Macro Prudential Policy and Credit; the right question but the wrong answer¹.

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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 univariate and multivariate early warning systems for crises in the post Bretton Woods period. We also discuss the relationship between GDP growth and credit growth in these countries, looking for changes in behaviour as a consequence of liberalisation. 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.

¹ Early versions of this paper have been presented at the AIECE conference at CEMFI, University Autonomia, Madrid, the BMRC conference, Brunel University, and at ESRI in Dublin. We would like to thank the participants for their comments.
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 some way in order to reduce the probability of a crisis occurring again. We discuss the proposals for the countercyclical buffer, and the existing evidence on the determinants of financial crises. The discussion of the determinants of crises is put within the context of cost benefit analyses of regulatory innovations. It is argued that we must understand the determinants of crises, and given we know these, we have to ask if the authorities can affect them. We then go on to investigate the role of credit in the determination of the probability of crises occurring in OECD countries and in Latin America and East Asia. The paper then discusses the Spanish dynamic provisioning system and the relationship between credit growth and real house price growth in OECD countries, and we suggest the link is weak.

Regulation and the Countercyclical Buffer

The financial crisis that engulfed the world in 2007 and 2008 has led to a wave of re-regulation and discussion of further regulation that has culminated in the proposals form the Basel Committee as well as those in the Vickers Committee report on Banking Regulation. It is now generally agreed that increasing core capital reduces the probability of a crisis occurring, and most changes in regulation that are being discussed see this as the core of their toolkit. The work Barrell et al (2009) and Barrell et al (2010) was the first to demonstrate that there was a statistically important role for (unweighted) capital in defending against the probability of a crisis occurring, and our findings were widely used in the policy community in the debate over reform.

Although banks and financial markets are very complex structures they serve very simple purposes, taking in the assets of agents in the economy and pooling them to lend money to other agents, and in the process providing a significant part of the means of payment for goods and services. The process of lending is a risky one, and banks have assets (loans) in excess of their liabilities (deposits) in order to absorb risk and ensure an adequate distance from default. If the level of capital is too low and hence the distance to default is too small or the losses too large then banks go under.

Financial markets are like any others, they exist within a framework of legislation and regulation. There are three functions for regulation, the protection of the direct interest of the consumer through product regulation, the protection of the consumer against monopoly power through structural regulation and the indirect protection of the consumer through regulations designed to reduce spillovers and contagion. The first two may be described as micro prudential and for the latter as macro prudential. Bank regulation has a number of layers of responsibility as well, with the overall framework being set by the Bank for International Settlements (BIS) in Basel with additional country specific additions to those regulations. In the European Union the most significant parts of the regulatory framework are agreed across the whole European Economic Area, and in particular the basic structures of
capital and competition legislation are shared. In all countries liquidity regulation and direct consumer protection have been a national responsibility, but (branch based) banking activity can be undertaken outside the home country with little restriction.

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 especially liquidity. The UK had a very lax attitude to liquidity regulation, and relied on the existence of market or wholesale liquidity to provide for individual banks. Indeed as the liquidity crisis struck in the summer of 2007 it would appear to be the case that the UK banking system was holding less liquidity in aggregate than the supposed floor of 3 per cent each bank was to hold. The non-systemic approach to regulation followed by the regulators meant that the authorities believed banks could, if they faced liquidity problems they could turn to the wholesale market.

The UK and the US along with many countries in Europe felt that there was little need for macro prudential regulation, as is discussed by Nier (2011) and as a result many of the barriers that would have prevented crises, and especially crisis contagion were not in place. Light touch regulation of the assets and activities of banks was supposed to stimulate growth and increase incomes, and in the decade to 2007 the financial sector increased in size in many countries, as Barrell, Holland and Liadze (2011) discuss. However this increase in size was at least in part the consequence of rent seeking activity based on the construction of complex products. It was also accompanied by an expansion of lending to people with limited ability to repay loans. Banking regulation could have been designed to take account of these issues, but it was not. The most important part of the regulatory framework, provisions for capital adequacy, was particularly weak.

