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Abstract: There are large and long-lasting negative effects on output from recurrent financial crises in market economies. Policy makers need to know if these financial crises are endogenous (to the macroeconomy) and subject to policy interventions or are exogenous events like earthquakes. We look first at the definition of crises, and then survey the literature from Jorda, Schularick and Taylor (2011) and from Bordo (2018) amongst others about the links between credit growth and crises over the last 150 years. We then go on to look at the determinants of financial crises in market economies, stressing the roles of bank capital, available on book liquidity, property prices and current account deficits. We look at the role of credit growth, the main link between macroeconomics and crises, and stress that it is largely absent. It is also useful to know if they are predictable, and if so, potentially preventable. We look at the role of the core factors discussed above in market economies from 1980 to 2017. We conclude that policy makers need to contain banking excesses, not constrain the macroeconomy.

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1. Introduction

The financial crises in 2007 and 2008 have left a long and depressing shadow over the North Atlantic economies. Not only did output fall sharply after those crises, but output growth has also been slow since 2009. It has been common to link this crisis, and others to the twin problems of excessive credit growth and the subsequent unsustainable growth of asset prices, and, particularly, property prices. The link between credit growth and financial crises has been emphasised in a series of papers covering a period of over 130 years of history in 17 developed economies by Jorda, Schularick and Taylor (2011), Schularick and Taylor (2012) and Jorda, Richter, Schularick and Taylor (2018) and has been supported by the views and the publications of the Bank for International Settlements (BIS). The evidence to link crisis incidence to credit growth over the last forty years is, however, weak, and evidence of the link for these economies from earlier periods may not be relevant for the analysis of policy problems in financially liberalised advanced economies. The prevailing view in the economics profession, and the policy community, is that constraining credit growth is essential for preventing a new round of financial crises. In this paper we evaluate this proposition and attempt to understand the causes of financial crises in advanced economies over the last forty years.

We look at the role of the defences against systemic bank failures, capital and liquidity as well as at the role of property prices and of credit growth in driving them. We argue that following the results in Jorda et al (2018) on the periods since the 1880s and since 1945, and hence rejecting a role for capital adequacy in explaining financial crises is misjudged. In the financially liberalising world that followed on from the collapse of Bretton Woods system in the early 1970s banks on balance sheet capital has been an important defence against the risk of crises, even if it was not significant in earlier historical periods. We conclude that the emphasis on credit growth and its control, rather than on capital adequacy, is misjudged and reduces the chances of preventing a new wave of damaging crises.

In the next section of the paper we review the related literature on the factors driving crises over the last 120 years, and we re-emphasise the conclusion of Bordo (2018) that there is little evidence to support the importance of credit growth over this period, with only the 1929-33 crisis and the 2007-8 crises showing links. House prices have been commonly linked to crises as well, and we look at these in section three, building on papers by Barrell and Karim (Barrell et al 2010, Karim et al 2013). In this section we discuss logit models of financial crises over the period 1980 to 2017 using published data from international organisations on capital, liquidity, current accounts and real house price growth for 14 countries. These models work well, catching two thirds of crises, whilst adding various excess credit indicators does not enhance them. In an appendix we decompose the drivers of crises, and suggest that credit growth has little effect, and that episodes of real house price growth that are independent of credit growth are important. The importance of the defences against crises, capital and liquidity, is discussed. In section four we look at the various definitions of crises we could use and test our framework on these definitions. We stress the Laeven and Valencia (2013 and 2018) crisis definition, which is tighter than the one used in the earlier sections, and we demonstrate that our conclusions on the roles of house prices and credit also hold in this tighter framework. In our last section policy conclusions for macroprudential policy on the importance of bank capital and liquidity are drawn, and we discuss implications for further research.

2. Defining and explaining crises

There has been an extensive technical and historical literature on the causes and consequences of crises, and it has expanded rapidly since 2007. For the sake of brevity, we do not discuss the consequences of crises, but rather focus on their causes and policy responses to them. The literature on the causes of crises is summarised in Bordo and Meissner (2016) and they bring out several strands, ranging from narrative accounts such as Reinhart and Rogoff (2009) and Bordo (2018) through simple univariate early warning indicators used by Reinhart and Kaminsky (1999) and by the Bank for International Settlements in a sequence of staff papers by Borio and Drehmann (2009) and others in subsequent papers, to more sophisticated logit based models as in Barrell et al (2010) and Schularick and Taylor (2012). The causes of banking crises remain disputed with Borio (2014) and Jorda, Schularick and Taylor (2011, 2013) and Jorda et al (2018) strongly supporting the view that excess credit growth is a major factor in driving banking crises. Bordo (2018) disputes this conclusion, and as does Kiley (2018) who shows that credit has contributed little to the explanation of the crises Jorda, Schularick and Taylor examine, even if it is statistically significant. We study the post Bretton Woods era in almost the same set of countries, and we draw the conclusion that credit (no longer) matters (much) in driving financial crises.

Research by Barrell, Davis, Karim and Liadze (2010) suggested that house price growth affected crisis incidence, but credit growth did not. This paper also found a role for bank capital and for liquidity, and we describe these two as the defences against the excesses associated with the problem indicators, house price increases and from Karim et al (2013) we add current accounts. Kiley (2018) extends this approach. However, Jorda et al (2018) in a long historical study find no role for a deficiency in bank capital as a precursor for crises either in the post 1870 world or in the post-World War II world in 17 advanced countries. The crises they choose are different from those we look at in this study, but they overlap. For our 14 countries after 1980 their crises and those in the Laeven and Valencia (2013) study are essentially the same, and we look at the determinants of these crises in section 4. We demonstrate that in these crises, and in a number of other taxonomies of crises in the post 1980, world capital has a major role to play in the determination of crisis probabilities.

Crises have been endemic in market based, or capitalist, economies, and they became increasingly common in OECD countries by decade after the ending of the crisis free Bretton Woods period of financial repression between 1940 and 1972. The Bretton Woods system was crisis free in part because financial systems were tightly controlled, and the liberalisation of controls has been seen as a major factor affecting crisis incidence. However not all crises in the last 40 years have followed on from liberalisation. We would argue that liberalisation of consumer credit lending, and the growth of housing related lending has been a factor behind a number of crises in the post Bretton Woods era, especially those in Scandinavia around 1990. This, along with the availability of internationally comparable published data justifies our decision to focus on crises in advanced economies since 1980.

