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Abstract

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JEL Classification: G01, E52, E32

Keywords: Banking Crisis, crisis prediction, Credit Booms, macroprudential policy

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When to Lean Against the Wind*

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Abstract

This paper shows that policy-makers can distinguish between good and bad credit booms with high accuracy and they can do so in real time. Evidence from 17 countries over nearly 150 years of modern financial history shows that credit booms that are accompanied by house price booms and a rising loan-to-deposit-ratio are much more likely to end in a systemic banking crisis. We evaluate the predictive accuracy for different classification models and show that the characteristics of the credit boom contain valuable information for sorting the data into good and bad booms. Importantly, we demonstrate that policy-makers have the ability to spot dangerous credit booms on the basis of data available in real time. We also show that these results are robust across alternative specifications and time-periods.

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1. Introduction

Banking crises are typically credit booms gone bust. But not all credit booms end in crisis. Some credit booms are equilibrium responses to improved fundamentals. Such booms are likely to be beneficial, and short-cutting them may come at a considerable long-run cost for the economy. From a policy-maker perspective, blanket measures to dampen credit booms may reduce the risk of a banking crisis, but also reduce growth and employment resulting in an unpleasant trade-off for policy-makers (Svensson (2016); Adrian and Liang (2016)). While financial stability is an important goal, policy-makers are rightly concerned about the collateral damage inflicted on the real economy. The question that jumps from these observations is whether it is possible to distinguish the good credit booms from the bad. Can policy-makers identify the subset of credit booms that are dangerous, and can they do so with data available in real time? This paper shows that the answer to both questions is affirmative. There are clear markers of bad booms that policy-makers can use to distinguish between good and bad credit booms with considerable accuracy. And they can do so in real time.

We arrive at this conclusion by studying long-run data for 17 advanced economies from 1870 to 2013. We rely on economic and financial data from the Macrohistory Database (Jordà *et al.* (2017b)), as well as the systemic banking crisis chronology contained therein, which in turn is based on a large number of historical sources as well as the crisis dataset compiled by Laeven and Valencia (2012). We use a recently proposed method for detrending time series (Hamilton (2017)) that relies on a flexible form for extracting forecast residuals from time-series regressions and avoids the drawbacks of the HP filter (Hodrick and Prescott (1997)). We then define credit booms as periods when the log of real private credit per capita exceeds its expected value by a country-specific threshold and identify 112 credit boom episodes in our sample of advanced economies over the past 150 years. About one-quarter of the credit booms are bad; that is they are followed by a systemic banking crisis.

Using logit models with and without country-fixed effects and a variety of control variables we examine the characteristics of booms that may help policy-makers distinguish bad booms from good booms. We test a large number of real and financial balance sheet variables, as well as asset prices, in addition to descriptive data for the size and duration of the boom. We start with models that use all available ex-post information about credit booms and show that bigger booms (as measured by the deviation of credit from trend), accompanied by increasing loan-to-deposit ratios and house price surges are substantially more likely to end badly. Among the economic variables, a deteriorating current account balance plays a subsidiary role in increasing the odds of a bad boom, at least in some specifications. Yet when we examine predictive ability, real economic variables generally do not add much predictive power compared to models based on the two key financial variables that characterize bad booms: a deteriorating banking sector liquidity situation, measured by the loan-to-deposit ratio, and house price booms measured by the deviation of real house prices from country-specific trends. We also demonstrate that our results are robust to different filtering

methods (using different filters for detrending), boom definitions (using deviations from the credit to GDP ratio instead of real private credit per capita) as well as across different subperiods.

Our paper connects to two important strands in the recent macro-financial literature. The growth of credit has been of interest to economic historians, development economists and students of macro-finance for the last 30 years for two very different reasons. First, there is a literature on the finance-growth nexus that associates credit deepening and the quality of financial intermediation with economic growth (King and Levine (1993); Rancière *et al.* (2008)). Much of the related literature uses post World War II panel data sets. The literature on finance and growth is surveyed by Levine (2005). The evidence indicates that countries with deeper financial markets, a higher credit to GDP ratio or larger stock market capitalization, experience more rapid growth. However, Rousseau and Wachtel (2009) indicate that positive growth effects of financial deepening might be weakening as more countries have well developed financial markets.[1] All in all, the finance-growth nexus literature suggests that financial deepening may be beneficial in early stages of financial development. The relationship appears to have weakened after the mid-1980s which coincides with a marked increase in the incidence of financial crises. In particular, Rousseau and Wachtel (2009) showed that the finance-growth nexus is weakened when a country experiences a banking crisis.

Second, there is an equally large literature that associates excesses of credit growth with banking crises. Despite the potential benefits of financial deepening, many credit booms end in often debilitating banking crises with severe effects on the real economy (Jordà *et al.* (2013); Mian and Sufi (2016)). Put differently, credit booms can be growth enhancing but can also be a precursor to banking distress and crisis.

In the aftermath of the 2008 financial crisis there has been increased interest in the distinction between credit expansions that are growth enhancing and those that are likely to end in financial crisis. There is a burgeoning literature on policies, macro-prudential and other, to deal with the risks emanating from credit booms and the appropriate policy response (Cerutti *et al.* (2015)). The prevailing opinion prior to the crisis was that monetary policy makers should focus on growth and inflation and rely on financial regulation to maintain financial stability (Bernanke and Gertler (2001)). Federal Reserve Board Chairman Alan Greenspan, commenting on the possibility of a bubble bursting famously said that "the job of economic policy makers [is] to mitigate the fallout when it occurs" (Greenspan (1999)). Even before the financial crisis, some economists, notably at the Bank for International Standards, suggested that systemic risks warranted the introduction of macro-prudential policy frameworks. Borio and White (2014) argued that "by leaning against the wind, it [the central bank] might also reduce the amplitude of the financial cycle, thereby limiting the risk of financial distress in the first place. While encouraging steps have been taken in recent years to strengthen the macroprudential perspective, there is still a long road ahead" (p.26).

Once the global financial crisis occurred, the literature on macro-prudential policies that can prevent a credit boom from developing into a banking crisis expanded rapidly (Svensson (2016),

[1] Moreover, Wachtel (2011) shows that it is difficult to distinguish the causal influence of credit from country characteristics with panel data for relatively short periods of time.

Mitra *et al.* (2011) and Adrian and Liang (2016)). This literature emphasizes overheating in credit markets (Stein (2013)) and argues that policy-makers should intervene to contain excessive credit growth. Yet, policy discussions remain concerned about the possible side effects of these efforts to identify crisis situations and lean against the wind and the debate regarding policy prescriptions remains unsettled.

