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

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Cycles, Crises and Credit

- For many years, the management of the proper operation of the financial system was a central task assigned to Central Banks, along with management of the currency.
- **No major financial crises** in the advanced economies in the period from 1940 to 1972.
- Systemic risk appeared to disappear – yet, 1970 to 2000 decade by decade, **financial crises** in the advanced economies became more **common**.
- These were not seen as a major focus of policy (e.g. Allen and Gale, 2007). Prevailing view that **risk** was **exogenous**, hence not requiring regulation.

Crises Bretton Woods and Liberalisation

	Systemic Crises in Advanced Economies					
1920s	Belgium 1925	Canada 1923	Denmark 1921	Spain 1920,1924	Finland 1921	
	Italy 1921	Japan 1927	Neths 1921	Portugal 1923	Sweden 1922	USA 1929
1930s	Spain 1931	Swiss 1931	Germany 1931	Belgium 1931, 1939	Finland 1931	
	France1930	Norway 1931	Neths 1939	Italy 1930, 1935	Portugal 1931	Sweden 1931
1940s						
1950s						
1960s						
1970s	UK 1974	Spain 1978				
1980s	UK 1984	Denmark 198	Norway 1988	USA 1984		
1990s	UK 1991	Swiss 1991	Finland 1991	Japan 1997	Italy 1990	Sweden 1991
2000s	Belgium 2008	Swiss 2008	Germany 2008	Denmark 2008	Spain 2008	France 2008
	Neths 2008	Portugal 2008	Sweden 2008	USA 2007	Italy 2008	UK 2008
Globally 4 in the 1970s, 39 in the 1980s and 73 in the 1990s. Only 7 to 2007						
Jorda, Shularick and Talor (2014) and Laevana nd Valencia (2013)						

Predicting crises

- What drives crises, what protects us? (Barrell et al JBF 2010, JFS 2016 Karim et al JFS 2013)
  - Bad lending causes crises. House price growth, current account deficits signal it.
  - Capital and liquidity are the safeguards. Risk weighting masks the problems
- We can use a logit model data 1980 to 2002

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

- We need to choose explanatory variables
  - Capital and liquidity in the banking sector
  - Growth in credit, GDP and real house prices

Modelling Crises

Estimation Period	1980 - 2002
Capital Adequacy Ratio(-2)	-0.479 (0.002)
Liquidity Ratio(-2)	-0.084 (0.054)
Δ Real House Price (-3)	0.079 (0.054)
Current Account Balance (% of GDP)(-2)	-0.455 (0.005)
Δ Real Domestic Credit(-2)	-0.006 (0.856)
Real Interest Rate	-0.046 (0.5)
ΔGDP(-2)	0.11 (0.541)
Total Observations	280

Belgium Canada Denmark Finland France Germany Italy Japan Netherlands Norway Sweden Spain US UK 1980-2002 from Caprio and Klingebiel (2003)

Forecasting crises probabilities from 2002

	2002	2003	2004	2005	2006	2007	2008	2009
Belgium	0.64	0.24	0.37	0.64	1.41	3.80	**7.25**	3.87
Canada	1.03	0.82	1.90	2.22	1.78	2.39	2.49	5.49
Denmark	0.94	1.77	0.95	2.04	1.36	4.20	**11.11**	3.40
Finland	0.00	0.00	0.04	0.06	0.23	0.18	0.37	0.99
France	2.14	2.30	3.07	**6.25**	**17.22**	**18.25**	**17.73**	**14.54**
Germany	3.01	0.91	0.85	0.36	0.28	0.26	0.17	0.13
Italy	1.19	1.90	2.40	3.10	3.38	6.21	1.33	1.64
Japan	0.67	0.50	0.23	0.16	0.06	0.09	0.14	0.13
Neths	**7.8**8	4.09	0.86	0.38	0.75	0.28	0.67	2.42
Norway	0.00	0.02	0.02	0.02	0.00	0.01	0.04	0.00
Sweden	0.95	0.76	0.23	0.22	0.40	0.21	0.19	0.15
Spain	4.76	3.81	**8.80**	**20.78**	**52.71**	**74.10**	**76.24**	**69.80**
US	**18.20**	**7.91**	**15.48**	**18.53**	**21.58**	**20.32**	**19.70**	**14.60**
UK	5.02	**7.75**	**11.06**	**7.98**	**10.66**	**10.03**	**5.30**	1.91

The New Regulatory Framework

- It was obvious that system wide shortage of capital led to bank failures and systemic collapse
- New regulations increased (slowly) capital in banks
  - Risk weighted capital rose to around 7 percent of total assets
  - A conservation buffer of 2.5 percent of assets was introduced
  - Large banks had to hold more capital
  - A leverage ratio of 3 per cent was introduced
- It was know that credit growth had been a major cause of problems
  - A countercyclical buffer based on credit has been introduced

But do all credit booms cause crises?

