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Towards an understanding of credit cycles: do all credit booms cause crises?[1]

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Towards an understanding of credit cycles: do all credit booms cause crises?

Macroprudential policy is now based around a countercyclical buffer, relating capital requirements for banks to the degree of excess credit in the economy. We consider the construction of the credit to GDP gap looking at different ways of extracting the cyclical indicator for excess credit. We compare different smoothing mechanisms for the credit gap, and demonstrate that some countries

this gap is an adequate policy indicator for the build-up of vulnerabilities on the financial side (Drehmann and Tsatsaronis, 2014).

Credit-to-GDP ratios represent a practical and appealing way to guide policy given the objective of the buffer. However, a growing literature supports the view that not all credit-to-GDP amplifications are “credit booms gone wrong”, underpinned by provide a better explanation of credit abnormalities in the economy and thus generate higher explanatory power[6].

We subject our gap-measures to an information criteria selection procedure, to isolate the optimal gap measure for each country[7] (similarly to Macchiarelli, 2013). The idea that credit-to-GDP gaps differ across countries, reflecting idiosyncratic factors, is discussed by Drehmann et al. (2012), Grintzalis et al. (2017), and Edge and Meisenzahl (2011). Bassett et al. (2015), particularly note how home mortgages in the US account for a large share of the observed increase in the one-sided trend in the credit-to-GDP ratio. Hence, measures of the credit-to-GDP cycle that explicitly accommodate this persistency are worth exploring.

Our filtering exercise reveals a natural "clustering" of countries into two gap-types: countries for which AR(2) cycles are preferred (Belgium, Canada, Finland, France, Italy, Norway, Sweden, Spain and the US) and the remaining group (Denmark, Germany, Japan, the UK, and the Netherlands) where a stochastic cycle is optimal. We find the BIS filtering procedure (which makes no assumptions on the cyclical dynamics) is not selected as the optimal gap in any of our countries.

To evaluate the credit cycles' crisis role in generating crises, we then embed the "optimal" gap for each country within a logit early warning system, using macroeconomic and regulatory variables, including capital adequacy, liquidity and

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[6] To escape the usual criticism of HP-filtered series suffering from end-point bias (see Hamilton, 2017), we retrieve our "HP-filtered" series using a one-sided Kalman filter where restrictions are put on the state space representation of the latter. An advantage of this method is that our filter can be estimated using maximum likelihood (Harvey and Trimbur, 2008; Harvey, 1989).

[7] All cycles are calibrated so the financial cycle is of medium term duration, consistent with the extant literature (Drehmann and Tsatsaronis, 2014).

property price growth, as standard controls. We also compare the efficacy of our cycle estimators. In the overall sample, we find that a mix of stochastic and AR2 cycles best describes crisis probabilities in terms of informational criteria. The AR2 cycle seems to apply to countries where credit growth and house prices interact and feed each other. Granger tests suggest in these countries, house price growth raised collateral values which propagated risky lending.

As a robustness test, we vary crisis timing to check the stability of our results. Additionally, we use end-point observations on the cycles to confirm the robustness of our credit-gap effects. Again, these tests suggest that credit-to-GDP growth in itself is not risky, but when it combines with feedback from house prices, regulation becomes warranted. The policy implication of our results is that financial regulators should combined to ensure that there were no financial crises in advanced economies in the period from 1940 to 1972. Systemic risk appeared to have disappeared, and consequently, after the 1970s, Central Bankers and regulators increasingly focused on inflation and micro-prudential regulation. However, from 1970 to 2000, decade by decade, although financial crises in advanced economies became more common, they were still not seen as a major focus of policy: the majority of the economics profession became convinced that macroprudential policy[8] was unneeded as systemic risk was either absent or unavoidable[9].

The financial crises that broke in 2007 and 2008 in the US, the UK and much of the Northern Hemisphere led to a re-evaluation of systemic and endogenous risk, driving the design of a new regulatory framework. In particular, attention was given to the role of credit cycles and their impacts on crisis risks. Whilst the Basel III regulatory architecture is still under implementation, the implications for credit growth, at least as far as this research is concerned, are in place. Both the quantity and quality of capital that individual banks must hold has increased, and systemically important banks are required to conserve more capital. In addition, there are two entirely new capital based buffers, the countercyclical buffer and conservation buffer. The conservation buffer (2.5 percent of risk weighted assets) allows regulators to impose capital distribution constraints when common equity capital (i.e. high quality Tier 1 capital) falls below 7%. These changes to core capital and the conservation buffer are micro-prudential

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[8] A term probably coined by Andrew Crocab842.16mpleab8n6(in)-8(eo)-2(b-3(c)-5(ro)]Tm)( )- te co5(roM(to i)-3In4(b)-6(lg)-3(s4(d)g TJroM

(individual bank based), although it is clear that the more capital the banks hold, the less risk there is of a systemic crisis developing (Barrell et. al (2010)).