The Sub Prime crisis demonstrated that the overall level of capital proved to be too low to protect a number of institutions against the losses they incurred. Up to 50% of capital could be held in the form of subordinated debt (Tier 2), which does not give the level of protection to banks that equity does. Indeed, in the crisis market participants focused on common equity only as a measure of banks’ robustness. The regulatory structure lacked a measure relating the total assets of a bank to its equity capital, and relied on inadequate and pro-cyclical measurement of risk. It gave incentives for disintermediation which led to banks’ effective exposures being undercapitalised. It lacked any international agreement on liquidity whereas liquidity risk was the key component of the crisis, particularly up to the Autumn of 2008. There was no recognition of the “too big to fail” problem which meant that large banks were left with uncontrolled incentives to take excessive risks at public expense. The quality of lending by banks was not monitored, and increasing amounts of low grade credit were issued. Financial innovations were permitted to spread, and their credit-ratings were assumed to be accurate, despite the fact they had not been tested in a downturn. Any new framework has to address these problems whilst ensuring that the changes in regulation do not cause a sharp contraction in activity.

The new regulations, which are basically complete will raise common equity from the previous minimum of 1 per cent of risk weighted assets to at least 4.5 per cent, and 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, and if this is exhausted in a crisis then the bank will be wound
up. Table 1 sets out details of the new capital structure, and the maximum proportion of 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 (unadjusted) assets of 3 per cent must be held. This should
substantially reduce the risk that banks will undertake regulatory arbitrage and hence 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. The regulation of subsidiaries and capital market
activities has been substantially tightened, including introduction of stress-related
benchmarks for trading book capital and counterparty credit risk. Two new regulations for
liquidity risk are being introduced: Although there is no proposal to harmonise emergency
liquidity or capital assistance, Basel III does penalise size to some degree via the proposal for
higher capital for systemic institutions.

<table>
<thead>
<tr>
<th>Table 1 Capital requirements and buffers (all numbers in per cent)</th>
</tr>
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<tbody>
<tr>
<td><strong>Minimum</strong></td>
</tr>
<tr>
<td>Common equity (after deductions)</td>
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<tr>
<td>Tier 1 capital</td>
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<tr>
<td>Total capital</td>
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</tbody>
</table>

Our main interest in this paper is in 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 is that provisions are based on
immediate risk of loss so cushions are not built up in advance of recessions. Saurina (2011)
outlines experience of one of the first systematic macroprudential policies, which long
predate the subprime crisis, namely the dynamic provisioning system applied in Spain since
2000, which builds up a buffer of provisioning in economic boom periods to be drawn on in
recessions. This system, he argues, has markedly enhanced the robustness of Spanish banks
and of the system as a whole. However, recent developments have suggested that this system
did not extend to the Caixa’s, where quality of lending was hard to monitor because of their
integration in to regional and local political structures.

The general problems with the buffer are discussed in Repullo and Saurina (2012). They
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. 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.

The BIS Countercyclical Capital Buffer Proposal suggests four objectives all of which assume capital in excess of minimum requirements is necessary to counteract cyclical systemic risk arising from excessive credit growth. Although there are theoretical reasons as to why excessive credit growth can generate systemic instability we believe the proposal is flawed because empirically there is no conclusive evidence that credit variables cause banking crises directly. The Signal Extraction Methodology (SEM) used in the construction of the countercyclical buffer should pass some robustness checks if it is to be seen as a useful tool for policy prescriptions. It is particularly problematic that the BIS method uses an HP filter on the relevant ratio, as this has a number of problems and in particular is of little use at distinguishing between deep recessions and changes in trend, as it will tend to treat both as trend issues.

The SEM used by Borio and Drehmann (2009) and Borio et al (2010) to justify the buffer is non-parametric so optimal indicators are chosen by minimising variants of loss functions which are dependant on the noise-to-signal ratio (NTSR). However for countercyclical provisioning against credit to be valid SEM models should be able to pass forecasting tests that can also be applied to the logit model in Barrell et al (2010). The decisive test of model validity is its out-of-sample performance; if credit really is robustly associated with banking crises, this relationship should also be stable out-of-sample. In BIS study if a signal is emitted, it is classed as correct provided a crisis materialises within 1, 2 or 3 years of the signal. Clearly, allowing for a longer horizon will raise the number of correctly called crises and in this sense improves model performance. Barrell et al (2010) estimated to 2003 and correctly call 75% of crises in the sub prime period as compared 29% by the BIS study, and has only 2% false calls as against 38% in the BIS study.

In terms of correctly called crises Barrel et al (2010) which excludes credit always outperforms BD over any forecasting horizon. Even if we allow for the most generous (3 year) horizon, this model calls 18% more crises correctly. This superiority also translates to the type II error rate where the differences in model performance are even more dramatic. 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, a model which excludes credit can correctly predict 75% of crises out-of-sample with comparatively negligible cost: only 6 in 100 signals will be false alarms.