While credit-fueled asset price bubbles pose some danger to the macro-economy (Jordà *et al.* (2015)), other credit booms might represent financial deepening or be the reaction to a positive productivity shock. Such booms are likely to be beneficial. An important precondition for minimizing the collateral damage of policy interventions to tame excesses in credit markets is the ability to tell apart good booms from bad booms. As Svensson (2016) argues, the relationship between credit growth and crisis probabilities is a reduced form correlation result and the underlying determinants relate to the shocks to the financial system as well as on its resilience. If bad booms can be identified in real-time then policy makers can react with targeted policies short-cutting dangerous booms while allowing good booms to run their course. Using historical data, we show that there are strong characteristics that distinguish booms that result in crisis from those that do not, based on the nature of possible shocks and on the resilience of the banking sector. Moreover, we are able to make that distinction at the onset of a credit boom using only real time data available at the time.

To the best of our knowledge, ours is the first paper to show that it is possible to identify bad booms with considerable accuracy in real time. Several recent papers have focused on the credit boom – financial crisis relationship by identifying credit boom episodes in a large number of countries with data that start in 1960 or later. These studies utilize various measures of credit and both mechanical definitions of booms and definitions based on credit detrended with a Hodrick-Prescott filter. Examples of such studies are Mendoza and Terrones (2012), Dell'Ariccia *et al.* (2016) and Gorton and Ordonez (2016). All of which conclude that many credit booms end in crisis. Yet since the time series examined are short and the country experiences are very heterogeneous, these studies face challenges to distinguish good booms from bad booms based on observable characteristics.[2] Our long-run historical data have the advantage that we can analyze within-country experiences as most of the sample countries have experienced both a good and a bad credit boom at some point between 1870 and today.

There is a small literature that uses historical data to examine both the finance growth nexus and the incidence of booms and crises. Rousseau and Wachtel (1998) examined the effect of credit deepening on growth with data starting in the 19th century for four countries: US, UK, Canada, Sweden. The link between credit growth and financial crisis is examined with historical data by Reinhart and Rogoff (2009) and Schularick and Taylor (2012). Rousseau and Wachtel (2017) use historical data for the period 1870-1929 and affirm the positive growth effects of financial deepening except when the episodes culminate in banking crisis. With the criteria that they adopt, about one-third of the episodes of financial deepening lead to a banking crisis. These observations suggest

[2] Dell'Ariccia *et al.* (2016) conclude that most indicators that have been suggested in the literature lose significance once one conditions for the existence of a credit boom.

the importance of the question we address here. What are the characteristics of a credit boom that lead to crises as opposed to ones that do not?

Measuring the consequences of credit booms and in particular understanding which credit booms turn into banking crises requires a methodology to identify credit booms. The methodology is presented in section 2 and section 3 presents descriptive statistics for good and bad credit booms. In section 4, we will specify a logit binary classification model and test its ability to sort boom episodes into those associated with a banking crisis and those that are not. We ask if there are economic variables that characterize bad booms but not good booms. We will argue that this is indeed the case. Credit booms accompanied by house price booms and deteriorating funding situation in the banking sector are more likely to end in a banking crisis.

In section 5, we will raise the bar for prediction. We put ourselves in the shoes of policy-makers and only use data that are available to policy-makers in real time. In other words, we are aiming to answer the question if policy makers are able to differentiate between good and bad credit booms as they unfold, giving them the possibility to react. We will again argue that the answer is affirmative. Classification tests show that even using exclusively variables that are available in real time, policy makers can achieve classification with high accuracy.

In section 6, we will subject our results to robustness tests for different de-trending methods, and boom indicator variables, as well as specific time periods and demonstrate that the core results remain unaffected. Conclusions are in section 7.

2. Identifying a credit boom

The notion of a boom implies a deviation from normal "non-boom" circumstances, but what constitutes such a deviation is not self-evident. A boom period reflects exceptionally high growth rates of credit or periods when credit is substantially above its trend. The literature offers a variety of methodologies to define these exceptional periods, most commonly some form of the HP filter (one- or two-sided) or an absolute growth threshold. For example, Rousseau and Wachtel (2017) among others use a mechanical growth thresholds to define extraordinary credit growth.[3] Mendoza and Terrones (2008) use the HP filter to de-trend the credit variable and a boom occurs when there is an exceptionally strong deviation of credit from its trend. Dell'Ariccia *et al.* (2016) use a combination of a deviation from a cubic 10-year trend and an absolute growth threshold, while Gorton and Ordonez (2016) focus on an absolute growth threshold. As a measure of credit, most papers rely on the bank-credit to GDP ratio or the real growth rate of bank credit per capita.

Our criteria for credit booms are based on detrended real private credit per capita, where the credit data come from Schularick and Taylor (2012) and updates thereof (Jordà *et al.* (2017b)).[4]

[3]Specifically, an episode of credit deepening – a boom – occurs when the ratio of M2 to GDP increases by more than 30 percent over a ten-year period.

[4]We choose this credit definition as GDP data often becomes available with a significant delay and is subject to major revisions. We show however that our main results do not depend on this choice of the credit variable.

To detrend the data we follow Hamilton (2017) who shows that the use of a HP filter introduces spurious dynamic relations into the data that have no basis in the underlying data generating process. He proposes an alternative, which we will use in the main analysis of the paper. The procedure is based on the assumption that the trend component of credit at time t is the value we could have predicted based on historical data. In particular let h denote the horizon for which we build such a prediction, then the cyclical component is the difference between the realized value at time t and the expectation about the value at time t formed at time $t-h$ based on the data available at that time. Hamilton proposes that this residual should be based on a regression of the value y at time t on recent values of y at time $t-h$, i.e. y_{t-h}, y_{t-h-1}.... Formally, this regression can be written as:

$$y_t = \beta_0 + \beta_1 y_{t-h} + \beta_2 y_{t-h-1} + \beta_3 y_{t-h-2} + \beta_4 y_{t-h-3} + v_t \tag{1}$$

The choice of h depends on the horizon we attribute to the cyclical component. We choose a horizon of 3 years so the residual is the deviation of the realized value y_t from the expectation formed at time $t-3$ based on information on y_{t-3}, y_{t-4}, y_{t-5} and y_{t-6}. The procedure is by construction forward looking (onesided) as we use values available at time $t-h$ for the prediction and therefore for the definition of a credit boom.