Financial crises happen when it becomes clear that a reasonable proportion of the banking system cannot meet their obligations, either because they are short on liquidity, or because they do not have enough capital (essentially the difference between their loans, or assets, and their liabilities or deposits) to cover their short-term losses, and hence they are potentially insolvent. Definitions on how many banks, and what proportion of loans are non-performing vary, and a number of definitions of crises have emerged. The most widely used have been those from the World Bank (Caprio et al 2005)[1] and those from the IMF in Laeven and Valencia (2013 and 2018)[2] who use a much more restrictive set of criteria.

We have complete, published data on the consolidated banking systems for 14 countries[3] (Belgium, Canada, Germany, Denmark, Spain, Finland, France, the UK, Italy, Japan, the Netherlands, Norway, Sweden and the US[4]). We start with the Caprio et al (2005) description of crises, and they identify them in Canada (1983), Denmark (1987), the US (1988), Norway (1990), Sweden and Finland (1991) and Japan (1992), France (1994) and marginally the UK (1984, 1991). Earlier versions of Caprio and Klingebiel, listed in Baron (2018) and used by Barrell et al (2010), put the Norwegian crisis in 1987, the Japanese one in 1991, and noted the 1984 crisis in the US. Putting a date on crises is always difficult, as in the 1980s and 1990s disclosure of bank problems was less systematic than it became a decade or so later. In the two UK cases Caprio et al (2005) record the failure of a small bank because of fraud by one of the parties involved. However, in each case it was clear that a (different) major clearing bank was in serious trouble and was only kept going with covert Treasury support. This will have been clear in the official international community, and we include them. In Barrell et al

[1] There are various versions of this paper, with varying authors, and these are discussed in Baron et al (2018)
[2] The post Great Financial Crisis study of this topic has benefitted from a sequence of papers from Laeven and Valencia on crisis dating, starting in 2008. Inevitably the timing of crises changed as new information on past events became available.
[3] The long database used by Jorda et al (2018) also includes, Australia, New Zealand and Switzerland.
[4] We have interpolated one value for capital in the US in 1983 as in Barrell et. al. (2010).

(2010) crises were identified in the UK and US in 2007 and 2008 and as in Laeven and Valencia (2013) crises in Belgium, Denmark, France, Germany, the Netherlands, Spain and Sweden in 2008 were included. In the first set of experiments in this paper we have also added crises in the US (1984), Norway (1987) from Barrell et. al (2010) and Japan (1997) from Laeven and Valencia, as these appear to be different incidents to those we include at other dates. It is the case that the scale of rescue in crises in the 1980s and 1990s often took a long time to be clear, and crisis dates emerge in the databases a long while after crises happened, and often the observed bank rescues significantly postdate the losses they are associated with. We discuss the importance of the definition of crises in attempts to explain them in section four below, and we compare both a wider definition drawn from Baron et. al. (2018) and a narrower one from Laeven and Valencia (2018).

3. Simple Models of Financial Crises

Logit models of crises have become common in the more technical literature, and we use them here. They were compared to simple signal extraction models and more complex decisions trees by Davis and Karim (2008) and have generally been seen as the most effective way to proceed. We model 14 OECD countries from 1980 to 2017 using logits, and we base our experiments on Barrell et al (2010), where the crises listed above are seen as being determined by the strength of the defences against bad bank lending and the determinants of such bad lending. For our defences we use OECD data published on the consolidated banking systems of our countries (no others are available from this source) on un-risk-weighted capital in the banking system and IMF data on narrow liquidity in the system[5]. Karim et al (2013) and Kiley (2018) emphasise the role of current accounts as well as real house price growth rates in leading to crises, as these are associated with poorly considered lending by banks to companies and individuals respectively, and we include them in our analysis.

We initially look at relatively parsimonious logit models to explain crises and include unweighted capital, bank liquidity, house price growth, the current account. If any of these significant, and relevant, variables are omitted, as they are in some of the longer period studies mentioned above, the included coefficients will be biased if the variables are not orthogonal to those excluded. This problem is important and dealing with it sometimes leads to over-specification and inclusion of irrelevant variables. However, over specification can also cause problems. We exclude variables that are shown to be insignificant in Barrell et.al. (2010) and a range of other studies. This has the advantage of reducing bias from over specification as including a variable that is irrelevant but not orthogonal to other regressors will induce biases in the coefficients on the other relevant variables that are included.

[5] See data appendix for details.

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:

$$Prob\ (Y_{it} = 1) = F(\beta X_{it}) = \frac{e^{\beta' X_{it}}}{1+e^{\beta' X_{it}}} \quad (1.)$$

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

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

Our results are reported in Table 1 below. The first column repeats the analysis in Barrell et al (2010) and Karim et al (2013) over a longer period, and the results remain robust, with increased capital reducing crisis probabilities and stronger house price growth raising them. As we have the intention to construct an Early Warning System we use only lagged variables to explain crisis incidence. This is also necessary as capital and liquidity are balance sheet variables, reported at end of year.

Table 1 Basic Models of Crises

	Base	Total Credit	Cons Credit	BIS Credit Gap
	1981-2016			
Current account (-1)	-0.1778	-0.1749	-0.1591	-0.1609
	0.004	0.004	0.010	0.007
Capital(-1)	-0.3737	-0.3954	-0.4373	-0.4029
	0.000	0.000	0.000	0.000
Real House Price Growth(-3)	0.0661	0.0529	0.0346	0.0487
	0.016	0.097	0.314	0.103
Liquidity(-1)	-0.0928	-0.0944	-0.1058	-0.0890
	0.000	0.000	0.001	0.000
test(-1)		0.0343	-0.0145	0.0417
		0.621	0.850	0.453
test(-2)		0.1093	0.1349	-0.0222
		0.194	0.212	0.808
test(-3)		-0.1209	-0.0422	0.0109
		0.084	0.591	0.851
Area Under Curve (AUC)	0.7226	0.7500	0.7656	0.7367
Direct Call Ratio (DCR)	19/27	19/27	17/25	17/27
False Call Ratio % (FCR)	33.33	31.66	32.19	31.87

Notes Probabilities under coefficients. Cols 1, 2 and 4 have 27 crises with 504 obs., prob 0.05357 whilst column 3 has 25 crises and 432 observations, prob 0.05787

The most significant variable is capital, with crises probabilities being reduced when the banking system has more capital. The other defence, liquidity, is also significant, reducing crisis probabilities noticeably. The causes of problems are current accounts and the growth of house prices. A deterioration of the current account increases crisis probabilities significantly, suggesting that lower quality lending has increased. Kiley (2018) uses only current account deficits, but we consider that both sides of zero matter. If there are good structural reasons for a surplus (or a deficit) in a country, then a deterioration in the surplus may involve a resort to more risky lending as patterns of finance change. We include the third lag in real house price growth as this was preferred in earlier work on Early Warning Systems, and it remains significant in the longer sample. We posit that when house prices are rising most rapidly banks are more willing to lend to more risky borrowers, and at some time in the future their mistakes will be uncovered by defaults on loans in excess of the scale they had built in to the lending rate. We have no empirical reason to assume that bad loans only turn up when house prices fall after the boom, although this may happen, and hence we do not describe this variable as picking up the housing cycle.