- Credit booms may increase the likelihood of **financial crises**, but they can also be the result of **sound economic developments**, and perhaps two thirds of credit booms since 1970 have not been associated with a subsequent financial crisis (Dell'Ariccia *et al.,* 2012).
- The best way to look at the association between credit cycles, assets booms and financial crises is to investigate the **interlinkages** (e.g., Schularick and Taylor, 2012; Jorda, Shularick and Taylor, 2011; 2013).
- BIS have investigated the Credit to GDP gap. This ratio clearly represent a practical to guide policy given the objective of the buffer.
- A growing emerging 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).

What we will look at

- We test the hypothesis that **excessive credit- to-GDP growth** causes banking crises in 14 OECD countries during 1980 – 2013, using:
  - long series on total credit to the private nonfinancial sector (BIS) to construct our credit-to-GDP gaps.
  - standard data on banking crisis, macroeconomic and regulatory control variables based on Karim et al (2013) Barrell *et al.* (2010, 2016), including capital adequacy, liquidity, current accounts and property price growth.
- We wish to examine the usefulness of countercyclical buffers as regulatory tools
  - We compare 4 ways of extracting a credit to GDP gap
  - We embed gaps in logit models of crises

Trends and Cycles

- Time series can be decomposed in to three components
  - Trend – there are many ways to extract trends
    - Moving averages (centred)
    - Univariate filters such a s Hodrick Prescott
    - Multivariate filters such as Beveridge Nelson
  - Cycle – there are many ways to extract cycles
    - We take the BIS Trend and derive different cycles
    - The HP trend is not a perfect way to proceed
    - Using HP makes us comparable with BIS
  - Random Components
    - These are things you may not need to react to

Modelling cycles

We use data for 14 OECD countries during 1980 – 2013, while we utilise long series on total credit to the private nonfinancial sector from the Bank of International Settlements to construct our credit-to-GDP gaps For the cycle we use the following specifications:

- ***Model 1*** - *Irregular*: where no explicit assumptions on the cycle are made (hence, the irregular or residual component is considered, matching Borio and Lowe, 2002)
- ***Model 2*** – *Stochastic* Harvey (1997)*:* where the statistical specification of the cycle is given by a stochastic cycle
- ***Model 3*** - *AR(1):* where the statistical specification of the cycle is described by an order-1 autoregressive process .
- ***Model 4*** - *AR(2):* where the statistical specification of the cycle is described by an order-2 autoregressive process .

Comparing Filters for the Credit to GDP gap

Model	T	p	log-likelihood	SC	HQ	AIC
CANADA						
Irregular	140	1	-291.020	4.1927	4.1803	4.1717
Harvey (1997)	140	3	-92.165	1.4225	1.3851	1.3595
AR(1)	140	2	-99.776	1.496	1.471	1.4539
AR(2)	140	4	-86.879	**1.3823***	**1.3324***	**1.2983***
BELGIUM						
Irregular	140	1	-309.420	4.4556	4.4431	4.4346
Harvey (1997)	140	3	-106.908	1.6331	1.5957	1.5701
AR(1)	140	2	-109.501	1.6349	1.6099	1.5929
AR(2)	140	4	-94.011	**1.4842***	**1.4343***	**1.4002***
GERMANY						
Irregular	138	1	-282.371	4.128	4.1154	4.1068
Harvey (1997)	138	3	-40.462	**0.69351***	**0.65574***	**0.62988***
AR(1)	138	2	-48.688	0.77703	0.75185	0.73461
AR(2)	138	4	-43.345	0.77101	0.72064	0.68616

