see Schularick and Taylor (2012).

the cost of high false positive rates may lead to "tail events" being missed with commensurate economic costs.

Since the true positive and false positive rates are functions of the threshold, a policy makers' risk attitude to crises may influence the choice of threshold and thus optimal model. Moreover once this optimal threshold is selected, an increase or decrease in the prevalence of crises will not affect the true positive or false negative rates. Thus the ranking of models based on ROC curves will vary depending on the chosen threshold range which in turn is a function of the policy maker's preferences.

To separate out preferences from the decision making process, an alternative but related "global" measure of model skill can be used to select between competing models: the Area Under the Curve (AUC). If the true positive rate declines more slowly than the false positive rate when the threshold is raised then the AUC is above a half. The larger the difference between these two rates of decline the higher the AUC. This avoids evaluating or the ranking of models at particular thresholds. An AUC of 0.5 is equivalent to a "naïve" estimator that replicates a random coin toss (corresponding to the 45^0 line) so an AUC above 0.5 implies the model adds value in terms of the ability to call crises correctly with low false negative rates.

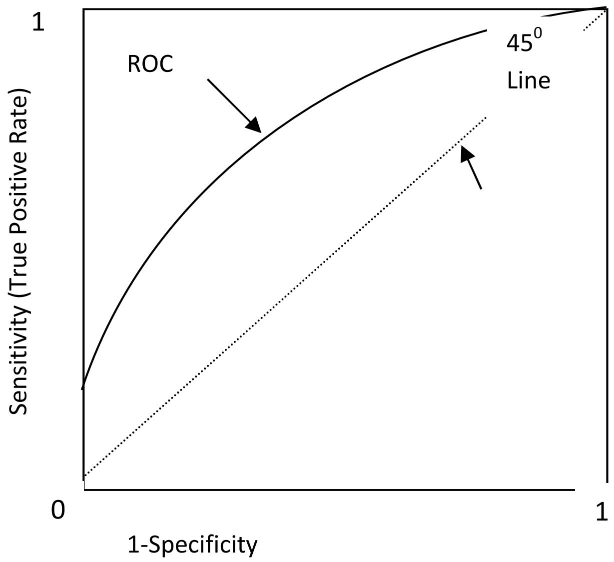


Figure 1: Receiver Operating Characteristic Curves

Table 6: Area Under the Curve (AUC) and model skill

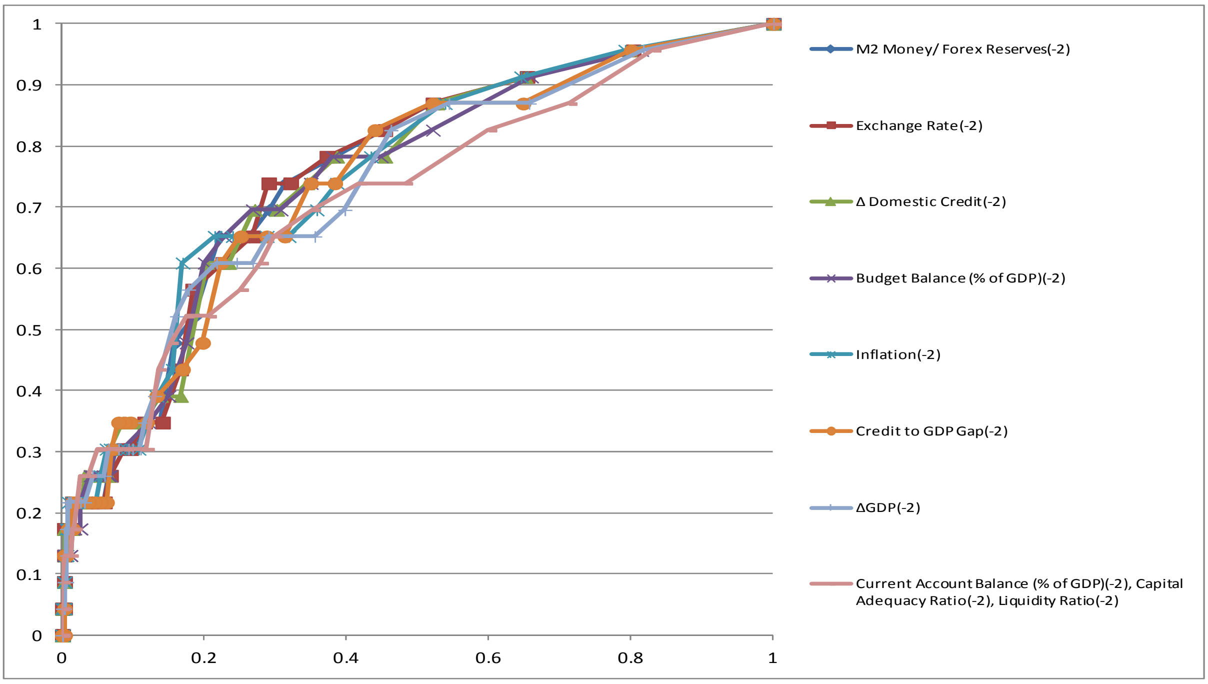
AUC = 0.5	No discrimination (equivalent to coin toss)
$0.7 \leq$ AUC < 0.8	Acceptable discrimination
$0.8 \leq$ AUC < 0.9	Excellent discrimination
AUC ≥ 0.9	Outstanding discrimination (not possible in logit frameworks)