The focus of this paper however, centres on the current macro-prudential framework which specifies a countercyclical buffer. In summary, as credit increases excessively, it is presumed that more potentially non-performing loans are issued and the balance sheets of banks face future deterioration. When macro-economic conditions worsen, there is a materialisation of credit risk and consequently the core capital of the banking system becomes compromised which curtails further lending. This creates solvency and liquidity risk for borrowers as their project net present values approach negative in the macroeconomic downturn. They exhibit even higher default rates and induce further reductions in bank capital. The buffer construction is therefore based on the assumption that this cyclical transmission between credit and asset values drives credit gaps and relies on results showing credit cycles to be good crisis predictors (BCBS 2010 a,b).

An obvious source of this transmission is the build-up of excessively risky lending that is driven by house price bubbles. At least in countries where debt default has low costs, mortgage borrowers effectively hold put options against the bank, which they can exercise by defaulting when property price bubbles burst. This behaviour was especially apparent in the US sub-prime crisis (Reinhart and Rogoff, 2008). As bank capital erodes to cover the defaults, mortgage credit is further rationed and hence house prices continue the decline. This in turn raises the value of the put option from the borrower’s perspective and increases mortgage default rates further. Structural changes in the banking industry may exacerbate the procyclicality by incentivising increased lending during the upturn. Such changes may manifest as new approaches to firm behaviour (e.g. increased focus on shareholder value and performance based bonuses) who note the link between external imbalances and crises has strengthened in the last 60 years.

Schulerick and Taylor (2012), use a 140 year panel of 14 developed economies to analyse bank credit growth and crises: broad money and credit cycles grew together in a generally stable fashion pre-1950, and both are good predictors of financial crises, but post- 1950, only credit predicts crises. This reflects the break down in the relation between credit growth and bank deposits that resulted from financial innovations in the last 60 years, in particular the increasing use of nonmonetary liabilities to increase leverage. Jorda, et. al (2013) examine the relation been financial crises and 200 economic downturns in their 140 year panel, and find that post-crisis downturns are worse than others. However, it is not obvious from this work that credit causes financial crises; standard controls, including known defences of crises such as capital and liquidity are omitted as are drivers of credit such as house prices[11]. The exclusions reflect a paucity of data availability for such long run studies[12] which means key post – 1945 trends in house prices and bank regulation cannot be assessed for their impact on credit dynamics[13]

(2010), Drehman et. al (2011) and supported by Alessi and Detken (2014). In this context, the role of the filter becomes crucial since the gap's reliability (as either an early warning indicator or calibrator of countercyclical buffers) is contingent on the filter used for extraction. A common view is that financial cycles last longer than business cycles. Drehmann et al. (2012), for instance, examined variables across a number of countries and found the average duration of the financial cycle to be about 16 years. Basset et al. (2015) suggest that some types of credit (government sponsored enterprises and other nonbank) are persistent well beyond business cycle frequencies, and are thus excluded from the extracted gap.

Methodologies for estimating credit gaps range from statistical models that extract information from observed series, to those using economic priors. The most popular filtering techniques typically include: *trends* (linear; split or spline), *univariate fiir* goodness of fit against smoothness. However, the filter is often criticised for generating biased end of sample values and also because it produces series with spurious dynamics that do not reflect the underlying data-generating process (Hamilton, 2017; Edge and Meisenzahl, 2011). Additionally, its statistical formalization produces values for the smoothing parameter at odds with common practice, particularly at quarterly frequencies (Hamilton, 2017; Ravn and Uhlig, 2002).

Alternative specifications make additional assumptions on the cycle's functional form, for instance. autoregressive dynamics or stochastic cycles à la Harvey and Jaeger (1993) and Koopman et al. (2006). These representations can accommodate alternative

Model 1 - *Irregular*: where no explicit assumptions on the cycle are made

Before presenting the model, we note how we avoid misspecification and bias in our models. Barrell and Karim (2013) show for a group of emerging markets, country heterogeneity induced biases

liquidity ratios (liquidity as a proportion of total bank assets) and real house price growth. We also add the current account as a driving variable, as in Karim et al (2013). The unweighted bank capital variable primarily comes from the OECD Consolidated Banking Statistics Database but missing values are supplemented using IMF/World Bank data and Norwegian and Swedish Central Bank sources. Liquidity data is drawn from the IMF's International Financial Statistics Database and national central banks, as are the data on the current account as a percent of GDP. Real house price growth and credit growth data are obtained from the BIS which publishes the time series used for its own gap estimations.