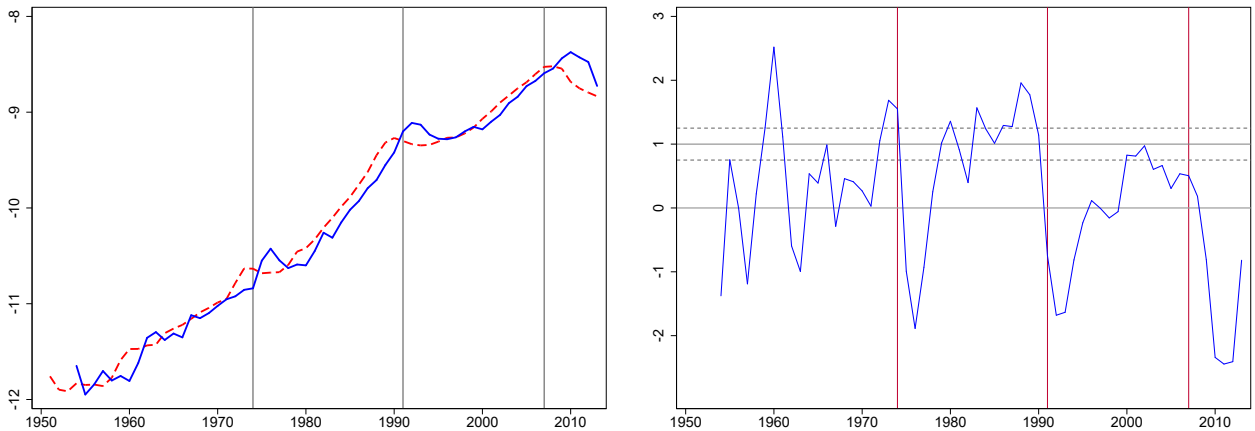
Figure 1a illustrates the procedure using post-WW2 data for the UK as an example: The dashed line refers to the realized values of private credit (specifically, the log of real private credit per capita) while the solid line plots the predicted value for the respective dates based on the procedure explained above. If the dashed line is above the solid line, then realized credit is above expectations formed three years earlier. These episodes are candidates for a credit boom if the difference exceeds a threshold we will define shortly. From the graph, booms are visible around 1960 and in the run up to financial crises, which are indicated by vertical bars. As can be seen, a banking crisis is often followed by a drop in the dashed line relative to the solid line indicating that we would have expected stronger credit growth based on historical data than actually observed. This comes as no surprise, as banking crises are often followed by credit tightening, which means that credit is below expectations.

A credit boom episode occurs when real credit per capita exceeds expectations by more than a specific amount, which we define in terms of the country specific standard deviation of the detrended credit variable (as in Mendoza and Terrones (2008, 2012)). The advantage of such a boom threshold is that it focuses on country-specific "unusually" large credit expansions, accounting for different volatilities of credit across countries. Formally, let us denote the detrended real credit per capita variable in country i at time t as $c_{i,t}$. The standard deviation of this variable over all non-war observations in country i will be denoted by $\sigma(c_i)$.[5]

[5]We exclude 4-year windows around wars from our analysis. Furthermore, when using the Hamilton filter we additionally discard two more years after wars, so that prediction residuals are not based on wartime data.

Figure 1: Detrended credit and cyclical component for the UK

(a) *Raw data and trend* **(b)** *Normalized cyclical component*



Notes: Panel (a) presents post-WW2 data for the log of real private credit per capita for the UK (dashed line). The solid line corresponds to the predicted value of credit using the Hamilton (2017) methodology. Panel (b) presents the normalized cyclical component of real private credit per capita in the UK. The solid horizontal line marks the one standard deviation boom threshold used in the main analysis of the paper. Dashed lines refer to alternative 0.75 and 1.25 standard deviation thresholds. Vertical lines indicate dates of systemic financial distress defined in Jordà *et al.* (2017b).

Our credit boom condition is now that the detrended credit measure is larger than one country specific standard deviation. With I denoting the indicator function, this can be written as:

$$\text{Credit Boom}_{i,t} = I(c_{i,t} > \sigma(c_i)). \tag{2}$$

We will show that our results are robust to thresholds other than one standard deviation.[6] We furthermore refer to the local maximum value of $c_{i,t}$ during a specific boom period (i.e. conditional on Credit Boom $= 1$) as the peak of the credit boom. The normalized detrended credit measure $\frac{c_{i,t}}{\sigma(c_i)}$, i.e. detrended log real credit per capita divided by the country specific standard deviation, will be our measure of the size of a credit boom as it accounts for cross-country differences in the volatility of credit. We can express our credit boom condition above now also in terms of this normalized credit variable; a country will be in a credit boom whenever this measure is at least one.

To identify boom episodes, we combine consecutive boom observations that are above the threshold and also combine years where the episode is interrupted by a single observation that does not fulfill our boom criterion. Using this definition and the Hamilton procedure to detrend the credit variable yields a sample of 112 credit booms. The frequency of booms ranges from 4 in the UK and in France to 10 in Denmark. Our analysis will focus on the "boom-to-peak" period, which refers to those observations in the boom until $c_{i,t}$ reaches its local maximum. Analyzing this period ensures that we capture characteristics of the expansionary phase of the credit boom and not

[6] We experimented with alternative thresholds of 0.5 and 0.75 and 1.25 $\sigma(c_i)$. We present some results in the robustness discussions in sections 5 and 6. Varying the thresholds clearly affects the number and duration of booms. The result of loan-to-deposit ratios and house prices being the main predictors of bad booms however remains unchanged.

episodes, where the boom is already collapsing, which might take some time as our credit measures are based on stock variables (outstanding credit).

We will be interested in the question which characteristics of a credit boom determine whether it turns into a banking crisis. The methodology is illustrated in Figure 1b, which shows the normalized cyclical component for the UK for the post-WW2 period. Booms are episodes when the normalized cyclical components is above the solid line that marks one standard deviation. The dotted lines mark alternative thresholds of 0.75 and 1.25 standard deviations. Crisis dates for the UK are indicated by the vertical lines. The UK experienced a large credit boom around 1960, unrelated to a banking crisis. The crises in 1974 and 1991 were at the end of a boom period. Finally, whether we detect a boom around the year 2002 depends on the choice of the threshold. In the next section we distinguish between credit booms that do ("bad booms") and do not result in a crisis and examine the characteristics of each.