Model	T	p	log-likelihood	SC	HQ	A
JAPAN						
Irregular	140	1	-389.841	5.6045	5.592	5.5
Harvey (1997)	140	3	-122.174	**1.8512***	**1.8138***	**1.7**
AR(1)	140	2	-134.405	1.9907	1.9657	1.9
AR(2)	140	4	-132.416	2.0328	1.983	1.9
NETHERLANDS						
Irregular	140	1	-287.964	4.1491	4.1366	4.1
Harvey (1997)	140	3	-109.527	1.6706	**1.6331***	**1.6**
AR(1)	140	2	-111.758	**1.6671***	1.6422	1.6
AR(2)	140	4	-112.422	1.7472	1.6973	1.6
NORWAY						
Irregular	140	1	-367.897	5.291	5.2785	5
Harvey (1997)	140	3	-195.782	2.9028	2.8654	2.8
AR(1)	140	2	-197.701	2.8949	2.87	2.8
AR(2)	140	4	-192.485	**2.8910***	**2.8411***	**2.8**

- T = no. of observations; p=parameters; SC = Schwarz criterion; HQ = Hannan-Quinn Criterion; AIC = Akaike information criterion

Results

- The results of the filtering exercise point out that there exist a natural statistical "clustering" of countries into two gap-types.
  - AR2 cycles are preferred for Belgium, Canada, Finland, France, Italy, Norway, Sweden, Spain and the US and stochastic cycles are preferred in Denmark, Germany, Japan, the UK, and the Netherlands
  - The former set of countries experienced **banking crises** that were associated with real estate booms in the early 1990s and during the sub-prime period (see also Reinhart and Rogoff, 2013).
  - When constructing a typical macroeconomic lagged information set for all countries in our sample including the cycle that is "optimally" selected for each country, 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.**

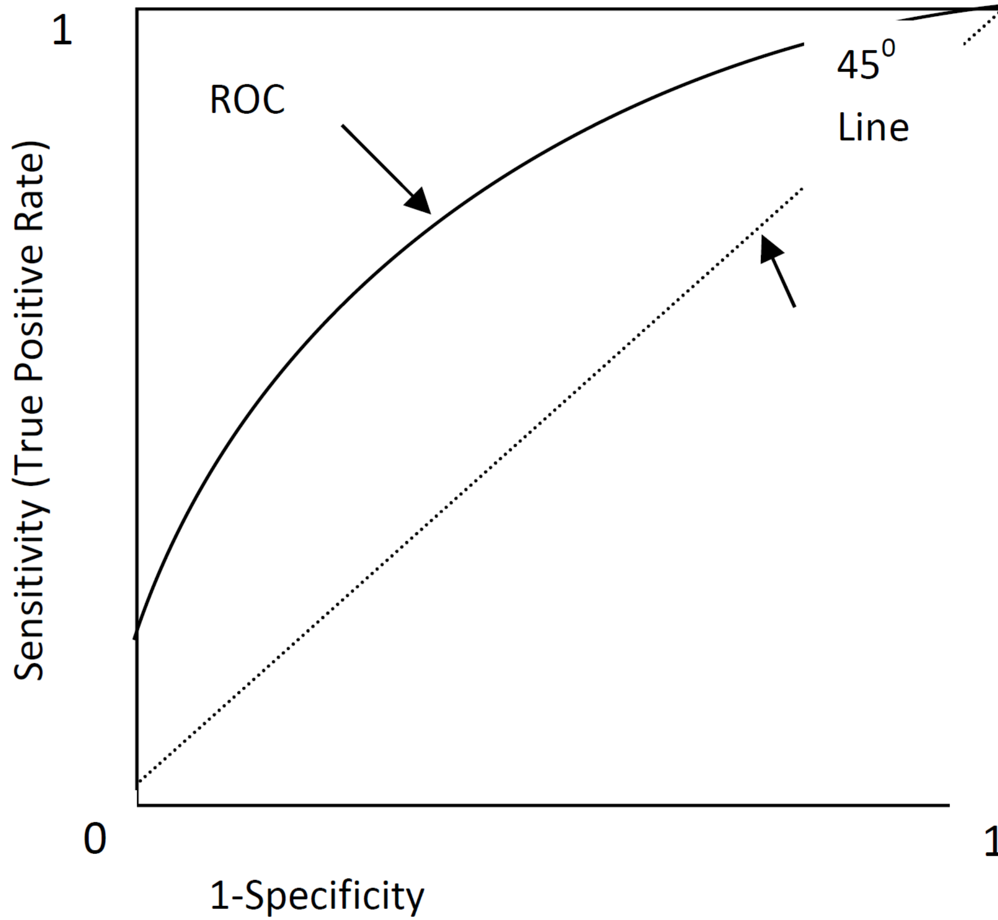
There is no country in our sample where a filtering procedure that makes no assumptions on the cyclical component (BIS view) is selected as optimal.