The timing and duration of crises are subjective to an extent, although work by Demirguc and Detragiachi (1998) set initial rules to identify systemic episodes: the proportion of non-performing loans to total banking system assets > 10%, or the public bailout cost >2% of GDP, or systemic crisis caused large scale bank nationalisation, alternatively bank runs were observed and if not, emergency government intervention was sustained. They focused on the 1997 Asian crises, but post-sub Prime it was recognised that revisions to international crisis episodes were required. As a result, subsequent work by the World Bank and IMF has updated the dating of crises, albeit using a more restrictive set of criteria and in combination, the two sources allow us to consistently estimate up to 2013, as all crises after 2007 were severe.

To construct our binary banking crisis dummy we use the World Bank Crisis Database covering 1974-2002, (Caprio *et al* ., 2003) as well as Laeven and Valencia (2013) for the subsequent crises. The former have crises in Canada (1983), Denmark (1987), the US (1988), Italy and Norway (1990), Finland, Sweden and Japan (1991), France (1994), and the UK (crises in 1984, 1991 and 1995).

Laeven and Valencia (2013) 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. These dating criteria underpin our results which we present in the next section.

5. Results

We first present the results of our filtering exercises and then discuss the performance of the alternative gap measures when embedded in our logit models.

5.1 Optimal Filters

We describe the results for our filtering process in Table 1. For each country we undertake four filtering exercises, and in each case we report four information related diagnostic tests, the log likelihood, the Schwartz Criteria, the Hannan-Quinn and the Aikake Information Criteria. In 13 of the countries all four criteria point to a single cyclical process being optimal, with only the Netherlands showing a conflict, with three indicating that the Harvey (1997) smoother is optimal, and one, the Schwartz criterion, suggesting an AR(1) process is to be preferred. The AR(2) process is optimal in Belgium, Canada, Finland, France, Italy, Norway, Sweden, Spain and the US, whilst the Harvey (1997) is optimal in Denmark, Germany, Japan, the UK, and we allocate the Netherlands to this group as well.

Insert Table 1 here

5.2 Logit Results

We report the results for the crisis logits in Table 2, and in each case we include one lag on credit growth, capital, liquidity and the current account. House prices are lagged by three periods, consistent with the Early Warning model of Barell et al. (2010). Within this model, we embed our variables of interest: credit growth and cyclical indicators for the credit to GDP gap. We choose the current version of this indicator because it is a smoothing process almost entirely dependent on past data, and hence it can be used in an Early Warning System as it is available in real time (at the current period). We report five logits, and in each case we also summarise the information content of the logit with the AUC at the bottom of the column.

Insert Table 2 here

Our previous exercise has been to identify the optimal cycle to individual countries, and we use these in the first logit (column 1; table 2), with nine countries taking the AR(2) cycle as an optimal indicator of the credit to GDP gap and five taking the Stochastic (Harvey, 1997) cycle. This “mixed cycle” variable is significant and has a positive sign, suggesting as the gap widens the probability of a crisis increases given the level of the other indicators. The presence of a significant credit to GDP gap, not surprisingly, is associated with a negative and insignificant coefficient on credit growth which remains insignificant even when the gap is excluded from the logit. Thus the gap indicator appears to contain all the information we need about credit in order to be able to predict crises

Other coefficients are consistent with previous results in Barrell et al (2010) and Karim et al (2013). Capital has a negative and significant coefficient, as does liquidity, confirming that strong systemic defences against bank failure reduce the probability of a crisis occurring. Omitting these significant and relevant variables would bias the results for other coefficients, and would lead to a misunderstanding of factors driving crises. As in Karim et. al (2013), we find that recent current account deficits raise the risk of a crisis occurring, as does an increase in house prices three years previously. Both may lead to poor quality borrowing and lending, fuelled by capital inflows and inflated collateral values, which may increase unexpected loan defaults and cause subsequent bank failures and crises.

In column 2 we split the two cycles and include them only for the countries where they were optimal. Although they have approximately the same coefficient as each other which is similar to that in the mixed regression, only the AR(2) cycle is a significant determinant of the probability of facing a crisis. However, including the two cycles separately appears to be a marginally better explanation of events (as judged by the AUC criterion) than that where they are constrained to have the same coefficient possibly because they are able to capture differences in credit dynamics across countries when entered separately

In column 3 we impose the AR(2) cycle on all countries, and it has a significant and positive coefficient, much as in columns 1 and 2, and the other variables have similar coefficients. Although this is an adequate explanation of the probability of a crisis, our information indicator, the AUC, suggests it signalling quality is lower than the previous two regressions. The same is true in column 4, where we impose the stochastic cycle from Harvey (1997) for all countries. The coefficients are similar, but in general slightly less significant. This reflects that fact that it is a less good explanation of the probability of having a crisis than those contained in columns one to three, as can be judged by its lower AUC.