The heterogeneous sample in the BIS proposal is problematic since the same upper and lower buffer thresholds (U and L respectively) are applied to Latin American countries such as Brazil, Argentina and Mexico and Asian countries such as Indonesia. The proposal also includes Islamic banking systems (Saudi Arabia) alongside fundamentally different non-Islamic banking systems. The objective of this paper is to show that the determinants of banking crises differ between the OECD and emerging economies. Nevertheless, the proposal is based on a sample that mixes OECD and emerging economies.
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 based on 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. 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. For multi-crisis countries they also found that credit/GDP does not decline during crises.

**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 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 (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

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2 Although reinforcement occurs to an extent in the US market based banking system.

3 Often called “leverage”. Aggregate data were obtained from the OECD Banking Income Statement and Balance Sheet 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.\(^4\)

Crises are often the result of poor quality lending, especially in real estate markets, as is discussed in Reinhart and Rogoff (2008) but residential property prices are again only available consistently for OECD countries.\(^5\) Where available, property price data can enhance crisis forecasting ability; Barrell, Davis, Karim and Liadze (2010) showed that real house price growth is a better crisis predictor than domestic real credit growth. Hence we avoid using 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.\(^7\) 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 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 in an unsustainable manner. These trends may be exacerbated by lower real interest rates than would otherwise be the case. Current account deficits may also indicate a shortfall of national saving relative to investment and hence a need for the banking sector 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.\(^8\) 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

\(^{4}\) 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.

\(^{5}\) We note that house prices are correlated with prices of commercial property, which has also been a source of major bank losses during financial crises, see Davis and Zhu (2009).

\(^{6}\) Our source for this variable is the National Institute of Economic and Social Research NIGEM database.

\(^{7}\) Hardy and Pasarabasioglu (1999) estimated logit models of crises for both advanced and developing countries and found that the current account was not significant.

economic activity. To accommodate the financial sector 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. Again, we utilise these variables, except for the latter three as they are more directly relevant to emerging markets than OECD economies. For similar reasons, we also excluded Demirguc-Kunt and Detragiache’s measures of institutional quality: real GDP per capita, law enforcement and deposit insurance.

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. The banking crisis dependent variable, a binary banking crisis dummy, is defined in terms of observable stresses to a country’s banking system, e.g. ratio of non-performing loans to total banking system assets exceeds 10%. 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.

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:

\[
\Pr(Y_{it} = 1) = F(\beta'X_{it}) = \frac{e^{\beta'X_{it}}}{1 + e^{\beta'X_{it}}}
\]

(6)

where \(Y_{it}\) is the banking crisis dummy for country i at time t, \(\beta\) 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:

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

(7)

Although the signs on the coefficients are easily interpreted as representing an increasing or decreasing effect on crisis probability, the marginal 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 \(\beta_i\) represents the effect of \(X_i\) when all other variables are held at their sample means. 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.

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9 Deposit insurance exists in all our OECD countries and thus the dummy would show no variation.
10 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.
Modelling OECD Countries

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 undertook the three logit regressions 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 OBS variable, a balance sheet item, would only be reported after the end of the accounting year and hence would not be available for forecasting purposes. Consequently we used the 2-lag model as the estimation start point.

We include in our analysis of the OECD countries a variable for the role of Off Balance Sheet (OBS) activity. Following Barrell, Davis, Karim and Liadze (2012) we look at the ratio of off balance sheet income to total income as indicator of OBS and the risks associated with it. The literature suggests that the effect of OBS may have changed during the course of our sample period (1980 – 2008). As banks became preoccupied with securitisation and the benefits of regulatory arbitrage, the risk-return trade-off on OBS activity may have altered. We cannot compute these changes directly due to the lack of reported detail on banks’ portfolio holdings of OBS assets, but the literature does identify the turning point between traditional risk-reducing OBS activity and risky securitisation. Acharya and Richardson (2009) date this switch to 2003, around the same period (2004) that Altunbas et. al. (2009) cite for European banks. To test the hypothesis that risky securitisation generated systemic risk, as opposed to traditional OBS activity (which was viewed as risk reducing), we use two OBS variables in our initial model: a general level of OBS activity (defined as the ratio of off-balance sheet income/ total income) and this same level interacted with a post-2003 dummy. If the latter is significant at the cost of the former we can attribute a particular risky effect to securitisation without having to know the relative risk-return trade-offs between normal OBS transactions and risky securitisation.