Source: Hosmer and Lemeshow, (2000)

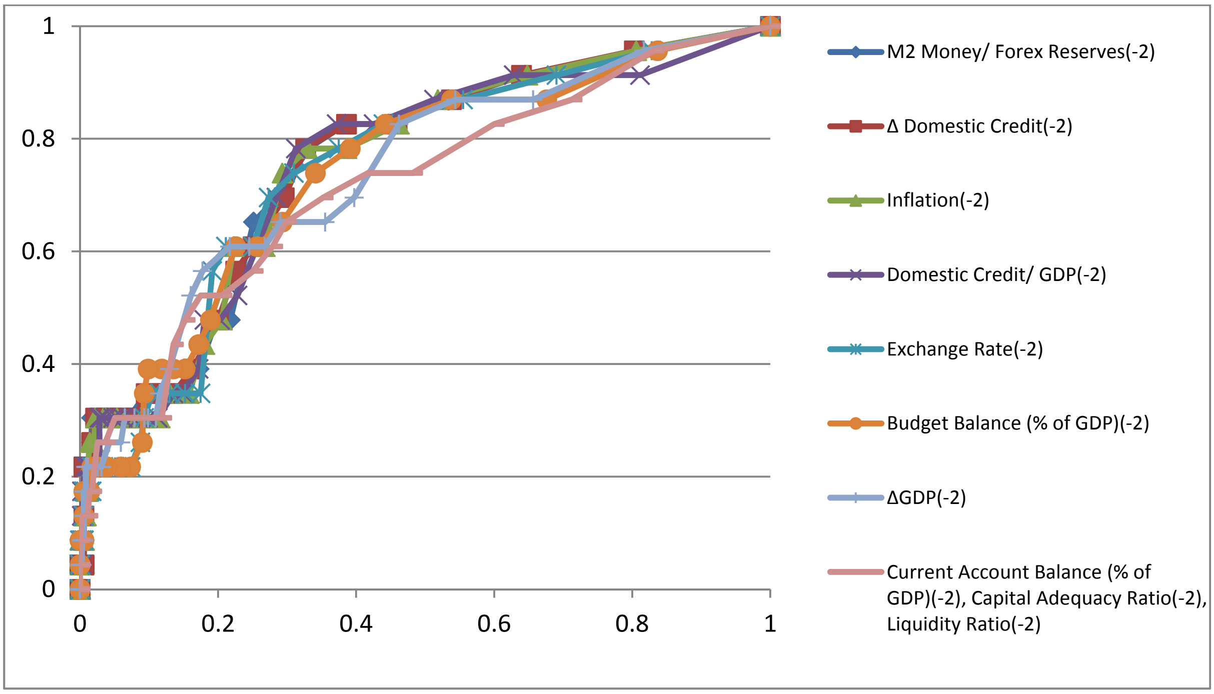
Table 6 indicates discrimination performance in terms of the AUC. Hosmer and Lemeshow (2000) indicate that an AUC ≥ 0.9 is highly improbable for logit models since this level of discrimination would require complete separation of the crisis and non-crisis event and the logit coefficients could not be estimated. Hence for our EWS approach we would accept models with AUCs ≥ 0.7. The AUCs for our competing models are given in Table 7 whilst the corresponding ROC curves are given in figures 2 and 3.