As one focus of this paper is the role of credit in driving crisis incidence, in Columns 2 to 4 we add a set of variables associated with lending growth[6]. All are derived from BIS data, as are our real house prices. We first add the growth in real total credit in column 2, with three lags, and then in column 3 we add the growth in real consumer credit again with three lags, and finally we add the BIS estimate of the gap between credit to GDP and trend credit to GDP which is based on data for real total credit and uses a Hodrick Prescott filter to estimate the gap. The gap uses a great deal of past information on both credit and on GDP, and as such it bears similarities to the longer term moving averages of credit growth used by Jorda et al (2018) for instance. The role of the gap is investigated further in Barrell et al (2018).

There are several ways to evaluate logit models, and the simplest are probably the hit and miss ratios, which we denote Direct Calls and False Calls. A Direct Call is when the projected probability exceeds the sample average, which in columns 1, 2 and 4 is the sample average proportion of crises in our data set of 5.357 percent. Our basic model hits 19 out of 27 crises in our 36-year data set, and hence is giving a reasonable warning. However, it also has 33.33 percent of its calls in excess of the sample average, and we describe this as the False Call (or False Positive) ratio. Up to half the false calls are in the three years before a crisis, or the three years after, and hence prompt corrective action would have been appropriate, or unnecessary, in these cases. Only about one sixth of our time periods are covered by genuine false calls, and hence can see them as useful indicators rather than pure false calls.

Evaluating whether a model is good depends upon the weights one puts on making correct calls for actions as against the number of times action is called for when it is not necessary. If

[6] The current account as a percent of GDP, along with capital and liquidity as a percent of assets, are (almost by construction) stationary. So are the series for real house price growth and for real total credit growth that we include. However, real consumer credit growth is only stationary after 1996, and hence results including that variable must be treated with a little caution. (see Appendix)

crises are expensive but prompt corrective action is cheap and effective then the Direct Call and False Call rates should have different weights reflecting this as compared to when prompt corrective action is expensive. However, it is useful to have a statistic that builds in a trade-off between Direct and False Calls independently of the optimal weights, and to do so we also report the widely used Receiver Operating Characteristic based Area Under the Curve indicator. This is derived from signal extraction problems in the use of radar, and an AUC of 0.5 is as good as tossing a coin, and anything above 0.85 is excellent discrimination. Our AUC in column 1 is 0.723, which is significant[7]. We could of course raise our AUC by dropping crises that are hard to call and that are not universally agreed. However, our objective is to explain the world we see, not maximise the AUC.

When we add three lags in the BIS credit indicators the AUC improves marginally, but not significantly, and in each case the real house price growth indicator becomes insignificant. However, if we follow the standard procedure of eliminating the least significant variable first all the lags in total real credit growth drop out in turn, leaving real house price growth as significant. Real total credit growth lagged three periods is significant at the ten percent level, but its coefficient is negative, which is at odds with the views of those who think high real credit growth is a precursor of a crisis. We can test for the joint significance of the three lags with a Wald exclusion test, which is passed with Chi^2 (3) = 3.89687 (prob 0.2728). When we include real total credit growth the model makes the same number of Direct Hits as our base model. The BIS Credit Gap is not close to significant at any lag and gives fewer Direct Hits than the baseline model, and a Wald exclusion test is passed with Chi^2 (3) = 2.28115 (prob 0.5161).

Adding real consumer credit growth reduces the number of observations we have to 432 and for crises to 25, with an in-sample crisis rate of 5.787 percent. In this experiment crises Italy in 1990 and Denmark in 1987 disappear because of lack of data on consumer credit in these countries. The US crises in 2007-8 are no longer hit, whilst Sweden and the Netherlands in 2008 are. A Wald exclusion test on the three lags is passed with Chi^2 (3) = 3.005448 (prob 0.3908). Failing to explain the US is perhaps a more serious problem in our description of the world. In no case do we have an explanation of the crisis in the US in 1984, Italy in 1990, Norway in 1991 or Germany and Italy in 2008. We return to the reasons for these misses later. In no case would we say that the BIS credit augmented explanations are clearly better than our base case.

[7] An AUC of 0.5 represent a coin toss, with half of crises being hit, and a fifty percent false call rate, whilst an AUC of 1.0 means all crises have been hit and there are no false calls. Given our sample proportion is 5.2 percent in the former case we have 20 false calls for every hit. At an AUC of 0.723 we get probably 10 false calls per hit. This is good if the costs of action in a false call are less than 10 percent of the cost of not acting on a true call, but bad if the cost of acting on a false call are noticeably higher.

The links between real house price growth and crisis incidence are clear, and when we add real total credit growth to a model with capital, liquidity, current accounts and house prices, the latter variable becomes insignificant. The growth rates of real house prices and real total credit are not orthogonal, as the coefficient on the former changes when we add the latter, and hence it is possible that house prices are picking up some of the relationship between credit growth and crisis incidence as they act as a pathway for the effects of credit growth. As we have stationary quarterly data on real house price growth and real (total) credit growth from 1975 as well as on the BIS credit gap from the late 1970s or 1980 we can undertake Granger causality tests. In Table 2 we look at the determination of current real house price growth by 12 lagged values of itself and test to see it 12 lagged values of real (total) credit growth add anything to the explanation, and then do the same for real (total) credit growth and test if real house price growth adds anything to the estimation[8].