Turning to our dependent variable, our dataset includes 23 crises in OECD countries. 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). That paper has 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. For the crises episodes in 2007 and 2008 we have used the crises dates from Laeven and Valencia (2010), who 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 2007 and 2008 as individual crises since 2008 was induced by the collapse of Lehman Brothers.

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. Our choice also reflects our view of the objective of our exercise. 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 take preventive action to avoid crises, where we need to know the most significant determinants and perhaps change their settings, as compared to acting to forestall a crisis once it looks likely. These are two different ‘public health’ models and they require different actions and hence different explanations of the problem.

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

<table>
<thead>
<tr>
<th>Regression Number</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>GDP growth(-2)</td>
<td>0.251</td>
<td>0.25</td>
<td>0.229</td>
<td>0.234</td>
<td>0.234</td>
<td>0.273*</td>
<td>0.256*</td>
<td>0.28**</td>
</tr>
<tr>
<td></td>
<td>(0.128)</td>
<td>(0.131)</td>
<td>(0.117)</td>
<td>(0.115)</td>
<td>(0.113)</td>
<td>(0.063)</td>
<td>(0.08)</td>
<td>(0.05)</td>
</tr>
<tr>
<td>2003 Dummy*OBS Income/Total Income(-2)</td>
<td>0.039**</td>
<td>0.04**</td>
<td>-0.33***</td>
<td>-0.516***</td>
<td>-0.316***</td>
<td>-0.041****</td>
<td>0.039***</td>
<td>0.038***</td>
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<tr>
<td></td>
<td>(0.02)</td>
<td>(0.017)</td>
<td>(0.00)</td>
<td>(0.001)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
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<tr>
<td>Narrow Liquidity(-2)</td>
<td>-0.111**</td>
<td>-0.112**</td>
<td>-0.112**</td>
<td>-0.115***</td>
<td>-0.123***</td>
<td>-0.114***</td>
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<td>-0.14***</td>
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<td></td>
<td>(0.013)</td>
<td>(0.012)</td>
<td>(0.012)</td>
<td>(0.009)</td>
<td>(0.003)</td>
<td>(0.004)</td>
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<tr>
<td>Current Balance (% GDP) (-2)</td>
<td>-0.329***</td>
<td>-0.334***</td>
<td>0.039**</td>
<td>0.034***</td>
<td>0.036***</td>
<td>-0.302***</td>
<td>-0.315***</td>
<td>-0.293***</td>
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<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.016)</td>
<td>(0.006)</td>
<td>(0.003)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
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<tr>
<td>Leverage(-2)</td>
<td>-0.526***</td>
<td>-0.525***</td>
<td>-0.524***</td>
<td>-0.329***</td>
<td>-0.514***</td>
<td>-0.438***</td>
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<td>(0.00)</td>
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<tr>
<td>Budget Balance(-2)</td>
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<td>0.098</td>
<td>0.087</td>
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<td></td>
<td>(0.223)</td>
<td>(0.202)</td>
<td>(0.211)</td>
<td>(0.244)</td>
<td>(0.256)</td>
<td>(0.262)</td>
<td>(0.212)</td>
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<td>M2/Reserves(-2)</td>
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<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
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<tr>
<td></td>
<td>(0.273)</td>
<td>(0.279)</td>
<td>(0.291)</td>
<td>(0.296)</td>
<td>(0.295)</td>
<td>(0.295)</td>
<td>(0.297)</td>
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<tr>
<td>OBS Income/Total Income(-2)</td>
<td>0.0154</td>
<td>0.015</td>
<td>0.015</td>
<td>0.02</td>
<td>0.017</td>
<td>0.017</td>
<td>0.017</td>
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</tr>
<tr>
<td></td>
<td>(0.505)</td>
<td>(0.518)</td>
<td>(0.525)</td>
<td>(0.323)</td>
<td>(0.383)</td>
<td>(0.383)</td>
<td>(0.383)</td>
<td>(0.383)</td>
</tr>
<tr>
<td>Inflation(-2)</td>
<td>-0.102</td>
<td>-0.102</td>
<td>-0.102</td>
<td>-0.042</td>
<td>0.048</td>
<td>0.056</td>
<td>0.058</td>
<td>0.058</td>
</tr>
<tr>
<td></td>
<td>(0.496)</td>
<td>(0.49)</td>
<td>(0.49)</td>
<td>(0.581)</td>
<td>(0.698)</td>
<td>(0.642)</td>
<td>(0.63)</td>
<td>(0.63)</td>
</tr>
<tr>
<td>Real Interest Rate(-2)</td>
<td>0.016</td>
<td>0.011</td>
<td>0.011</td>
<td>0.011</td>
<td>0.011</td>
<td>0.011</td>
<td>0.011</td>
<td>0.011</td>
</tr>
<tr>
<td></td>
<td>(0.729)</td>
<td>(0.796)</td>
<td>(0.796)</td>
<td>(0.796)</td>
<td>(0.796)</td>
<td>(0.796)</td>
<td>(0.796)</td>
<td>(0.796)</td>
</tr>
<tr>
<td>Growth Credit to GDP(-2)</td>
<td>0.018</td>
<td>0.018</td>
<td>0.018</td>
<td>0.018</td>
<td>0.018</td>
<td>0.018</td>
<td>0.018</td>
<td>0.018</td>
</tr>
<tr>
<td></td>
<td>(0.762)</td>
<td>(0.762)</td>
<td>(0.762)</td>
<td>(0.762)</td>
<td>(0.762)</td>
<td>(0.762)</td>
<td>(0.762)</td>
<td>(0.762)</td>
</tr>
</tbody>
</table>