Figure 2: ROC Curves for the OECD Models

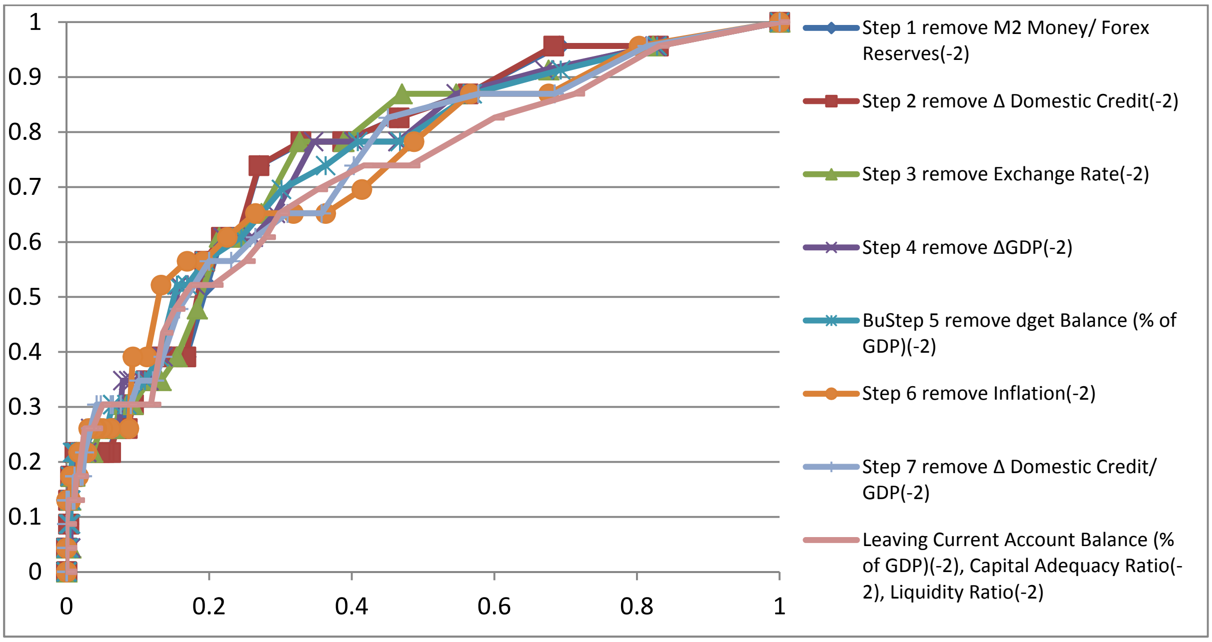
Panel 1 Credit to GDP Gap



Panel 2 Credit to GDP Ratio



Panel 3 Credit to GDP Growth

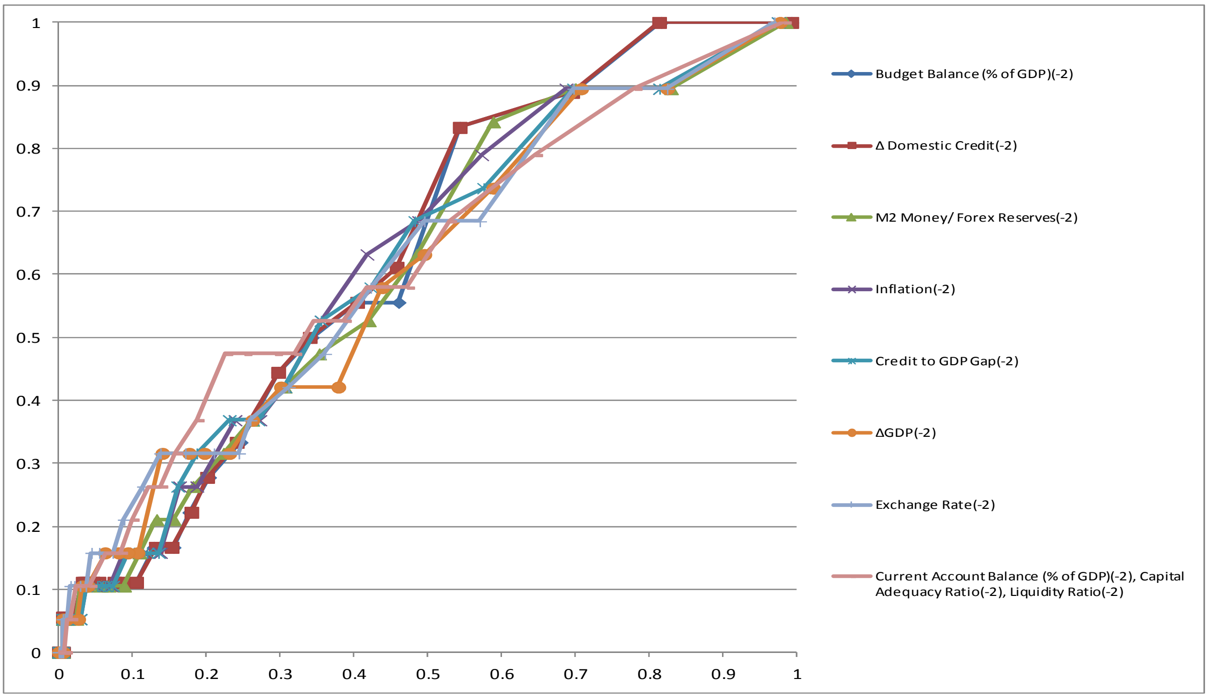


We plot ROC curves for each of the three models for the OECD countries and then for the Emerging Markets. In each case we plot a ROC curve for each step in the elimination. If one ROC is inside another then it is clearly dominated by the one further out, which has a lower generalised Signal to Noise Ratio. However, it is not always the case that it is clear which model dominates. At low cut off thresholds the 'final model is not as good as the others, but as the threshold rises its relative performance improves. A more complicated method of judging overall signal to noise ratios is clearly required, and this is reported in table 6 where we have the sequence of AUCs for the three OECD models. As they all end up with the same model they have the same AUC at an acceptable level of 72, and in each case the addition of the penultimate variable raises the AUC to 74. In two cases this is the growth of GDP, and in the third it is the growth of credit to GDP (which is related). The AUC is unchanged when we remove the credit gap in the first experiment and the ratio of credit to GDP in the second and hence their generalised signal to noise ratio is low. Only in the case of the growth of credit to GDP is there an impact on the AUC, and a case may be made for monitoring it in the OECD. However, Barrell et al (2012) show that either the increase in off balance sheet activity or the growth of house prices (lagged 3 periods) is superior to this variable.