Table 2 Causality structure between Credit and House Prices

	Total Credit			Credit Gap		
	CR to PH	PH to CR	Causality	CG to PH	PH to CG	Causality
Belgium	1.05687 (0.4019)	1.75509 (0.0624)*	No Causality	1.50056 (0.1349)	0.66215 (0.7839)	No Causality
Canada	0.72136 (0.7285)	2.06066 (0.0239)**	House prices to credit	0.99217 (0.4603)	0.86300 (0.5861)	No Causality
Germany	2.68363 (0.0029)**	1.02729 (0.4279)	Credit to house prices	2.81764 (0.0019)***	2.22556 (0.0142)	Bidirectional Causality
Denmark	1.43694 (0.1572)	1.35912 (0.1938)	No Causality	1.34429 (0.2024)	0.67996 (0.7680)	No Causality
Spain	0.58837 (0.8485)	0.65440 (0.7918)	No Causality	0.65451 (0.7915)	1.09101 (0.3736)	No Causality
Finland	0.73418 (0.7159)	2.30509 (0.0107)**	House prices to credit	2.21264 (0.0158)**	0.62396 (0.8178)	Credit to house prices
France	0.83206 (0.6173)	0.83206 (0.6173)	No Causality	1.40714 (0.1730)	0.57061 (0.8617)	No Causality
UK	0.90401 (0.5449)	1.12612 (0.3447)	No Causality	1.15919 (0.3200)	0.76995 (0.6801)	No Causality
Italy	2.04917 (0.0248)**	0.75645 (0.6937)	Credit to house prices	1.25576 (0.2536)	1.64318 (0.0881)*	No Causality
Japan	1.18964 (0.2971)	2.65840 (0.0032)**	House prices to credit	0.37864 (0.9689)	1.52105 (0.1252)	No Causality
Neths	1.12652 (0.3443)	1.84429 (0.0474)**	House prices to credit	1.15337 (0.3243)	1.15337 (0.3243)	No Causality
Norway	0.54555 (0.8811)	1.43869 (0.1564)	No Causality	1.61749 (0.0950)	0.61472 (0.8264)	No Causality
Sweden	0.50817 (0.9064)	1.28792 (0.2331)	No Causality	1.44516 (0.1564)	0.74159 (0.7081)	No Causality
US	0.96945 (0.4813)	3.07521 (0.0008)***	House prices to credit	2.32129 (0.0104)**	1.56241 (0.1114)	Credit to house prices

Notes Results of Granger causality tests between real credit growth and real house price growth, quarterly data 1975q1 to 20017q2, using 12 lags and 155 observations. Significance in brackets, *,**, *** 10%, 5% , 1% . PH quarterly real house price growth, CR quarterly Real (total) credit growth, CG is the BIS constructed gap between actual credit to GDP and the HP filtered trend of credit to GDP.

[8] We do not undertake tests for real consumer credit growth, as there is less data and we cannot guarantee stationarity over the whole period (see data appendix for details). This in part reflects the strong growth in consumer lending by banks in the early years after the post Bretton Woods liberalisation.

As we can see from Table 2 there is no causality link between real house price growth and real total credit growth in UK, France, Denmark, Spain, Norway and Sweden, and perhaps also in Belgium. All had at least one crisis in our sample. In Canada, Finland, Japan, Netherlands and the US real house price growth ‘causes’ real (total) credit growth, which is a worry to policy makers, as collateral is used to increase borrowing, and in a downturn this extra borrowing is exposed. This may well describe Canada in the early 1980s along with Finland and Japan in the late 1980s, and the US in the 2000s, but amongst this group of 5 countries only the US had a crisis in 2007-8. It does not describe the Netherlands experience in 2008 as the housing boom peaked at the start of the decade. Only in Italy and Germany do house prices cause credit growth, and in neither country have crises been associated with domestic housing markets (and indeed we cannot easily ’predict’ these crises). In half our countries there is no link between real house price growth and real credit growth, and the in other half the causality is predominantly from house prices to credit, but mainly in countries where house prices were not a concern in 2007-8. Our two competing variables show few links in Table 2, and hence we can see our tests as discriminating between them. The use of house prices in the regressions in Table 1 is not masking the role of credit. We discuss this further in the Appendix, decomposing explanation of crises into the contribution of causes and of defences.

The links between house price growth and the BIS credit gap are even more limited, and in 11 cases there is no evidence of any causality between the two series, suggesting that they do not compete for information. In Finland, the credit gap ‘causes’ house prices, but there was no crisis in 2008, so this may reflect earlier experience. In the US the credit gap causes real house price growth, over our sample period.[9] In Germany we see bi-directional causality, where credit expansions may feed on themselves. However, Germany had stable or falling real house prices until 2011, and hence we may see a circular set of causes for house price declines not associated with the 2008 crisis.

We conclude that the causal links between house price growth and credit growth are weak, and hence we can rely on our results where one, house price growth, is significant, and is associated with bad lending. We do not test for the impacts of consumer credit growth on house prices because of the paucity of data over our time period described in the appendix.

4. Robustness to Changes in Crisis Definitions

Financial stress is common if not endemic, as Romer and Romer (2017) show, but not all periods of stress turn in to periods of rupture. As noted above, we start with the Caprio et al (2005) definition of a financial crisis, which was that the proportion of non-performing loans

[9] The time period over which this BIS data is available varies by country, In general the causality works from about 1983, although I some countries we have earlier evidence to support our results.

to total banking system assets was greater than 10%, or the public bailout cost exceeded 2 percent of GDP, or systemic crisis caused large scale bank nationalisation, and if not, emergency government intervention was sustained. Crises could also occur when bank runs were observed, but these have been rare in our set of countries since 1980. Not all of the crises identified by Caprio et al (2005) were publicly visible as sustained government intervention can be hidden by careful management of the publicly available accounts, and this was common before the era of central bank transparency but would be obvious ex-post to officials. The definitions were tightened and updated by Laeven and Valencia (2013 and 2018), who stressed the role of public sector interventions, and they revised and extended the dataset. The Laeven and Valencia revision raised the threshold bailout cost to 3 percent of GDP and focused on crises that Caprio et al (2005) had noted as systemic. The crises in in 2007-8 that we and they include can all be described as systemic.