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

The results of this sequential elimination process are reported in Table 2. It can be seen that throughout all stages of the elimination process, the four of the first five variables in the table (namely leverage and liquidity ratios, the current account balance/GDP ratio and post-2003 OBS activity) are generally significant with slight variation in their parameters. The opposite
is true for all the remaining variables, all of which were highly insignificant. In our previous work we have found that real house price growth (with a lag of 3) is an important determinant of the probability of having a crisis. Barrell et al (2012) show that house prices lead off balance sheet activity, and hence in order to forecast crises after 2003 it is possible to replace the OBS variable with lagged house prices and perform well. We will return to the issue of house prices below. 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, although they were the last to drop out. Recent changes to the single financial market in Europe may have changed this relationship. The real interest rate and the inflation rate are eliminated in the process, suggesting that over the period they did not raise risks. Most importantly, the growth of the ratio of Credit to Gdp drops out first, suggesting it played no role in changing the probability of the emergence of a banking crisis in liberalised OECD financial markets.

These results show that in OECD countries, growth in real output and lower defences from less stringent bank regulation, along with current account imbalances and recent OBS activity were the most important factors driving the probability of a banking crisis occurring between 1980 and 2008. Although lax monetary policy and credit booms 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. The pertinent result is the significance of post-2003 OBS activity as opposed to the general level of OBS activity for the whole sample period. This clearly accords with the findings of Acharya and Richardson (2009), Altubas et. al. (2009) and other commentators who became concerned with the particular systemic risks associated with securitization prior to the sub-prime episode. As a result, the coefficient on recent OBS activity is positive and ceteris paribus, such activities raised the crisis probability in OECD banking systems.

Table 3. In sample performance of the model

<table>
<thead>
<tr>
<th></th>
<th>Dep=0</th>
<th>Dep=1</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>P(Dep=1)&lt;=0.0608</td>
<td>252</td>
<td>7</td>
<td>259</td>
</tr>
<tr>
<td>P(Dep=1)&gt;0.0608</td>
<td>103</td>
<td>16</td>
<td>119</td>
</tr>
<tr>
<td>Total</td>
<td>355</td>
<td>23</td>
<td>378</td>
</tr>
<tr>
<td>Correct</td>
<td>252</td>
<td>16</td>
<td>268</td>
</tr>
<tr>
<td>% Correct</td>
<td>70.99</td>
<td>69.57</td>
<td>70.9</td>
</tr>
<tr>
<td>% Incorrect</td>
<td>29.01</td>
<td>30.43</td>
<td>29.1</td>
</tr>
</tbody>
</table>

Using the in sample proportion of crisis years (0.0608) as a cut-off

Note Dep is the (binary) dependent variable

We check the in-sample performance of the final model using the sample average crisis rate as a cut-off. As shown in Table 3, the false call rate when there is no crisis (known as the Type II error), is 29.0% and the false call rate when there is a crisis (known as the Type I error) is 30.4%. The overall successful call rate (both crisis and no crisis called correctly) is 71%, with 16 out of the 23 crisis episodes captured correctly at a cut-off point of 0.0608\textsuperscript{11}.