Core variables in testing

- We estimate LOGIT models as above. We do not use 'signal extraction' methods which are at best 'non parametric' and can be just guess work
- **Capital** is a buffer that protects banks against the variability of losses on non-performing loans which are a function of macro risks
- **Liquidity ratios** show the degree to which banks are robust to sudden demands for withdrawal by depositors or the lack of wholesale funds.
- **Residential property prices -** crises are often the result of poor quality lending in real estate markets, as is discussed in Reinhart and Rogoff (2008).
- **Current Account -** crises are often associated with the growth of external debt (Reinhart and Rogoff, 2008; Karim et. al, 2013, Jorda et. al, 2013)
- **Credit gap measures –** based on different ways of constructing the gap

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..
- The two variables of interest are: sensitivity (true positive rate) and 1 – specificity (false positive rate). Sensitivity is plotted on the y-axes and 1 – specificity on the x- axes. The overall results can be summarised by the **Area Under the Curve** (AUC).
- An AUC of 0.5 is equivalent to a "naïve" estimator that replicates a random coin toss (corresponding to the 450 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 (typically 0.6 < AUC < 0.9).



Identifying crisis episodes

- We use Caprio and Klingebeil (2003) from Honohan and Laeven (2005) and Demirguc-Kunt and Detragiache, (2005),
  - The definitions were updated by Laeven and Valencia (2010)
  - Dates change (eg for Japan) depending on which version we use.
- The banking crisis dependent variable, a binary banking crisis dummy, is defined in terms of observable stresses to a country's banking system:
  - proportion of non-performing loans to total banking system assets exceeding 10%,
  - public bailout cost exceeded 2% of GDP,
    - in Laevan and Valencia 2013 this is raised to 3% of GDP
  - systemic crisis caused large scale bank nationalisation,
  - extensive bank runs were visible and if not, emergency government intervention was visible.
- It may not always have been obvious to the public that a crisis was under way, especially before the era of central bank transparency

Where we have crises

Our dataset includes **23 crises in OECD countries** over the period 1980 to 2010 and our data spans **1980 - 2013**. Over half the crises are from the World Bank Crisis Database covering 1974-2002, (Caprio *et al* ., 2003):

- Canada (1983); Denmark (1987); US (1988); Italy and Norway (1990); Finland, Sweden and Japan (1991); France (1994); UK (1984, 1991, 1995).
- For the crises episodes in 2007 and 2008 we have used the crises dates from Laeven and Valencia (2010):
- Belgium, Denmark, France, Germany, the Netherlands, Spain and Sweden (2008); US and UK (2007). We treat the US and the UK in 2008 as separate crises since it was induced by the collapse of Lehman Brothers.

Cyclical Credit indicators in logit models

	Mixed	Decomp	AR2	Stochastic	Irregular (BIS)
Credit (-1)	-0.013 (0.803)	-0.013 (0.802)	-0.018 (0.726	-0.014 (0.786)	-0.029 (0.614)
Cycle (**Mixed**)	**0.051 (0.022)**				
Stochastic Cycle		0.051 (0.295)		**0.033 (0.04)**	
AR2 Cycle		**0.052 (0.03)**	**0.049 (0.038)**		
Irregular Cycle					0.015 (0.493)
Capital (1)	**-0.347 (0)**	**-0.347 (0)**	**-0.332 (0)**	**-0.347 (0)**	**-0.301 (0)**
Current Account (-1)	**-0.139 (0.013)**	**-0.139 (0.013)**	**-0.13 (0.018)**	**-0.123 (0.022)**	**-0.119 (0.033)**
Real House Price Growth (-3)	**0.079 (0.019)**	**0.079 (0.019)**	**0.082 (0.014)**	**0.084 (0.012)**	**0.083 (0.013)**
Liquidity (-1)	**-0.128 (0)**	**-0.128 (0)**	**-0.13 (0)**	**-0.126 (0)**	**-0.129 (0)**
Area Under the Curve AUROC	0.7698	0.7702	0.7648	0.7608	0.7553