Our preferred credit to GDP gaps are one component of a decomposition of the credit to GDP ratio into a trend, a cyclical component and a random component. It is of course possible to add the random component back in to the cyclical component and

judge that crises have followed on from house prices cycles, whilst in three of our stochastic cycle countries (Netherlands, Denmark and Germany) we would judge that their crises in 2008 were more related to the international nature of their banking systems activities rather than their domestic house price cycles.

We first run a regression of credit on lagged values of itself[19] and test whether house prices add information to this time series explanation. We then run a regression of the credit to GDP gap on lagged values of itself and check whether house prices are growth raising house prices, and rising house prices subsequently raising credit growth. In these circumstances bad lending is possible, as the lending inflates the value of collateral. Conversely, when credit growth slows, house prices begin to grow more slowly or even fall as refinancing of property loans becomes difficult. Collateral for loans thus disappears, and this is a potential cause of banking crises. In our other group of countries (Germany, Denmark, Japan, Netherlands and the UK), a decline in credit growth does not feedback on to house prices, and hence collateral is maintained for loans and default rates will be much lower. These results suggest there may be an association between crises and credit growth in some of our countries, but not in all of them. Hence the major policy related credit gap indicator appears to be relevant in only some countries but not in others.

5.4 Robustness

We subject our optimal logit model to three robustness tests. First we change the timing of a crisis, limiting them to the smaller number of systemic crisis listed in Laevan and Valencia (2013) [20]. Crisis dating varies to an extent across studies (see Barrell et al. 2010) and it could be argued that our optimal model relies on a particular set of dates. Although Laeven and Valencia (2013) use a broader set of policy responses relative to Caprio et al (2003) to identify crisis episodes, two conditions must be met for them to be systemic: 1) Significant signs of financial distress in the banking system (as indicated by significant bank runs, losses in the banking system, and/or bank liquidations, and 2) Significant banking policy intervention measures in response to

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[20] The new set of crisis are Belgium Denmark, France, Germany, Italy, Neths, Spain and Sweden in 2008, the UK and US in 2007, and the US in 1988, Spain in 1978, Sweden, Norway and Finland 1991 and Japan 1997. We use the date range from Laevan and Valencia (2013) for these crises.

significant losses in the banking system. They list six potential policy responses[21], three of which must occur for condition 2) to be met. This means that their definition is more restrictive than that of Caprio et al (2003), and we have preferred to continue to use that definition of a country in a banking crisis.

Our second robustness test repeats our initial Early Warning system estimates using the lagged (rather than current) value of the cyclical indicator. Although we have followed the Basel III suggestion that current credit dynamics affect bank lending behaviour, we test the possibility that utilising lagged credit gaps could change our conclusion. Finally, we test the out-of-sample performance of our optimal model since it could be that our AUROC results are a result of overfitting; in this case the model should not have good out-of-sample performance. For this exercise we use data from 2014-2016.

The new logit is given in Table 5, and we can see that our results are generally robust even after a large change in the dependent variable. Only our housing market indicator changes noticeably in size and significance. This is unsurprising as the 2008 crisis was partly triggered by housing developments in the US, but in some of the 8 countries that experienced a crisis in that year, house price increases had not induced lax lending. This was the case in Germany, for instance, where banking sector involvement in the US subprime market was a major driver behind banking failures.

Insert Table 5 here

Changing the timing of a cyclical indicator in our Early Warning regressions has much less effect than it would for some other variables as the cycle indicators are

[21] 1) extensive liquidity support (5 percent of deposits and liabilities to nonresidents); 2) bank restructuring gross costs (at least 3 percent of GDP); 3) significant bank nationalizations; 4) significant guarantees put in place; 5) significant asset purchases (at least 5 percent of GDP); 6) deposit freezes and/or bank holidays.

6. Conclusion

To test the hypothesis that excessive credit- to-GDP growth causes banking crises in 14 OECD countries during 1980 – 2013, we construct an HP credit gap to mimic the BIS approach. We then estimate three additional gaps, making additional specific assumptions on the functional form of the cycle: an AR(1) cycle, an AR(2) and a stochastic cycle *à la* Harvey and Jaeger (1993) and Koopman et al. (2006). These representations are designed to accommodate alternative cycle processes. The AR(2) and the stochastic cycle are naturally calibrated so the financial cycle is of medium term duration, consistent with the extant literature (Drehmann and Tsatsaronis, 2014).