\textsuperscript{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
These results stand up well against the wider literature. For example, Demirgüç-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. To calculate an “adjusted” number of false calls, we specify an alternative call horizon following the early warning literature whereby only calls up to three years prior to the crisis are accepted. This leaves us with 70 instead of 103 initial false calls. In the majority of cases, adjustment for timing significantly reduces the false call rate; for half of the countries this drops by between 30 – 40%.

**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 widely used as EWS inputs most probably due to lack of data. 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.

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

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12 A similar forecasting horizon is used by Borio and Drehmann (2009) which underpins the latest capital proposals by the Bank for International Settlements.

13 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. 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. Full details of the bank coverage for each country are given in the data appendix. 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. In comparison to capital ratios, liquidity data is easier to obtain although it also needs to be constructed. We use the Barrell et. al. (2010) definition of liquidity which we construct from the IMF’s International Financial Statistics database. 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 (see Demirguc-Kunt and Detragiache, 1998; Davis and Karim, 2008): domestic credit/ GDP, exchange rate, real GDP growth, terms of trade, inflation, budget balance/ GDP, real domestic credit growth, GDP per capita, current account balance/ GDP and M2/ foreign exchange reserves. These data were obtained from the IMF and World Bank.

Our dependent variable is constructed as a binary series such that a value of one represents the occurrence of a systemic crisis whilst a value of zero indicates no crisis has taken place. 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.


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14 The Banker data is not available electronically for all of our sample of interest and hence manual transcription of the BIS ratios was required.
15 For Panama, The Banker provides no data. For this country we relied on IMF Global Financial Stability Reports and IMF Country Reports.
Once a crisis ensues it will impact on the explanatory variables either directly or due to associated policy responses. To remove this endogeneity we use the crisis onset only (see Barrell et. al., 2010). In addition, each explanatory variable in the logit model is lagged by one period to further address this issue.