3. Good and bad booms

3.1. Incidences of booms and crises

For an initial examination of the relationship between credit booms and banking crises we pool all our country-year observations and ask whether our identification of credit boom years is related to financial crises. The binary dependent variable $S_{i,t}$ takes value one if country i is experiencing a banking crisis at time t. The banking crisis chronology comes from Jordà *et al.* (2017b) and is based on banking crisis events as defined in Laeven and Valencia (2012), which focuses on systemic financial distress. [7] In particular, we estimate

$$log\left(\frac{P[S_{i,t}=1|X_{i,t}]}{P[S_{i,t}=0|X_{i,t}]}\right)=\alpha_i+\beta X_{i,t}+\epsilon_{i,t}, \tag{3}$$

where α_i is a fixed effect that captures differences in countries' probabilities to experience banking crises. We report results for two different choices of $X_{i,t}$: first, the lagged normalized detrended real private credit per capita measure and second, the lagged credit boom dummy as defined above (equation (3)). The first two columns present results for the entire data period. As in the previous literature (Schularick and Taylor (2012)), we find that excessive private credit increases the odds of incurring a banking crisis (column (1)). In column (2) we show that this is also the case when $X_{i,t}$ refers to the credit boom dummy. As expected, credit booms are a risk to financial stability. These observations are not only true for the whole period, but also hold when we split period into the pre-WW2 (columns (3) and (4)) and post-WW2 ((5) and (6)) subsamples.

While the previous analysis shows that credit booms are associated with an increase in the likelihood of a crisis, not all booms end in a banking crisis. Others are followed by a recession without a banking crisis and in many instances there is no macroeconomic downturn at all. In

[7] Banking crisis dates are shown in the Appendix.

Table 1: Logit models with banking crises as dependent variable

	All years		Pre-WW2		Post-WW2	
	(1)	(2)	(3)	(4)	(5)	(6)
Detrended credit	0.61***		0.70***		0.86***	
	(0.15)		(0.18)		(0.23)	
Credit boom		1.27***		1.61***		1.54***
		(0.30)		(0.52)		(0.42)
Pseudo R^2	0.054	0.054	0.082	0.078	0.080	0.072
AUC	0.69	0.68	0.72	0.69	0.73	0.69
s.e.	0.04	0.04	0.05	0.05	0.06	0.07
Observations	1517	1517	516	516	942	942

Notes: Detrended credit is standardized at the country level, see text. Credit boom is a dummy that is 1 if detrended credit exceeds the boom threshold, 0 otherwise. Both variables are included as first lag. Country fixed effects are included. Clustered standard errors reported in parentheses. AUC is the area under the receiver operating curve (see text for explanation), and s.e. is its standard error.

the following sections we will refer to those booms that end in a banking crisis as "bad" booms. Specifically, a boom is bad if the banking crisis dummy is one during the boom or in the 3 years following the peak of the credit boom. With this definition, 29 of the 112 or 26% of the identified booms are bad. This frequency is close to that reported in Mendoza and Terrones (2012) and in Dell'Ariccia *et al.* (2016). Two countries in our sample do not experience any bad booms – Germany and the Netherlands – and Denmark has the most (5). In the following sections the unit of observation will be a credit boom, some of them bad in the above sense, others good.

The incidence of good and bad booms is shown in Figure 2 where the vertical bars indicate the number of ongoing credit booms in our 17 sample countries for each year with the war years excluded. Similar to the previous literature we find that credit booms seem to be synchronized internationally. The darker shading indicates booms that will eventually end in a banking crisis. The figure shows that booms often end in banking crises, except in the period from the end of WW2 to 1980 which was characterized by many credit booms, only a few of which ended in a banking crisis. The number of credit booms is partly due to our boom definition which can be seen when we make a comparison with other definitions of a credit boom. Appendix Figure A1 shows the distribution of booms using a two sided HP filter to detrend real private credit per capita and also the distribution of booms defined with the credit to GDP ratio detrended with both the Hamilton procedure and the HP filter. There are some differences in the number and incidence of booms, but all the definitions have in common a large number of booms without any banking crises in the post war period. In addition, there were many booms in the late 1980s and early 1990s, and again in the early 2000s that eventually turned into crises. In the analysis that follows we use booms defined by detrending real private credit per capita with the Hamilton procedure. Subsequently, we show that the results are uniformly robust to the other boom definitions.

3.2. Characteristics of good and bad booms

Our main question in the remainder of the paper is, whether we can say anything about the differences between good and bad booms based on country-specific characteristics of the macroeconomy and the financial system. The Jordà-Schularick-Taylor Macrohistory Database provides for the first time extensive historical information on a wide variety of characteristics. Clearly, these characteristics are all considered as "leading" indicators – relatively slow-moving, low frequency balance sheet aggregates (Mitra *et al.* (2011)) that allow early recognition. In the following table we present descriptive statistics for relevant characteristics, showing the good booms and bad booms separately. These characteristics fall into four broad categories:

- The first set of variables are characteristics of the detrended credit variable, such as duration of the credit boom and the deviation from trend (Dell'Ariccia *et al.* (2016));
- The second set of variables are real economic fundamentals including GDP, consumption, investment, the current account balance and interest rates, where the literature suggests that we should expect a deteoriating current account balance to be associated with a higher risk of banking crisis;
- The third set of variables relates to the financial sector itself. Here, the risk of a banking crisis might be related to the financing of credit on the liability side (capital-to-asset ratio and wholesale funding), aggregate illiquidity measures such as the loan-to-deposit ratio and the size of the financial sector (e.g. Mitra *et al.* (2011));
- A last set of variables refers to asset prices, especially in stock and housing markets.

All of these economic and financial measures are detrended and normalized with the same procedure used for real private credit with the exception of the duration of the boom in years and the credit-to-GDP ratio which is presented as the log of 100 times the ratio in order to account for booms at different initial levels of financial deepening. Each country time series is detrended with the explained procedure and normalized by the country specific standard deviation to account for different volatilities across countries. To compare boom observations, we use the value of each variable one period before the peak of the boom in order to capture vulnerabilities before the boom collapses. Table 2 presents summary statistics of the control variables for the 29 bad booms and 83 good booms separately.

The detrending and normalization allows us to compare the behavior of diverse variables across different countries. The variables with highest values in bad booms are house prices and the Loan-to-Deposit ratio which are both more than one standard deviation higher than the country average. This is not the case in good credit booms where the means for these variables are only around 0.3. Another variable with a large difference between good and bad booms is the current account balance which is more negative in bad booms than in good booms (-0.76 compared to -0.25).