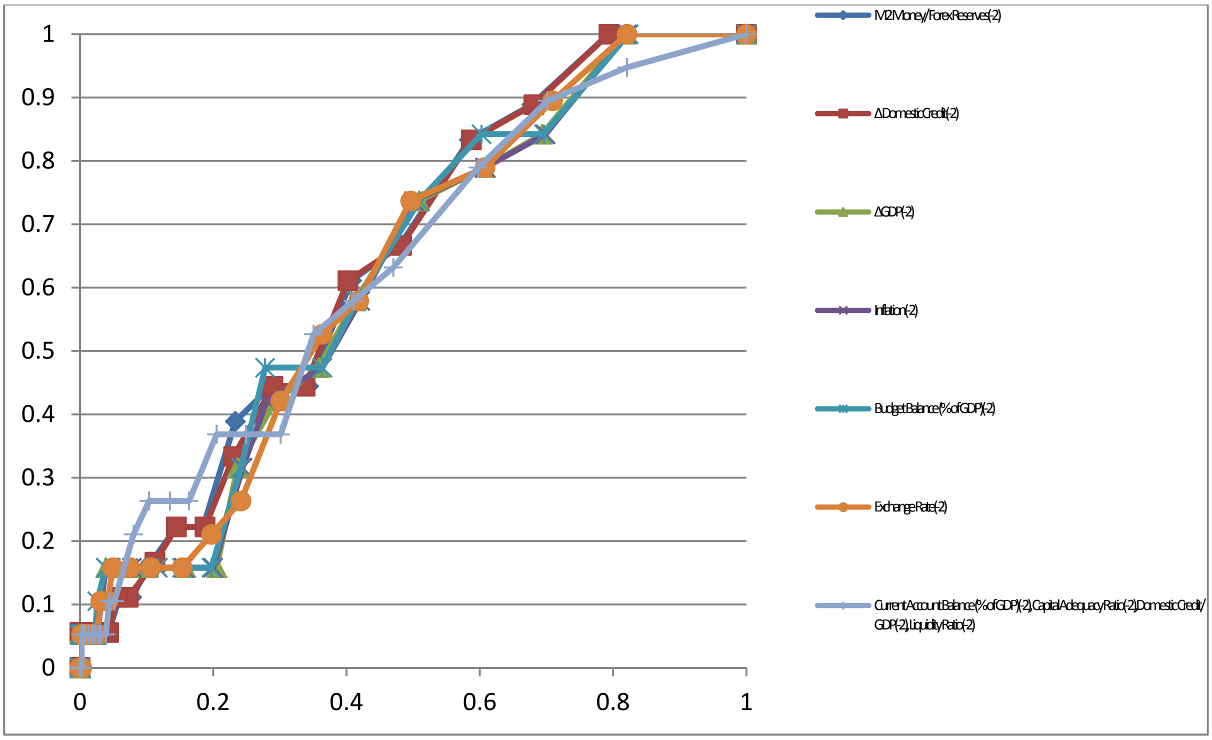
The ROC curves for Latin America and East Asia look generally much flatter than do those for the OECD countries, and the models are disparate in their end points. In general within each experiment no model is dominant at all thresholds, with ROC curves crossing. And the final parsimonious model does not look in any way worse than the steps toward it. As we can see from Table 7 the model with the credit to GDP gap in it at the start has AUC values that are very low, so the generalises signal to noise ratio is high with this variable. At the point where the gap drops out the AUC is 59 and falls to 58. If we include the ratio of credit to GDP this stays the model, and the AUC hovers around 63, which is lower than really acceptable, and not greatly better than coin toss. The model with the growth of credit to GDP is noticeably better, with an AUC of around 70, and this is at a relative maximum when we reach the most parsimonious model.