The recent paper by Baron et al (2018) pulls together these and a number of other definitions of crises over a longer timer period than we use here, and also proposes a new definition of a crisis which depends upon movements in bank equity prices. As Baron et al (2018) notes, these often occur before a crisis becomes obvious, as shareholders may look more carefully at the structure of the balance sheet than does the public. Although most crises identified by bank equity price movements are similar to those we use, there are some problems with this definition, and we look at two early examples. Baron et al (2018) removes our two earlier UK crises in 1984 and in 1991 as bank equity prices did not fall. These predate central bank transparency (and even independence in the UK) and the problems were either not obvious to shareholders or they were clear that the Treasury had taken sufficient action to deal with any shortfalls at any banks involved. In 2001 bank equity prices fell in Japan sufficiently to meet the criteria used by Baron, but this may have been because banks were in a strong enough position to restructure their balance sheets and be clear about problems that had been partly hidden by collusion between the banks and the Bank of Japan in the 1990s. Shareholders may not have fully realised the problems until new capital was raised, and bank equity prices fell. However, we must not confuse an adjustment in bank capital (its balance sheet equity) because of the emergence of more honest accounting with a financial crisis.

In addition, Baron et al (2018) adds a set of crises in the Euro Area in 2011 associated with the collapse of the value of Greek government debt, and increases in yields on new debt in Ireland, Italy, Spain and Portugal. Problems for banks holding the debt of these governments were also apparent in Belgium, Germany, Denmark, France, and the Netherlands. These holding were unwise but reflected a previously held view that no Euro Area government could default, which was wrong, and a politically motivated view that all government debt in the Area should be equally risk weighted in banks evaluation of their assets. It took some time for it to be clear that the ECB 'would do what it takes' to deal with the problem, and share[10]holders suffered from the unwise behaviour of the banks. However, the solvency of the banking system was not in doubt, as the subsequent settlements made clear.

Table 3 Comparing crisis definitions

	Base	Laeven	Baron	All
	1981-2016			
Current account (-1)	-0.1778	-0.0738	-0.1030	-0.1213
	0.004	0.290	0.046	0.015
Capital(-1)	-0.3737	-0.4896	-0.3606	-0.3078
	0.000	0.000	0.000	0.000
Real House Price Growth(-3)	0.0661	0.1068	0.0414	0.0388
	0.016	0.004	0.112	0.117
Liquidity(-1)	-0.0928	-0.1344	-0.0711	-0.0842
	0.000	0.000	0.001	0.000
Area Under Curve (AUC)	0.7226	0.7441	0.6694	0.6611
Direct Call Ratio (DCR)	19/27	10/14	16/30	21/34
False Call Ratio (FCR)	33.33	31.43	43.04	39.57

Note probs under coefficients. 504 observation in all cases.

In Table 3 we report on our base model and on the same model using the narrower Laeven and Valencia definition of crises and the wider set of crises from Baron et al (2018). Laeven and Valencia (2018) includes only Finland, Norway and Sweden in 1991, Japan in 1997, the UK and the US in 2007 and Belgium, Germany, Denmark, Spain, France, Italy, the Netherlands and Sweden in 2008. As we can see, this definition of crises does not substantially change our base model, and we discuss extensions below. In that equation real house price growth, liquidity and capital retain their significance, the AUC is higher than in the Base regression and the Hit rate of 10/14 is the same, and the False Calls Ratio is lower.

In column 3 the removal of four disputed crises and the addition of others including the Euro Area crises in 2011 leaves capital, liquidity and the current account significant. The AUC falls, and the Hit rate is noticeably lower, whilst false calls are markedly higher. We would suggest that the Baron et. al (2018) extension of the crisis definition is not necessarily helpful, not because it produces different results, but because it uses a different aspect of the accounts of the banking system. A bank with stronger capital, or book value (the difference between assets and liabilities) may be one with a lower stock market equity value because it has fewer assets that involve significant risk and therefore higher returns, and the impact on prices depends on the preferences of shareholders.

We also have an all-encompassing definition of crises in the last column, where if anyone thought there was one, we include it, which involves adding back in four crises to the Baron set from the base case, and the model performance is in some senses better, as the Hit Rate is

[10] UK 1984 and 1991, UK and US in 2008 as well as 2007

higher. This logit has the lowest AUC on the table, suggesting it has relatively weak signalling power. This emphasises our point above that crisis choice affects the model selection criteria and strengthens our view that we should take external crisis definitions such as Caprio et al (2005) and Laeven and Valencia (2013) rather than construct our own at the same time as selecting the data set.

Table 4 The Laeven and Valencia Crisis Definition

	Laeven Base 1981-2016	Total Credit	Consumer Credit	BIS Credit Gap
Current account (-1)	-0.0738	-0.0720	-0.0792	-0.0717
	0.290	0.299	0.257	0.300
Capital(-1)	-0.4896	-0.3691	-0.5487	-0.5102
	0.000	0.000	0.000	0.000
Real House Price Growth(-3)	0.1068	0.1463	0.0724	0.1014
	0.004	0.001	0.090	0.014
Liquidity(-1)	-0.1344	-0.1382	-0.1286	-0.1308
	0.000	0.000	0.002	0.001
test(-1)		-0.0162	-0.0041	0.0083
		0.874	0.967	0.913
test(-2)		0.0081	0.1647	-0.0172
		0.946	0.241	0.888
test(-3)		-0.1614	-0.0970	0.0264
		0.100	0.346	0.728
Area Under Curve (AUC)	0.7441	0.7722	0.7171	0.7485
Direct Call Ratio (DCR)	10/14	11/14	10/14	10/14
False Call Ratio (FCR)	31.43	28.57	31.1	32.04

Notes as Table 1

In Table 4 we turn to evaluating our model using the Laeven and Valencia definitions of crises, which are essentially the same over our period as in the sequence of papers by Schularick and Taylor and others, and hence we can directly compare our results to Jorda et al (2018). We repeat the Laeven and Valencia regression from Table 3 in the first column, and then add three lags in real total credit growth in column 2. The pattern is the same as in Table 1, except that real house price growth remains significant when we add real total credit growth and the BIS credit to GDP gap, whilst only the negative third lag on real total credit growth approaches reasonable levels of significance. None of the lags in real total credit growth would be kept if we sequentially eliminated the variable with the least significance and estimated again until only significant variables were left. Column 2 has a higher AUC than column 1, and a better hit ratio and a smaller False Calls ratio, but the gain is not particularly large. We can test for the joint significance of the three lags with a Wald exclusion test, which is passed with Chi^2 (3) = 5.519857 (prob 0.1375). The unbalanced sample with lags in real consumer credit growth also gives the same message as in Table 1, as this variable is never significant, and no individual lag would be significant on its own, but the inclusion of consumer credit reduces the significance of real house price growth. A Wald exclusion test on the three lags is passed with Chi^2 (3) = 2.198130 (prob 0.5323). The equation with the BIS Credit Gap in column 4 has a marginally, but not significantly, higher AUC than the base model, but the common coefficients are essentially the same, whilst the credit gap contributes nothing to the explanation, and a Wald exclusion test is passed with Chi^2 (3) = 0.473281 (prob 0.9247).