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

Granger causality results

Granger tests suggest in the AR(2) countries

Belgium, Canada, Finland, France, Italy, Norway, Sweden, Spain, US,

house price growth raised collateral values, stimulating more credit growth and further house price acceleration. This viscous circle propagated **risky lending, and when house prices start to fall the collapse feeds itself**

Not the case in our second group of countries

Germany, Denmark, Japan, Netherlands, UK

where **house prices** cause **credit**, but the **reverse** does **not** hold

Table 3: Granger Causality AR(2) Cycle

	F-Statistic	Prob.
RHPG (X) → CRED (Y)	14.879	0
CRED (X) → RHPG (Y)	2.723	0
RHPG (X) → Cycle (Y)	18.002	0
Cycle (X) → RHPG (Y)	3.095	0

Table 4: Granger Causality Stochastic Cycle

	F-Statistic	Prob.
RHPG (X) → CRED (Y)	10.666	0.000
CRED (X) → RHPG (Y)	2.211	0.068
RHPG (X) → Cycle (Y)	2.506	0.059
Cycle (X) → RHPG (Y)	0.884	0.449

Changing Crisis Dummy Dates

- Laevan and Valencia (2013): 16 crises (vs. 23): lose all pre-2007 UK crises and one in each the US, France and Canada
- new crisis set more heavily weighted toward 2008, and timings of other crises also differ
- results are generally robust even given a large change in the dependent variable
- In many countries with crises in 2008 there had been no house price increases causing poor lending

Credit (-1)	-0.171 (0)
Mixed	0.146 (0)
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)

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

Changing Lags: Impact on Area Under the ROC Curves (AUCs)

Cycle Type	Mixed	AR2 + Stochastic	AR2	Stochastic	Irregular
Lags on Cycle: None	0.7698	0.7702	0.7648	0.7608	0.7553
Lags on Cycle: One	0.7573	0.7734	0.7609	0.7622	0.7491

- We have used a current cyclical indicator based on past data
- Lagging the cycles makes little difference to AUC
  - For the two best cycles separately it is marginally better
  - It is worse for the BIS cycle.

Forecast Crisis Probabilities

- No crises since 2013 in our dataset
- Worry clear in Norway and Sweden in 2014
- France criticised in 2014/15 stress tests
- Liquidity definition may no longer be useful after QE

	2014	2015	2016		2014	2015	2016
Belgium	**3.0**	**6.5**	**5.9**	**Japan**	**0.0**	**0.1**	**0.0**
Canada	**19.1**	**15.7**	**15.4**	**Netherlands**	**5.5**	**4.1**	**4.9**
Denmark	**2.3**	**0.7**	**0.7**	**Norway**	**31.4**	**4.9**	**5.2**
Finland	**10.5**	**13.3**	**7.0**	**Sweden**	**8.9**	**7.7**	**6.3**
France	**5.7**	**9.3**	**6.6**	**Spain**	**1.6**	**1.2**	**0.9**
Germany	**1.7**	**3.1**	**1.7**	**UK**	**2.2**	**1.6**	**1.1**
Italy	**0.9**	**0.5**	**0.4**	**USA**	**0.0**	**0.0**	**0.1**

Can we always explain Crises: Italy 2017

A call from Commissario Brunetti to the Venice Casino Director

‘Ah, Dottor Brunetti’ he heard the Director say in his friendliest tones, ‘how may I be of service?’

‘Dottor Alvino,’ Brunetti responded, honey in his voice, ‘I hope things are fine down there’

‘Ah,’ came the drawn out sigh, ‘as well as can be’

‘Still losing money?’ Brunetti asked, using his best bedside manner.

‘Unfortunately, yes. No one can explain it’

Brunetti could, but this was a friendly call.

Donna Leon ‘By its Cover’ p215

Conclusions

- **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 collateral** which in turn propagates further credit growth.
- This **transmission mechanism** is **understudied** and appears to be captured by only one of the four gap measures we use. Hence, we suggest that the most commonly used indicators cannot provide useful policy rules since they do not detect financial vulnerabilities.
- **This result challenges** the **prevailing view** that excessive credit growth (defined by a different gap measure) requires banks to hold excess regulatory capital.
- Regulators acknowledge the link between credit-to-GDP gaps and capital buffers is not mechanical, but ample consensus that the credit-to-GDP gap is a robust single indicator of financial vulnerabilities (Drehmann and Tsatsaronis, 2014). Our findings suggest this is not always the case.