Table 2: Summary Statistics

	Bad booms					Good booms				
	Mean	Min.	Max.	S.D.	Obs.	Mean	Min.	Max.	S.D.	Obs.
Banking crisis	1.00	1.00	1.00	0.00	29	0.00	0.00	0.00	0.00	83
Size	1.77	1.03	3.11	0.48	29	1.51	1.00	3.44	0.51	83
Duration	2.69	1.00	8.00	1.79	29	1.93	1.00	7.00	1.27	83
Duration to peak	1.90	1.00	6.00	1.32	29	1.52	1.00	4.00	0.77	83
GDP	0.64	-1.47	1.77	0.72	29	0.71	-3.54	2.81	0.91	83
Consumption	0.75	-1.23	2.98	0.97	29	0.70	-2.63	2.46	0.77	81
Current Account	-0.76	-2.99	1.58	1.15	28	-0.25	-2.17	2.47	0.84	80
Investment	0.71	-0.92	3.26	0.94	27	0.53	-2.44	2.64	0.90	81
Short term rate	0.16	-1.57	4.07	1.21	26	0.21	-1.66	3.70	1.07	76
Long term rate	0.10	-1.35	1.86	0.81	29	0.14	-2.63	2.88	1.00	82
Credit-to-GDP	4.09	2.43	5.14	0.67	29	3.84	1.04	4.72	0.66	83
Capital ratio	-0.10	-5.19	3.60	1.57	28	-0.25	-3.02	3.63	0.84	79
Noncore	0.05	-2.45	3.86	1.24	27	0.04	-2.16	2.46	0.78	79
Loans-to-Deposits	1.13	-1.42	3.68	1.37	27	0.26	-3.28	2.41	0.91	79
House price index	1.30	-0.46	4.18	1.10	22	0.34	-1.21	4.33	0.94	72
Stock price index	0.50	-2.40	2.89	1.17	23	0.23	-2.73	4.71	1.05	75

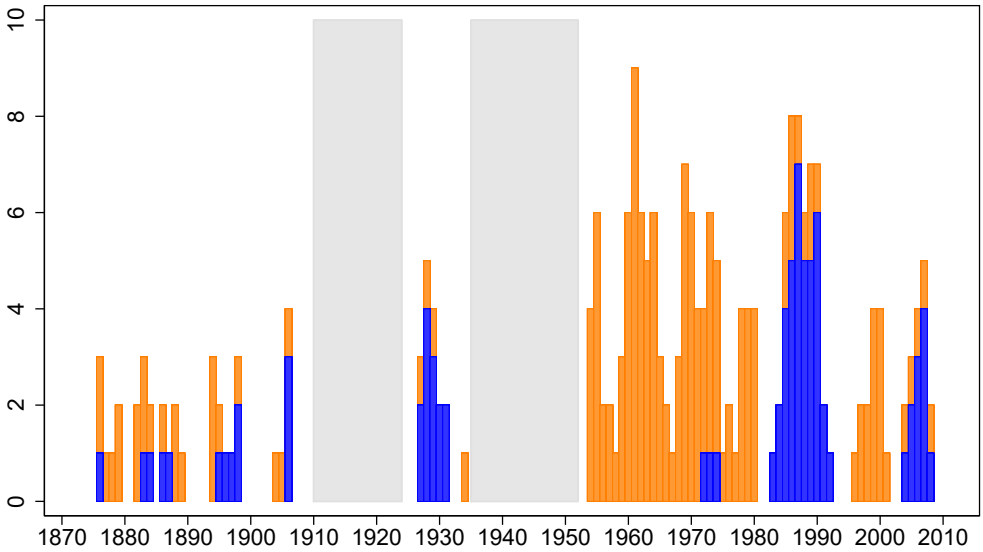
Notes: Summary statistics for credit booms split by association with a banking crisis: Duration is in years and size is averaged over the boom-to-peak period. All other variables are detrended and normalized at the country level (except credit to GDP) and the values presented are one-period lagged values at the peak of the credit boom.

Table 3: Test of equality of means: Credit booms split by associated banking crises

	Coefficient	t-stat
Boom with crisis	1.00	.
Size	0.26*	2.40
Duration	0.76*	2.49
Duration to peak	0.38	1.86
GDP	-0.06	-0.33
Consumption	0.06	0.32
Current Account	-0.51*	-2.49
Investment	0.19	0.92
Short term rate	-0.05	-0.20
Long term rate	-0.05	-0.22
Credit-to-GDP	0.25	1.77
Capital ratio	0.15	0.62
Noncore	0.01	0.05
Loans-to-Deposits	0.87***	3.73
House price index	0.96***	4.05
Stock price index	0.28	1.08
Observations	112	

Notes: This table presents tests of differences in the means presented in Table 2. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 2: Number of ongoing credit booms by year



Notes: This figure presents the number of credit booms according to our definition. Dark bars refer to booms that turn into a banking crisis. Shaded areas mark windows around wars that we exclude from our analysis. See text.

Tests for the differences between good and bad booms are in Table 3 which reports the t-tests for the equality of means in good and in bad booms. The positive coefficients for size and duration indicate that bad credit booms are larger and longer, both variables being weakly significant (at the 5% level). Additionally, a bad boom is associated with significantly higher (at the 1% level) house prices and loan-to-deposit ratios of the banking sector. Housing bubbles and the funding of the credit boom by the banking sector might be the most important distinguishing features of bad booms.[8] Finally, the mean of the detrended current account balance is lower in bad credit booms , i.e. the current account deficit is higher. We confirmed that these results hold when analyzing only the post-WW2 era which includes 48% of all the bad booms and 76% of all the good booms.

4. Classifying booms

In this section we will shift our analysis of the differences between good booms and bad booms to a multivariate setting. We will estimate logit classification models in order to understand which economic and financial variables are associated with higher odds of a boom ending in a crisis. We will start with a parsimonious model and then add additional variables while tracking the improvement in the classification ability that the additional variables bring.

[8] We repeated these comparisons with country level demeaned variables instead of detrended normalized variables and the results are very similar. We prefer the detrended and normalized approach for our long time series data.

Our unit of observation will be credit boom episodes, where credit booms are defined as before using the deviations of real private credit per capita from the trend determined using the Hamilton technique. Further, we define a dummy $B_{i,b}$ that takes the value of one if boom b in country i is associated with a banking crisis during the boom or within a three year window after the peak of the credit boom. In all other boom episodes, this value will be zero and we will call such episodes good booms. In the model, the vector $Z_{i,b}$ contains boom level characteristics of boom b in country i. We will then estimate probabilistic models for the log odds ratio of witnessing a bad boom as shown by:

$$log\left(\frac{P[B_{i,b}=1|Z_{i,b}]}{P[B_{i,b}=0|Z_{i,b}]}\right)=\alpha+\beta Z_{i,b}+\epsilon_{i,b}, \tag{4}$$

We estimate the model with the full sample that includes all boom observations and with a reduced sample that enables us to include country fixed effects. The inclusion of fixed effects affects the number of available observations as some countries did not experience any bad booms so that the dependent variable displays no variation. As a result, these country observations must be omitted when fixed effects are included. The number of observations also changes due to missing data for some conditioning variables. For this reason, we start with a parsimonious specification that includes all boom observations and subsequently add additional controls and always use as much data as are available for the controls. Our initial specification, the baseline, includes two variables that describe the boom: the duration of the credit boom until the peak is reached and the average deviation of credit from trend in the period up to the peak of the boom (the size of the boom). Together these variables can be interpreted as measuring the cumulative size of the credit boom. The inclusion of these two variables follows recent contributions to the crisis prediction literature (Jordà *et al.* (2017b); Gourinchas *et al.* (2001)). Table 4 presents the baseline results, both for the full sample of 112 booms in 17 countries in Panel A and the reduced sample with fixed effects that includes 98 booms in 15 countries in Panel B. As expected, larger and longer booms both increase the likelihood of a bad end of the boom.