We should note that capital and liquidity are significant in all of our experiments, even those with the more restricted crisis definition in Table 3. This is contrary to Jorda et al (2018) and would lead us to very different policy conclusions from theirs for the current, post Bretton Woods, period. If we added the 35 years between the end of the Second World War to the start of our data set we would add no crises until after 1972, and then only crises in the UK and Spain. The pre-1972 period was one where real credit growth was very stable because of financial repression. Over the same period capital varied across time and countries, much in the same way as it did from 1980, at least as far as estimates in Jorda et al (2018) suggest. Hence it would not surprise us if capital became insignificant if we added those 25 to 35 years to our data, and the lack of growth in credit up until 1972 meant that it seemed to explain (the lack of) banking crises. However, we think the liberalised post-Bretton Woods era should be explained by different factors than the repressed 1940s to early 1970s, and it does not surprise us that our results differ from those of Jorda et al (2018) and hence so do our policy conclusions.

5. Conclusions

Our results suggest that crisis probabilities are driven by variations in capital and liquidity – the defences - as well as by the current account and house prices – the lending quality indicators that signal problems. There appears to be no role for any overall lending or credit indicator in any crisis model in the post 1980 OECD. This does not mean we have an excellent understanding of the factors driving crises, and we would not expect one, as Caprio and Honahan (2015) discuss. Crises are difficult to explain, and even in our best models some countries remain difficult to evaluate. In no case do we have an explanation of the crisis in the US in 1984, Italy in 1990, Norway in 1991 or Germany and Italy in 2008. The first two are not included in Laeven and Valencia, but they are in our base model. The Norwegian crisis in 1991 is perhaps too close to the 1987 crisis in that country, which is easy to explain with our standard variables. Laeven and Valencia date it in 1991 because that is when bank balance sheets were adjusted for bad loans and final nationalisation took place. The German crisis in 2008 was the result of over-ambitious involvement in the US sub-prime market by small and medium sized banks, many of them in public ownership. They were perhaps misled on the risks in the US mortgage backed securities market because there had been a thriving market in such securities in Germany since 1919. It is hard to model lack of wisdom in poorly regulated banks.

There are other causes of crises that are even harder to model. The collapse of Continental Illinois, the seventh largest bank in the US, in 1984 was the result of internal fraud rather than general bad lending. The bank had been involved in commercial and industrial lending, especially in energy, and one member of staff took on significant, but faulty, assets in return for a side payment. It is hard to catch that with a general macro model. The two Italian crises in 1990 and 2008 are perhaps even harder to explain[11].

When we are modelling crises, it is important to look at evidence, and not assume we know answers. Logit models allow for numbers of factors and enable us to look at causes of problems and defences against them. We would conclude that capital requirements are the best macroprudential tool available to policy makers in the post Bretton Woods era, and that some concern should be shown for liquidity, but that this is a complex issue. Obviously, policy should respond to imbalances, but there are few reasons for constraining credit growth. Laeven (2013) gives us many reasons for constraining the quality of lending, but this is not a macroprudential issue. However, we can draw conclusions about the defences against crises, and therefore about macroprudential policy. It is clear that capital and liquidity matter a good deal in the liberalised, but government supported, banking system that has developed since the end of Bretton Woods. Capital not only reduces the costs of crises, but it also reduces the probability of crises in this world, as does on book liquidity. Policy should respond to any macro indicator of increased crisis risk, but our evidence suggests that it will be limited to trying to deal with excess house price growth, and if such bubbles cannot be contained, policy should strengthen defences against a collapse in loan quality.

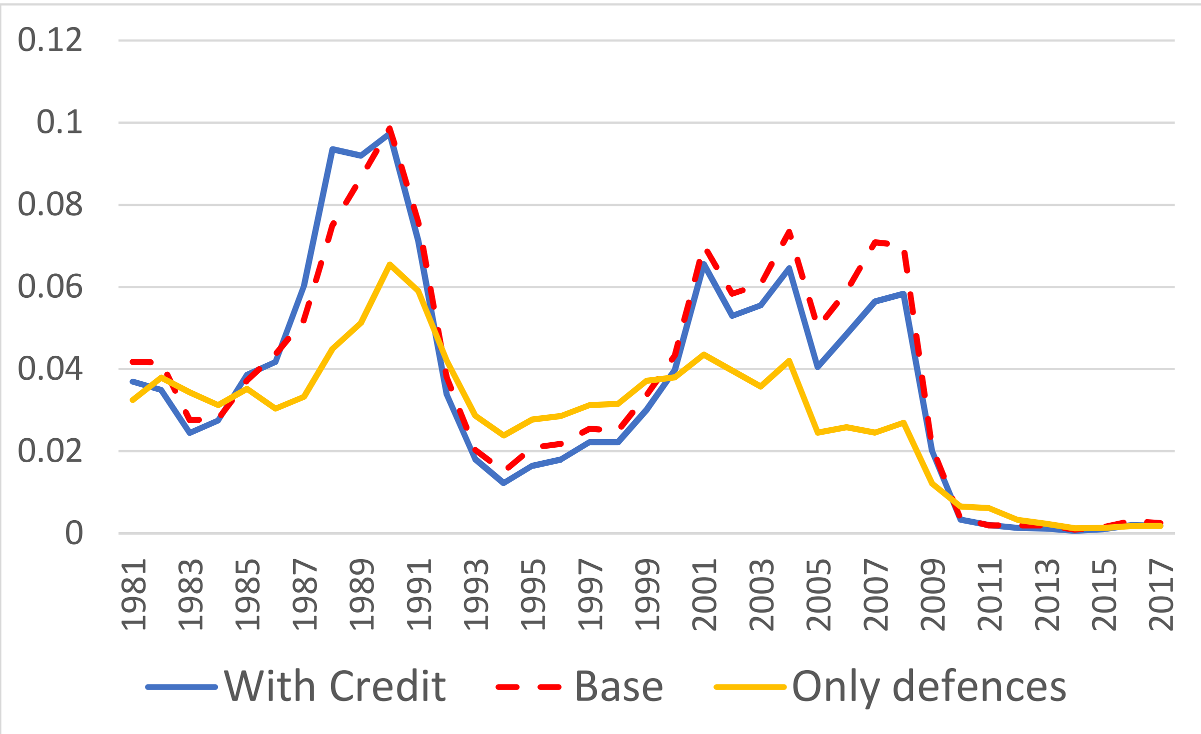
In a world where governments would not intervene frequently and bail out banks, as before the First World War, capital may have been less relevant for crisis incidence, although as Jorda (et al 2018) show, rather more of it was held in the banking system than we now observe. It may also not be relevant to crisis incidence in the 25 years after the Second World War, in part because there were no crises, and government restrictions constrained the banking sector, and bank bail outs would have been performed in the discreet atmosphere of a gentleman's club in St James's, Midtown, or in the 16th. It is perhaps a good thing we no longer live in that world, but an open society needs defences against crises, and capital reserves are clearly core to macroprudential policy in the post 1972 world.