Figure 3: ROC Curves for the Latin America and Asia Models

Panel 1 Credit to GDP Gap



Panel 2 Credit to GDP Ratio



Panel 3 Credit to GDP Growth

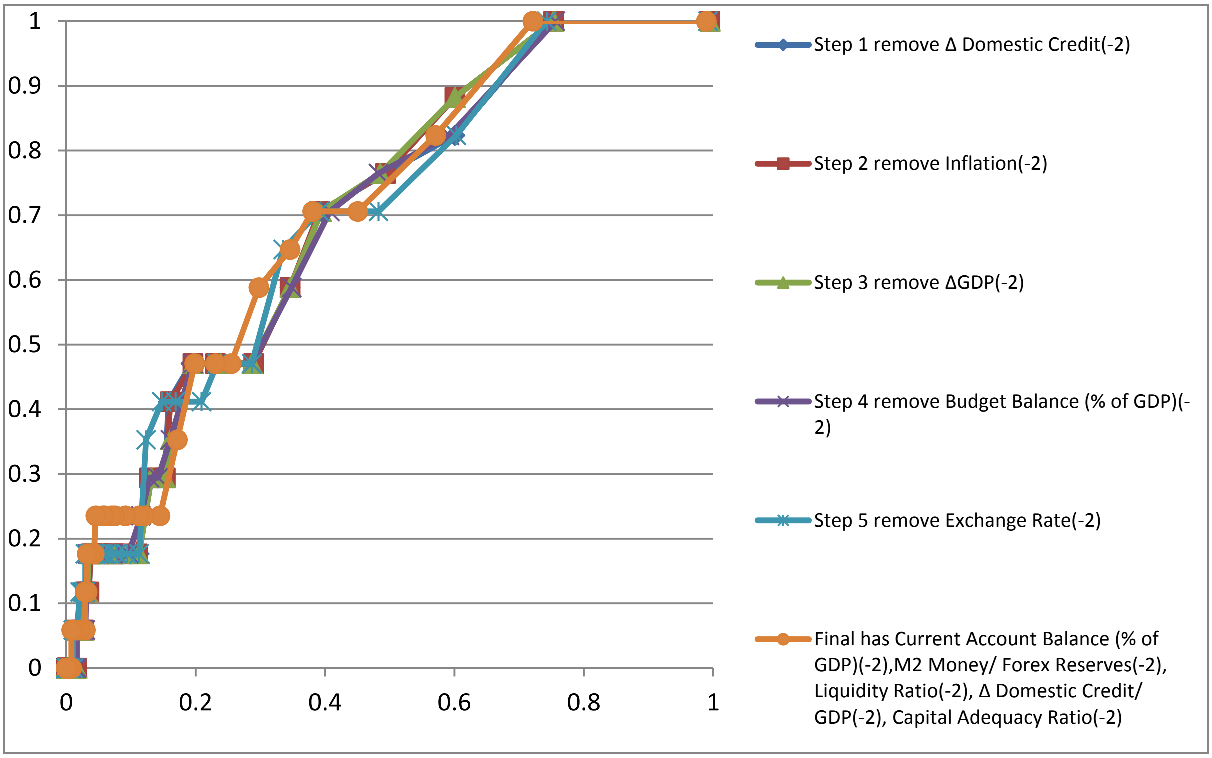


Table 7: Area Under the Curve (AUC) for general to specific estimations

Regression Number	1	2	3	4	5	6	7	8
OECD *Credit to GDP Gap*	0.76	0.76	0.76	0.75	0.75	0.74	0.74	0.72
OECD *Credit to GDP Ratio*	0.76	0.76	0.75	0.75	0.75	0.74	0.74	0.72
OECD *Credit to GDP Growth*	0.76	0.76	0.76	0.75	0.75	0.74	0.74	0.72
LA and EA *Credit to GDP Gap*	0.63	0.63	0.60	0.60	0.59	0.58	0.59	NA
LA and EA *Credit to GDP Ratio*	0.64	0.64	0.62	0.62	0.63	0.63	0.63	NA
LA and EA *Credit to GDP Growth*	0.69	0.70	0.70	0.69	0.69	0.70	NA	NA

Note: NA indicates not applicable

If we wished to immunise the financial system against crises we would select the variables in the final models as candidates for further investigation. This suggests that countercyclical buffers may, subject to further investigation, have a regulatory role in Latin American and Asian banking systems but they could be counterproductive in the OECD. Clearly capital and liquidity should play a role in any strategy, as they are clearly warning indicators, and also have a clear causal role (which we do not address) in relation to crisis prevention. In ORCD countries there is also a case for feeding policy back off current account imbalances to reduce the risk of financial crises. This would mean raising capital in a calibrated way in response to an increased current account deficit, and releasing the capital slowly some years after the deficit has disappeared. We know from Barrell et al 2012 that responding to property price booms and changes in off balance sheet activity would also be good countercyclical buffer triggers. There might also be a case for responding to the growth of credit to GDP, but this has to be seen as a second order response. It is far more important in emerging markets where there are credit constraints, where the risks of sharp currency movements that might flow from inadequate reserves should also indicate that the ratio of M2 to reserves should act as a trigger. In no case can we see a role for the credit to GDP gap, despite its prominence in BIS work and its role in current legislation.