Our main interest is whether, conditional on being in a boom, economic variables add information helping us to classify booms into good ones and bad ones. We measure the predictive ability of different models by comparing their AUC statistics which is the area under the receiver operating curve (ROC). The statistic measures the ability of the model to correctly sort credit booms into a "good" and "bad" bin as combinations of true positive and false positive rates that result from changing the threshold for classification (Jordà and Taylor (2011)). In other words, it yields a summary measure of predictive ability that is independent of individual cut-off values chosen by the policy-maker. The AUC is a summary statistic of classification ability whose asymptotic distribution is Gaussian in large samples, making inference straightforward. In the simplest models, the AUC takes on the value of 1 for perfect classification ability and 0.5 for an uninformed classifier or the results of a 'coin toss'. We then compare the predictive ability of different models and the effects of adding particular control variables by tracking changes in the AUC and their standard errors.

Table 4: Baseline specification

	Size (1)	Duration (2)	Both (3)
Panel A: Full sample			
Size of boom	1.38**		1.26**
	(0.62)		(0.63)
Duration to peak		0.38*	0.30
		(0.20)	(0.21)
Pseudo R^2	0.047	0.025	0.062
AUC	0.68	0.56	0.68
s.e.	0.06	0.06	0.06
Observations	112	112	112
Panel B: Reduced sample —including country fixed effects			
Size of boom	2.28**		2.09*
	(1.12)		(1.15)
Duration to peak		0.49**	0.33
		(0.24)	(0.24)
Pseudo R^2	0.149	0.100	0.162
AUC	0.76	0.70	0.78
s.e.	0.06	0.06	0.06
Observations	98	98	98

Notes: Logit classification models for systemic banking crises associated with credit booms. The dependent variable is a dummy that is 1 when a banking crisis is associated with the credit boom, 0 otherwise. Size of boom is the average of the detrended and normalized credit variable between start and peak of the boom, duration is the number of years spent in boom until the peak is reached. The AUC in Panel A should be compared to a coin toss reference of 0.5. Panel B includes additionally country fixed effects. The fixed effects only model has an AUC of 0.68 (standard error 0.06). Clustered (by country) standard errors are presented in parentheses.

The AUC of the prediction model for the full sample including the size of the credit boom (Table 4, column (1)) is 0.68, and hence significantly better than the reference value of 0.5 for a coin toss model. Put differently, including the size of the boom significantly improves the accuracy of the prediction model. The results for the model with the boom duration (column (2)) are weaker, however. The coefficient is positive, but the AUC is not significantly higher than the coin toss reference. The estimates in Panel B include country-fixed effects to control for unobservable country characteristics that may make some countries more prone to incur a banking crisis once a credit boom is under way. The fixed effects alone have considerable predictive powers; the AUC based on a fixed effects only classification of booms is 0.68. Including both size and duration increases the AUC to 0.78 (column (3) in Panel B), an improvement over the country fixed effects prediction.

In the next three tables we will examine the importance of additional economic controls against the AUC for baseline models that include the size and duration of the boom. We will augment the baseline model by adding additional controls and checking whether these variables significantly improve our ability to distinguish good booms from bad booms. We distinguish between three

Table 5: Real variables

	Base	GDP	Cons.	Invest.	Current account	Short-rate	Long-rate
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Full sample							
Size of boom	1.12	1.12	1.14	1.03	1.25	1.05	1.08
	(0.82)	(0.81)	(0.84)	(0.89)	(0.91)	(0.76)	(0.76)
Duration to peak	0.35	0.35	0.37*	0.31	0.35	0.36	0.35
	(0.22)	(0.22)	(0.22)	(0.23)	(0.22)	(0.23)	(0.22)
Real variable		-0.04	-0.13	0.52**	-0.76**	-0.21	-0.14
(see column header)		(0.27)	(0.32)	(0.26)	(0.31)	(0.40)	(0.30)
Pseudo R^2	0.063	0.063	0.064	0.081	0.144	0.067	0.066
AUC	0.68	0.68	0.69	0.71	0.76	0.69	0.67
s.e.	0.07	0.07	0.06	0.06	0.06	0.06	0.06
Observations	90	90	90	90	90	90	90
Panel B: Reduced sample —including country fixed effects							
Size of boom	2.03	2.05	2.14	1.96	2.51	1.73	1.88
	(1.40)	(1.35)	(1.39)	(1.45)	(1.56)	(1.41)	(1.29)
Duration to peak	0.42	0.50*	0.56*	0.40	0.60*	0.46	0.43
	(0.30)	(0.30)	(0.29)	(0.31)	(0.36)	(0.34)	(0.30)
Real variable		-0.36	-0.59	0.26	-1.25***	-0.35	-0.18
(see column header)		(0.42)	(0.54)	(0.27)	(0.40)	(0.65)	(0.35)
Pseudo R^2	0.162	0.169	0.178	0.165	0.299	0.169	0.165
AUC	0.77	0.77	0.77	0.77	0.83	0.76	0.76
s.e.	0.07	0.07	0.06	0.07	0.05	0.06	0.07
Observations	72	72	72	72	72	72	72

Notes: Logit classification models for systemic banking crises associated with credit booms. The dependent variable is a dummy that is 1 when a banking crisis is associated with the credit boom, 0 otherwise. There is one observation for each credit boom. Real economic variables are in one-period-lagged normalized deviations from trend at the peak of the boom. Panel B includes additionally country fixed effects. Clustered (by country) standard errors in parentheses.

categories of variables, real economic variables, financial balance sheet based variables and asset prices. Importantly, all these variables have been detrended and normalized with the same procedure used for the credit measure and they are entered as the first lag at the peak of the credit boom. As a result, the full sample specifications (reported in panel A for each table) already address concerns related to heterogeneity in the volatility of variables across countries, while the fixed effects models (in Panel B) will additionally control for unobserved country specific factors driving the probability of a boom being bad.