[11] They bring to mind an in interchange on page 2015 in Donna Leon's 2015 crime novel 'By its Cover' concerning a call from police 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."

Appendix A Decomposition of the Factors Affecting Crisis Incidence

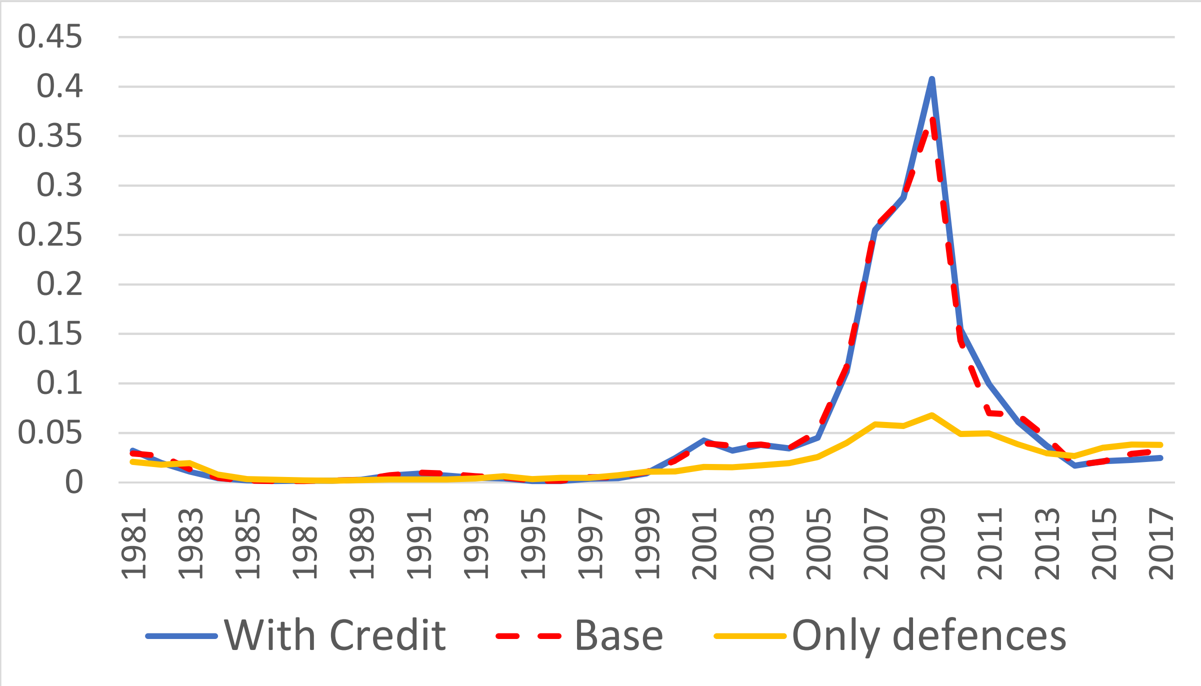
In our first set of experiments in Table 1 the population probability of a crisis occurring is 0.054 and any logit model will assign probabilities that approximately 'add up' to this number. Our models are better than a random assignment which would have a coin toss AUC of 0.5, and we can investigate which factors in them really contribute to our understanding of crises. One way to do this is to start with a model with all our driving variables and remove them in turn. There is of course no unique way of doing this, but a sensible one would be to group them into the defences against crises, the causes of crises in our baseline model and our additional variable, total lending, and remove the least significant group and look at the results for some significant countries, and then repeat this removing the less significant group among the two we have left. We take our Base model from table 1 with real total credit growth added to it, and we then take the base model, as credit is not significant, and then remove the least significant group, which are real house price growth lagged three periods and the lagged current account, leaving a model with only the defences, capital and liquidity. The Hit Rate falls to 17/27 and the False Calls rate rises to 45.3 percent when we include only defences. We decompose crisis probabilities in this way for the US, Spain and Belgium as examples.

Figure 1 Decomposing Crisis Probabilities in the US



We undertake this decomposition for the US in Figure 1 over the period 1981 to 2017 using the predicted probabilities from three logit models. Our baseline model is signalling problems in the late 1980s and from 2000 onwards, and in the latter case it is clearly early enough for prompt corrective action to have been effective. If we add total lending growth to this model the performance in the late 1980s improves, but after 2000 the expanded model signals less strongly than the baseline. If we believe we should add lending growth to our preferred explanation all of the parameters change, as we can see from Table 1, and the true driving variables, which are not orthogonal to the irrelevant variables included, become less useful. We can see that the defences weakened after the 1988 crisis, but they were significantly strengthened after 2008, reducing crisis probabilities to very low levels.