Conclusion

We have constructed early warning systems for the OECD and emerging markets using variables that can be directly influenced by policy makers in the latter for the first time. We then test for the crisis inducing role of credit in both regions. In contrast to previous work, we include all variations of credit that have been cited in the literature to comprehensively examine the validity of the BIS countercyclical buffers. There is little evidence that the credit to GDP gap, the ratio of credit to GDP or credit growth are factors affecting the incidence of crises in OECD countries, although the last two may have a role in crisis determination in emerging markets. Hence there is inadequate justification to provision against credit growth in the countercyclical buffer. Our results imply that in the OECD at least, this could ration credit to sectors with good growth opportunities. Given the importance of the credit to GDP gap in the current macroprudential framework it is important that it is augmented by a number of other indicators that policy makers can use to absorb shocks. These should of course have a sound empirical basis as precursors of financial crises. We have found these variables to include the current account balance amongst others.

In order to discriminate between competing hypotheses and extend the recent literature on crisis models we utilise ROC curve analysis which allows policy makers to select between competing hypothesises based on their preferences. We argue that ensuring financial stability generates social costs, and policies that increase stability must be judged against those costs. The problem faced by the policy maker is not dissimilar to many public health choices where tradeoffs between false negatives (type I) and false positives (type II errors) become important. A remedy based on a procedure that minimises false negatives may be too much of a catch all and will generate too many false calls. The policy maker needs to choose between action beforehand to reduce the probability of the event happening and acting only when a signal is emitted. Action beforehand may be likened to immunisation, whilst acting once a signal is emitted is analogous to diagnostic and curative care. For the purposes of "immunisation" against financial instability, a policy maker needs a parsimonious set that indicates what 'causes the problem, and hence suggests instruments that can be used in an immunisation programme. There may be a number of indicators of the need for an increased immunisation drive, and these should be included in the macro-prudential toolkit.

We find that two policy variables, capital adequacy and liquidity have clear crisis reducing effects in both the OECD and Latin America and Asia. This latter result is new and suggests the improvement of capital standards and liquidity coverage under Basel III should yield future benefits. We note that previous results (such as Jorda et. al., 2012; Borio and Drehmann, 2009 and Borio et. al., 2010) on the importance of credit were obtained in the absence of capital adequacy indicators. Once an early warning system recognises that a portion of each unit of credit is used to provision against bad lending, the crisis inducing effect of credit growth is relegated below other determinants. Such measures were already in place under Basel II and have been strengthened under Basel III.

It is thus possible that conditioning bank capital on credit growth alone may not avert future crises in financially liberalised economies especially when these are driven by property prices in an otherwise benign environment. Under these circumstances, countercyclical buffers may not accumulate because business lending continues in line with GDP growth but risky lending may continue in the housing markets or commercial property markets. It is also clear form our work above, that we should provision against the current account, and that the triggers for building capital buffers should include different variables in liberalised and un-liberalised financial markets. In particular there may be a role for the credit related buffer and for monitoring foreign exchange reserves in emerging market economies whilst they remain unliberalised. Judging the tools is the same as judging the economy..

Therefore, more work is required on the links between credit cycles and property prices in both regions since as we have already shown (Barrell et. al., 2010) residential property price growth outperforms credit as a crisis determinant on the OECD. Strong house price appreciation is currently a concern in many emerging market economies and some of these now have fully liberalised, globalised financial systems. Unless the dynamics of property prices and their relation to credit growth are properly examined, the latest generation of banking reforms may not be sufficient to ensure future financial stability.

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