We start with a set of real variables: GDP, consumption, investment, the current account balance, and the short-term and the long-term interest rate. Table 5 shows the results for both the full sample

(Panel A) and the reduced sample including country fixed effects (Panel B). Note that these variables are not available for all credit booms episodes so that the number of observations in Table 5 drops to 90 with the full sample and 72 with the reduced (fixed effects) sample.

In column (1) we show re-estimates of the baseline specification for these samples in order to obtain comparable AUCs. The coefficients and the AUCs are similar to those obtained before. We then include the other variables one at a time in columns (2) to (7). Most of the real sector measures are neither significant nor do they add predictive accuracy to the baseline model. In line with some of the previous literature, we find that larger current account deficits are positively related to the odds of a bad credit boom (Jordà *et al.* (2011)) and the AUC reaches 0.83 in the fixed effects model with the current account. A larger current account deficit represents increased financial flows from abroad which might increase financial fragility because of possible capital flow reversals. Somewhat unexpectedly, investment booms appear positively associated with bad outcomes with the full sample, but the AUC does not rise significantly when we add investment to the baseline model.

In Table 6 we add indicators of the funding structure of the banking sector during the credit booms. As before, we start with the baseline model for the subset of available observations and add financial variables one at a time. Column (1) shows again that coefficient and AUC for the baseline model are very close to previous results. In column (2) we add the ratio of credit to GDP as an indicator for the level of financial development and the depth of the financial sector. One might assume that credit booms are less likely to end in crisis at low levels of financial depth whereas the destabilizing effects of credit booms are more pronounced in financially developed economies. Yet we find only marginal evidence for this hypothesis in the full sample. The coefficient is positive, but it is insignificant and the AUC shows little improvement over the baseline specification.[9]

Turning to the capital ratio in (3) we find that a higher capital ratio is positively related to increasing odds of the boom being bad. This mirrors the findings in (Jordà *et al.* (2017a)). The share of non-core liabilities in the funding mix of banks seems to be unrelated to the probability of a boom being bad (column (4)). The estimates in column (5) include the detrended loan-to-deposit ratio. This ratio has been identified to increase prior to banking crises (Jordà *et al.* (2017a)). The coefficient is highly significant and the AUC is also higher than in the baseline specification. This measure for aggregate liquidity of the banking sector adds valuable predictive power. Higher loan-to-deposit-ratios are related to a substantially higher risk of credit booms ending badly. This is true in the full sample and in the fixed effects regressions.

In our next set of experiments in Table 7, we investigate the role of asset prices. To the baseline regressions without and with fixed effects, (1), we add house prices, as well as stock prices and then include both variables jointly. The results are clear. Including the house price index increases the AUC significantly by 0.10 in Panel A and 0.08 in Panel B – substantial improvements in the predictive ability of the model. By contrast, the inclusion of stock prices barely changes the AUC of the model and the coefficient is even negative and significant in the fixed effect regressions.

[9]The coefficient becomes significant when looking at post-WW2 data only.

Table 6: Banking variables

	Base (1)	Credit-to-GDP (2)	Cap. Ratio (3)	Noncore (4)	Loan-to-Dep. (5)
Panel A: Full sample					
Size of boom	1.19	1.22	1.26*	1.19	1.31*
	(0.73)	(0.75)	(0.74)	(0.73)	(0.71)
Duration to peak	0.31	0.26	0.30*	0.30	0.07
	(0.19)	(0.20)	(0.18)	(0.20)	(0.26)
Banking variable		0.49	0.35	0.02	0.66***
(see column header)		(0.57)	(0.31)	(0.18)	(0.22)
Pseudo R^2	0.060	0.070	0.082	0.060	0.116
AUC	0.68	0.67	0.68	0.68	0.74
s.e.	0.06	0.07	0.07	0.06	0.06
Observations	101	101	101	101	101
Panel B: Reduced sample —including country fixed effects					
Size of boom	2.07	2.04	2.11	2.07	2.16
	(1.45)	(1.44)	(1.44)	(1.47)	(1.47)
Duration to peak	0.41	0.37	0.38	0.37	0.16
	(0.28)	(0.28)	(0.27)	(0.26)	(0.33)
Banking variable		0.30	0.23	0.08	0.65**
(see column header)		(0.71)	(0.34)	(0.21)	(0.26)
Pseudo R^2	0.169	0.172	0.179	0.170	0.208
AUC	0.78	0.79	0.79	0.78	0.80
s.e.	0.06	0.06	0.06	0.06	0.06
Observations	86	86	86	86	86

Notes: Logit classification models for systemic banking crises associated with credit booms. The dependent variable is a dummy that is 1 when a banking crisis is associated with the credit boom, 0 otherwise. One observation for each credit boom, banking variables are in one-period-lagged normalized deviations from trend at the peak of the boom. See text. Panel B includes country fixed effects. Clustered (by country) standard errors in parentheses.

This result meshes nicely with recent contributions in the crisis prediction literature that have stressed the interaction of credit and house price booms as a key vulnerability of modern economies (Jordà *et al.* (2015)). This literature supports the idea that unleveraged "irrational exuberance" stock price booms pose much less of a threat to financial stability than "credit bubbles" in highly leveraged real estate markets. Our results in Table 7 also point to an important role of house price booms in increasing the likelihood of bad booms.

In Table 8, we bring together the individual control variables that had the strongest associations with bad booms and the largest increments to the AUC. These were, in descending order, house prices, the loan-to-deposit-ratio and the current account balance. We control again for the size and the duration of the boom and re-estimate the baseline model using identical samples for which all variables are available in order to be able to compare the AUCs. The baseline model is shown in

Table 7: Asset prices

	Baseline (1)	House prices (2)	Stock prices (3)	Both (4)
Panel A: Full sample				
Size of boom	1.61	1.61	1.81*	2.00*
	(0.99)	(1.13)	(0.98)	(1.15)
Duration to peak	0.49**	0.42	0.51**	0.47
	(0.23)	(0.28)	(0.24)	(0.31)
House Price Index		0.84**		0.91**
		(0.38)		(0.38)
Stock Price Index			-0.20	-0.40
			(0.28)	(0.34)
Pseudo R^2	0.111	0.207	0.116	0.223
AUC	0.72	0.82	0.73	0.82
s.e.	0.07	0.05	0.07	0.05
Observations	85	85	85	85
Panel B: Reduced sample —including country fixed effects				
Size of boom	2.36	2.59	3.73**	6.12**
	(1.75)	(1.66)	(1.79)	(2.46)
Duration to peak	0.75**	0.71	0.91**	0.97
	(0.35)	(0.46)	(0.40)	(0.68)
House Price Index		1.43**		2.14***
		(0.57)		(0.65)
Stock Price Index			-0.95**	-1.86***
			(0.41)	(0.68)
Pseudo R^2	0.232	0.380	0.283	0.499
AUC	0.81	0.89	0.84	0.92
s.e.	0.07	0.04	0.06	0.03
Observations	64	64	64	64