### Table 4: General to Specific Results for Pooled Sample

<table>
<thead>
<tr>
<th>Regression Number</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
</tr>
</thead>
<tbody>
<tr>
<td>Terms of trade(-1)</td>
<td>-0.013</td>
<td>-0.014</td>
<td>-0.015</td>
<td>-0.016</td>
<td>-0.018</td>
<td>-0.019</td>
<td>-0.023</td>
<td>-0.02</td>
<td>-0.019</td>
</tr>
<tr>
<td></td>
<td>(0.029)</td>
<td>(0.024)</td>
<td>(0.012)</td>
<td>(0.007)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0)</td>
<td>(0)</td>
<td>(0)</td>
</tr>
<tr>
<td>%Δ Domestic Credit/ GDP(-1)</td>
<td>0.049</td>
<td>0.049</td>
<td>0.049</td>
<td>0.053</td>
<td>0.055</td>
<td>0.053</td>
<td>0.052</td>
<td>0.065</td>
<td>0.069</td>
</tr>
<tr>
<td></td>
<td>(0.051)</td>
<td>(0.052)</td>
<td>(0.056)</td>
<td>(0.031)</td>
<td>(0.026)</td>
<td>(0.034)</td>
<td>(0.03)</td>
<td>(0.005)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>Capital Adequacy Ratio(-1)</td>
<td>-0.132</td>
<td>-0.135</td>
<td>-0.147</td>
<td>-0.142</td>
<td>-0.131</td>
<td>-0.141</td>
<td>-0.153</td>
<td>-0.142</td>
<td>-0.145</td>
</tr>
<tr>
<td></td>
<td>(0.041)</td>
<td>(0.035)</td>
<td>(0.02)</td>
<td>(0.021)</td>
<td>(0.024)</td>
<td>(0.019)</td>
<td>(0.007)</td>
<td>(0.01)</td>
<td>(0.006)</td>
</tr>
<tr>
<td>Current Account Balance (% of GDP)(-1)</td>
<td>-0.06</td>
<td>-0.054</td>
<td>-0.062</td>
<td>-0.06</td>
<td>-0.069</td>
<td>-0.079</td>
<td>-0.081</td>
<td>-0.084</td>
<td>-0.084</td>
</tr>
<tr>
<td></td>
<td>(0.261)</td>
<td>(0.285)</td>
<td>(0.2)</td>
<td>(0.208)</td>
<td>(0.152)</td>
<td>(0.09)</td>
<td>(0.079)</td>
<td>(0.079)</td>
<td>(0.07)</td>
</tr>
<tr>
<td>M2 Money/ Foreign Exchange Reserves(-1)</td>
<td>0.048</td>
<td>0.047</td>
<td>0.046</td>
<td>0.049</td>
<td>0.049</td>
<td>0.064</td>
<td>0.072</td>
<td>0.072</td>
<td>0.072</td>
</tr>
<tr>
<td></td>
<td>(0.231)</td>
<td>(0.247)</td>
<td>(0.261)</td>
<td>(0.232)</td>
<td>(0.232)</td>
<td>(0.102)</td>
<td>(0.092)</td>
<td>(0.092)</td>
<td>(0.092)</td>
</tr>
<tr>
<td>Liquidity Ratio(-1)</td>
<td>-0.035</td>
<td>-0.035</td>
<td>-0.035</td>
<td>-0.033</td>
<td>-0.034</td>
<td>-0.025</td>
<td>-0.092</td>
<td>-0.103</td>
<td>-0.111</td>
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<tr>
<td></td>
<td>(0.061)</td>
<td>(0.062)</td>
<td>(0.055)</td>
<td>(0.063)</td>
<td>(0.055)</td>
<td>(0.107)</td>
<td>(0.379)</td>
<td>(0.306)</td>
<td>(0.259)</td>
</tr>
<tr>
<td>Government Budget Balance (% of GDP)(-1)</td>
<td>-0.092</td>
<td>-0.103</td>
<td>-0.108</td>
<td>-0.111</td>
<td>-0.11</td>
<td>-0.092</td>
<td>-0.103</td>
<td>-0.111</td>
<td>-0.111</td>
</tr>
<tr>
<td></td>
<td>(0.379)</td>
<td>(0.306)</td>
<td>(0.273)</td>
<td>(0.259)</td>
<td>(0.271)</td>
<td>(0.379)</td>
<td>(0.306)</td>
<td>(0.259)</td>
<td>(0.271)</td>
</tr>
<tr>
<td>%Δ Exchange Rate(-1)</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>(0.434)</td>
<td>(0.427)</td>
<td>(0.441)</td>
<td>(0.444)</td>
<td>(0.434)</td>
<td>(0.427)</td>
<td>(0.441)</td>
<td>(0.444)</td>
<td>(0.434)</td>
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<tr>
<td>Inflation(-1)</td>
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<td>0</td>
<td>0</td>
<td>0</td>
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</tr>
<tr>
<td></td>
<td>(0.599)</td>
<td>(0.54)</td>
<td>(0.508)</td>
<td>(0.508)</td>
<td>(0.599)</td>
<td>(0.54)</td>
<td>(0.508)</td>
<td>(0.508)</td>
<td>(0.599)</td>
</tr>
<tr>
<td>GDP per Capita(-1)</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>(0.557)</td>
<td>(0.559)</td>
<td>(0.559)</td>
<td>(0.559)</td>
<td>(0.557)</td>
<td>(0.559)</td>
<td>(0.559)</td>
<td>(0.559)</td>
<td>(0.557)</td>
</tr>
<tr>
<td>%Δ GDP(-1)</td>
<td>-0.019</td>
<td>-0.019</td>
<td>-0.019</td>
<td>-0.019</td>
<td>-0.019</td>
<td>-0.019</td>
<td>-0.019</td>
<td>-0.019</td>
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<tr>
<td></td>
<td>(0.723)</td>
<td>(0.723)</td>
<td>(0.723)</td>
<td>(0.723)</td>
<td>(0.723)</td>
<td>(0.723)</td>
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<td>Observations</td>
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<td>401</td>
<td>402</td>
<td>402</td>
<td>402</td>
<td>402</td>
</tr>
</tbody>
</table>

Note: p-values in parentheses

The sample results (Table 4) show 8 sequential variable deletions culminating in a 3 variable equation. The final specification is the most parsimonious model that can be used to explain systemic banking crises across Latin America and Asia. The variable deletions themselves are of interest since they suggest changes in GDP growth, inflation, GDP per capita and M2/foreign exchange reserves do not significantly affect crisis probabilities. These results
contrast with those of Demirguc-Kunt and Detragiache (1998; 2005) who found these variables to be associated with emerging market crises, albeit contemporaneously\(^{16}\).