We subject our gap measures to an optimal selection procedure based on the information criteria using the results of our trend-cycle decomposition, which allows us to isolate the best gap measure for each country. The results of the filtering exercise point out that there exist a natural statistical “clustering” of countries into two gap-types: countries for which a AR(2) is optimal (Belgium, Canada, Finland, France, Italy, Norway, Sweden, Spain and the US), and a remaining group (Germany, Denmark, Japan, Netherlands, UK) where a stochastic cycle is preferred.

The three cycle indicators are then embedded in a logit model in order to estimate their crisis prediction strength. Our logit early warning system utilises standard data on banking crisis, macroeconomic and regulatory control variables, including capital adequacy, liquidity, the current account and property price growth. We find that a mix of stochastic and AR2 cycles best describes crisis probabilities in terms of AUROCs. The AR2 cycle seems to apply to countries where credit growth and house prices interact and feed each other. Granger tests suggest in these countries, house price growth raised collateral values which propagated risky lending. Our conclusions are robust to changes in crisis timing, the use of lagged credit gaps and out-of-sample testing.

We conclude that credit growth is sometimes a good indicator of potential problems but note that this is restricted to cases where excessive lending fuels a cycle of rising housing prices and hence collateral which in turn propagates further credit growth. This transmission mechanism appears to be captured by only one of the four gap measures. Hence, we suggest that the most commonly used indicators cannot provide useful policy rules since they do not detect financial vulnerabilities. This result contrasts with the prevailing view that excessive credit growth (defined by a different gap measure) requires banks to hold excess regulatory capital. In particular, Basel III uses the “HP-filtered” gap between the credit-to-GDP ratio and its long term trend to guide policy in setting countercyclical capital buffers. We call this conclusion in to question and suggest that it is urgent that regulators change their view of how to measure and respond to the credit to GDP gap.

Credit-to-GDP ratios clearly represent a practical and appealing way to guide policy given the objective of the buffer. However, a growing literature supports the view that not all credit-to-GDP amplifications are “credit booms gone wrong”, underpinned by “reckless lending” (Schularick and Taylor, 2012; Gorton and Ordoñex, 2016). In these cases, financial intermediation disseminates credit towards productivity gains as opposed to risky lending, and hence taxing via countercyclical buffers would be socially undesirable. Hence, these types of credit cycle are unlikely to display high crisis prediction power.

Our results suggest that credit-to-GDP growth per se is not risky but that credit booms driven by house price acceleration require dampening. The policy lesson that we derive from this exercise is that financial regulators should carefully identify the nature of credit growth before taxing banks in order to minimise social welfare losses from financial disintermediation.

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Table 2. Choosing Cyclical credit indicators in logit models

	(1) Mixed	(2) Split	(3) AR2	(4) Stochastic	(5) Irregular
Credit (-1)	-0.013 (0.803)	-0.013 (0.802)	-0.018 (0.726	-0.014 (0.786)	-0.029 (0.614)

Cycle (

Table 3. Granger Causality between Credit Growth or Cyclical Components and House Price Growth for Countries where the AR2 Cycle is Optimal

	F-Statistic	Prob.
REAL HOUSE PRICE GROWTH (X) → Credit Growth (Y)	14.879	0.000
Credit Growth (X) → REAL HOUSE PRICE GROWTH (Y)	2.723	0.029
REAL HOUSE PRICE GROWTH (X) → Cycle (Y)	18.002	0.000
Cycle (X) → REAL HOUSE PRICE GROWTH (Y)	3.095	0.027

. Null Hypothesis: X does not Granger Cause Y

Table 4: Granger Causality between Credit Growth or Cyclical Components and House P

Table 5. Changing crisis dates

Credit (-1)	-0.171	(0.000)
Cycle **(Mixed)**	0.146	(0.000)
Capital (1)	-0.121	(0.038)
Current Account (-1)	-0.142	(0.002)
Real House Price Growth (-3)	0.044	(0.092)
Liquidity (-1)	-0.104	(0.000)

p-values in parentheses; 1981 - 2013; binary logit estimator

Table 6. Changing Lags: Impact on Area Under the Roc Curves (AUCs)

Cycle Type	Mixed	AR2 + Stochastic Decomposition	AR2	Stochastic	Irregular
Lags on Cycle: None	0.7698	0.7702	0.7648		