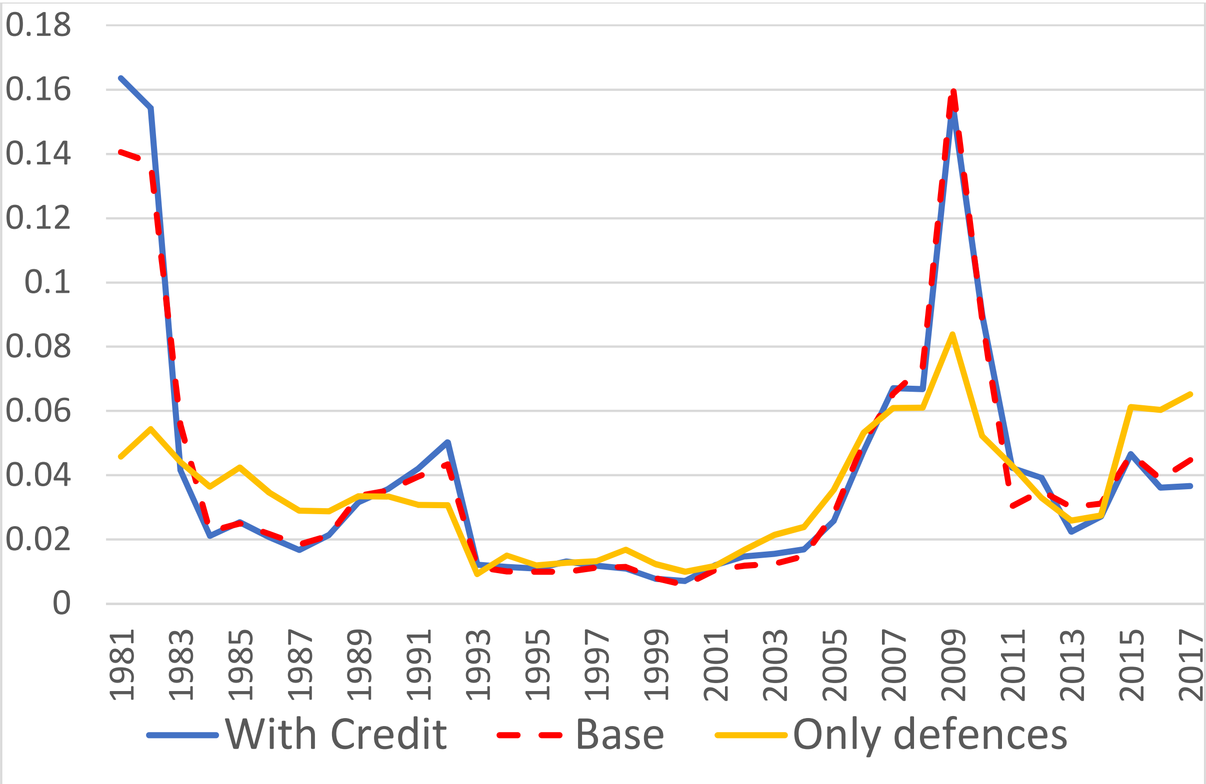
Figure 2 Decomposing Crisis Probabilities in Spain



We can see from Figure 2 that Spanish crisis probabilities were low from 1980 to 2004, and then the rise in house prices fuelled by low interest rates in the newly established Euro Area plus the increase in the current account deficit driven in part by the construction boom that flowed from the housing boom indicated that bad lending might take place. Our model picks up the problems very well and is signalling the need for corrective action in 2005-6. From 2000 onwards the defences weakened, with liquidity (on our narrow IMF based measure) falling from 15.9 percent of assets in 2000 to 7.5 percent of assets in 2007, whilst capital fell from 8.2 percent of assets in 2000 to 7.2 percent of assets in 2006. Although Spanish banks held a lot of risky assets, and therefore more un-risk weighted capital than others, it proved to be inadequate. We can see that credit growth was sometimes adding and sometimes subtracting from the explanation, but it clearly adds little to the capacity of the EWS. After 2009 the probability of a crisis emerging falls, in part because defences were strengthened.

A similar story can be told for Belgium. Apart from some residual risks at the start of our period, crisis probabilities remained low throughout the 1980s and 1990s and only signalled a potential crisis (at our 5.4 percent threshold) in 2006, two years before the crisis emerged, and hence there would have been time to take corrective action. Credit growth may have played a role in raising risks around 1980, but after that it contributes little to evaluating the risk of a financial crisis. From 2000 onwards the defences weakened, with liquidity (on our narrow IMF based measure) falling from 28.9 percent of assets in 2000 to 13.1 percent of assets in 2007, whilst capital fell from 3.6 percent pf assets in 2000 to 2.2 percent of assets in 2006. The decline in liquidity was particularly important as the 2008 crisis was sparked by lack of liquidity after the collapse of Lehman Brothers.

Figure 3 Decomposing Crisis Probabilities in Belgium



Our overall conclusion is that credit growth adds little to our ability to pick up crises. This is in part because the most significant credit variable in Table 1, the third lag, has a negative coefficient. It would be 'unfair' to credit growth to use this equation for a formal decomposition where we, for instance, set each of the variables in turn to their sample mean and looked at the resulting probability projections, which would have been another way we could have proceeded.

Data Appendix

Real Credit Gaps: BIS online database quarterly 1974q1 t0 2017q1 with additions for some early quarters in 1980 for Canada and Finland from Barrell, Karim and Macchiarelli (2018) using BIS data on total credit and GDP in an equivalent filter. The data are all stationary.

Real house prices: Nominal house prices from BIS online database, quarterly 1974q1 to 2017q1, divided by OECD online database consumer prices for the same period, to convert to real and then annual averages taken before annual growth rates are calculated. The quarterly growth rate series are all stationary.

Real Total Credit: Credit from banks to private non-financials from BIS online database quarterly 1974q1 to 2017q2, converted to real and to growth rates in the same way as real house prices. The quarterly growth rate series are all stationary.

Real Total Consumer Credit: Credit from banks to households and NPISHs from BIS online database quarterly 1974q1 to 2017q2, converted to real and to growth rates in the same way as real house prices. Start dates vary by country, as does stationarity, as is detailed below.

A1 Real Consumer credit data

	Start data	Stationary from 1975	Stationary from 1996
Belgium	1982	Yes	-
Canada	-	No	Yes
Denmark	1996	-	Yes
Finland	-	Yes	-
France	1979	Yes	-
Germany	-	No	Yes
Italy	-	Yes	-
Japan	=	No	Yes
Neths	1992	-	Yes
Norway	1976	No	Yes
Spain	1982	No	Yes
Sweden	1982	No	No
UK	-	Yes	-
US	-	Yes at 10%	-

The annual current account to GDP data are taken from the OECD online database

The unweighted bank capital variable primarily comes from the OECD Consolidated Banking Statistics Database and the World Bank Global Financial Stability Indicators online database, and Norwegian and Swedish Central Bank sources.

Liquidity data is sourced from the IMF and calculated as the ratio of liquid assets to total assets: [reserves + claims on central government]/ [reserves + claims on central government + foreign assets + claims on private sector]

Post 2006 Canadian liquidity is calculated using Statistics Canada Data using:

> [Canadian dollar cash and cash equivalent + Canadian dollar total securities issued or guaranteed by Canada, Canadian province, Canadian municipal or school corporations]/ Total Assets

Post 2012 Norwegian data is calculated from Statistics Norway using:

> [Notes, coins and deposits] / Total Assets

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