Some of these differences may be attributable to our inclusion of capital and liquidity which remain untested in the extant literature on these regions. The final specification suggests the most important determinants of combined Latin American and Asian crises are: the terms of trade, changes in domestic credit/GDP and bank capital adequacy. An improvement in the terms of trade and capital soundness of banks reduces the likelihood of systemic bank failures while an increase domestic credit relative to income raises the failure probability. This latter result is significant in terms of our objectives, as this variable was the first to drop out in the OECD sample.

**Credit Constraints and the role of Credit to GDP**

The 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. 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 of 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 constraint 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.

Previous work cited above has suggested that house price growth may be an important factor in driving the probability of crises because it is associated with the growth of bad lending where default is more likely. Barrell, Holland and Karim (2010) look for causality links between house price growth and credit growth, and show they are largely absent. We would argue that we need to look more closely at the structure of causality between real house price growth and real domestic credit growth. It may of course be that house prices are a proxy for credit growth, and if they move together we should find they cointegrate. Table 5 presents tests for cointegrating relationships\(^ {17}\) which show that a long-run relation exists between credit levels and property price indices in Denmark, Finland, France, Sweden and Italy\(^ {18}\), but not elsewhere. However, the existence of a vector does not hint at the direction of causation, and we have to test whether the time series of changes in house prices helps explain the current change in credit when the cointegrating vector and lagged changes in credit (and vice versa for house prices) are included in a regression

---

\(^{16}\) Credit growth was the only variable to be lagged (by two periods) in their specifications.

\(^{17}\) Granger causality in the first differences when cointegrating relationships are absent is revealing only about the dynamics of adjustment. Barrell Holland and Karim (2010) report on these tests and find that credit growth Granger causes house prices in Germany, whilst house prices Granger cause credit growth in Canada and Japan

\(^{18}\) The cointegration is assumed to be homogenous of degree one.
Table 5: Cointegrating Relations and Causality; real house price and real credit growth

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Ho: Unit Root</td>
<td>House</td>
<td>Credit</td>
</tr>
<tr>
<td></td>
<td>Exists (one</td>
<td>prices</td>
<td>causes</td>
</tr>
<tr>
<td></td>
<td>lag)</td>
<td>credit</td>
<td>house</td>
</tr>
<tr>
<td>Denmark</td>
<td>-1.95*</td>
<td>NO</td>
<td>NO</td>
</tr>
<tr>
<td>Finland</td>
<td>-2.06*</td>
<td>NO</td>
<td>YES</td>
</tr>
<tr>
<td>France</td>
<td>-2.74**</td>
<td>YES</td>
<td>NO</td>
</tr>
<tr>
<td>Italy</td>
<td>-4.12**</td>
<td>NO</td>
<td>NO</td>
</tr>
<tr>
<td>Sweden</td>
<td>-2.61**</td>
<td>NO</td>
<td>YES</td>
</tr>
</tbody>
</table>

*Significance at level * 95%, **99%

We find evidence from an error correction specification over the whole data period, including that used for forecasting, that credit Granger causes property prices in Finland and Sweden and that in France there is a link from property to credit. We also test whether the dynamic effects differ pre-1995 and post-1995 in order to evaluate both our estimation results and our forecast tests. These results suggest that property price increases lead the growth of credit in the post-1995 period in Finland while in Sweden the same effect was observed prior to 1995. In France the effect is not present in the shorter sample periods. For Denmark and Italy the result does not change for split samples. We would conclude that real house price growth is not acting as a proxy for real credit growth in our sample of countries, and that bad lending associated with house price growth and current account deficits were more important over our sample than real credit growth in determining whether there might be a financial crisis.

Conclusion

There is little evidence that the ratio of credit to GDP or credit growth are factors affecting the incidence of crises in OECD countries, although they may have a role in crisis determination in emerging markets. Hence there is little reason to provision against credit growth in the countercyclical buffer proposed by the BIS. It would be better to act against bad lending, especially in housing markets rather than increase the procyclicality of the financial system.

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19 In financially repressed systems credit rationing means that prospective homeowners would have been restricted in their property transactions and once the restriction are lifted upwards pressure on house prices may emerge. Barrell and Davis (2007) 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.
References


Hardy, D. C; Pazarbasioglu, C (1999), “Leading Indicators of Banking Crises: Was Asia Different?” , IMF Staff Papers, 46, 247-258