Notes: Logit classification models for systemic banking crises associated with credit booms. The dependent variable is a dummy that is 1 when a banking crisis is associated with the credit boom, 0 otherwise. One observation for each credit boom, asset price variables are in one-period-lagged normalized deviations from long-run trend at the peak of the boom. Panel B includes country fixed effects. Clustered (by country) standard errors in parentheses.

column (1) of Table 8 with the full sample in Panel A and the reduced sample with fixed effects in Panel B. In column (2) we add the house price index, in column (3), the loan-to-deposit ratio and in column (4), we include all variables jointly. All variables remain statistically significant at least at the 10% level with the full sample. The joint inclusion of the three conditioning variables increases the predictive power considerably from 0.70 with the baseline to 0.87 in the full sample (with 86 boom observations available) and from 0.77 to 0.92 for the reduced sample with fixed effects which includes 62 observations.

Table 8: Full model

	Baseline	House prices	LtD ratio	Full	Full (lower threshold)
	(1)	(2)	(3)	(4)	(5)
Panel A: Full sample					
Size of boom	1.42	1.27	1.18	1.48	1.56**
	(1.00)	(1.08)	(1.10)	(1.11)	(0.66)
Duration to peak	0.43*	0.39	0.15	0.18	0.05
	(0.22)	(0.27)	(0.33)	(0.30)	(0.19)
House Price Index		0.86**	0.80**	0.83**	0.93**
		(0.39)	(0.39)	(0.42)	(0.42)
Loan-to-Deposits			0.72**	0.61*	0.44
			(0.30)	(0.34)	(0.37)
Current Account				-0.81**	-0.87**
				(0.39)	(0.36)
Pseudo R^2	0.089	0.185	0.242	0.287	0.263
AUC	0.70	0.80	0.85	0.87	0.86
s.e.	0.07	0.05	0.05	0.04	0.05
Observations	86	86	86	86	102
Panel B: Reduced sample —including country fixed effects					
Size of boom	1.54	1.43	1.40	1.82	2.35**
	(1.59)	(1.60)	(1.71)	(2.12)	(0.99)
Duration to peak	0.73**	0.61	0.33	0.84	0.36**
	(0.32)	(0.51)	(0.47)	(0.96)	(0.16)
House Price Index		1.18*	1.21*	1.51***	1.32**
		(0.65)	(0.66)	(0.56)	(0.56)
Loan-to-Deposits			0.99***	0.88	0.72
			(0.35)	(0.57)	(0.53)
Current Account				-2.36***	-1.67***
				(0.88)	(0.58)
Pseudo R^2	0.191	0.313	0.382	0.501	0.413
AUC	0.77	0.86	0.88	0.92	0.89
s.e.	0.07	0.05	0.05	0.03	0.04
Observations	62	62	62	62	81

Notes: Logit classification models for systemic banking crises associated with credit booms. The dependent variable is a dummy that is 1 when a banking crisis is associated with the credit boom, 0 otherwise. One observation for each credit boom, added variables are in one-period-lagged normalized deviations from trend at the peak of the boom. Columns (1) to (4) are based on booms identified with a one standard deviation threshold. Column (5) presents the full model for an alternative threshold of 0.75 standard deviations. Clustered (by country) standard errors in parentheses.

These results indicate that looking back at almost 150 years of macroeconomic data, it is possible to identify the factors that distinguish credit booms that end in crisis from those that do not. Moreover, we are able to do so with rather parsimonious predictive models. In addition to the size of the boom itself, the most important variables are banking sector liquidity (the loan-to-deposit ratio),

a boom in housing prices and the inflow of foreign capital (as measured by the current account balance).

5. Real time classification

The analysis so far has been backward looking in the sense that we used data observed at the peak of the credit boom to determine which variables help us distinguish between good and bad booms. A stronger forecast test would address the question in real time as soon as a country entered a credit boom, only with data available at that time. In real time, policy-makers do not know how long a credit boom will last and whether a peak has been reached. We will therefore redo the previous analysis with data available to policy-makers at the start of a credit boom. The thought experiment is the following: imagine we observe that a credit boom has started, i.e., we observe that credit growth has been so strong that it crosses a boom threshold, can we say something about the probability of the boom ending badly on the basis of economic data available at this moment in time? The policy maker who takes offsetting action can successfully prevent the credit boom from ending in a crisis. At the same time, policy that prematurely ends a credit boom can at best lead to reduced growth and worst cause a contraction in economic activity.

For our real time forecast exercise, we omit boom observations where the country is in a banking crisis as soon as the boom threshold is passed. It would make no sense to try to forecast a bad boom that has already turned into a full-blown banking crisis; there is no time for a policy reaction. We also omit the real sector variables which are not quickly available, are subject to data revision and furthermore had less impact on the predictive accuracy in our previous analysis. The specification used for the real time forecast tests in Table 9 includes the initial size of the boom, i.e. in the first year of the boom, the loan-to-deposit ratio and the house price index. As before, the bad boom dummy is the dependent variable and all variables are de-trended using the Hamilton (2017) method which is a forward looking prediction.

We start with the baseline in column (1) in Table 9. The initial size of the boom is weakly significant and does add some predictive power compared to a coin toss model (AUC of 0.65 compared to 0.50). Note that we cannot include the duration of the boom in the baseline because it is unobserved in the first boom year. As in the previous analysis, adding house prices and loan-to-deposit ratios yields strongly positive coefficient estimates, and the AUC rises substantially from 0.65 to 0.83 in the full sample and to 0.91 in the reduced sample with fixed effects. The coefficient for house prices is not significant in the full sample in (3), but the AUCs show that their addition to the model still improves predictive accuracy considerably.

In Figure 3, we compare the ROC curves for real time forecasting models shown in Table 9. The figure graphically compares the AUCs for different models and displays the tradeoff between true and false calls of the classification technology. The larger the area between the respective line and the diagonal, that is the further the curve is shifted to the upper right corner, the better is the ability of the model to sort the data into the good and bad credit boom bin. On the left we use models with

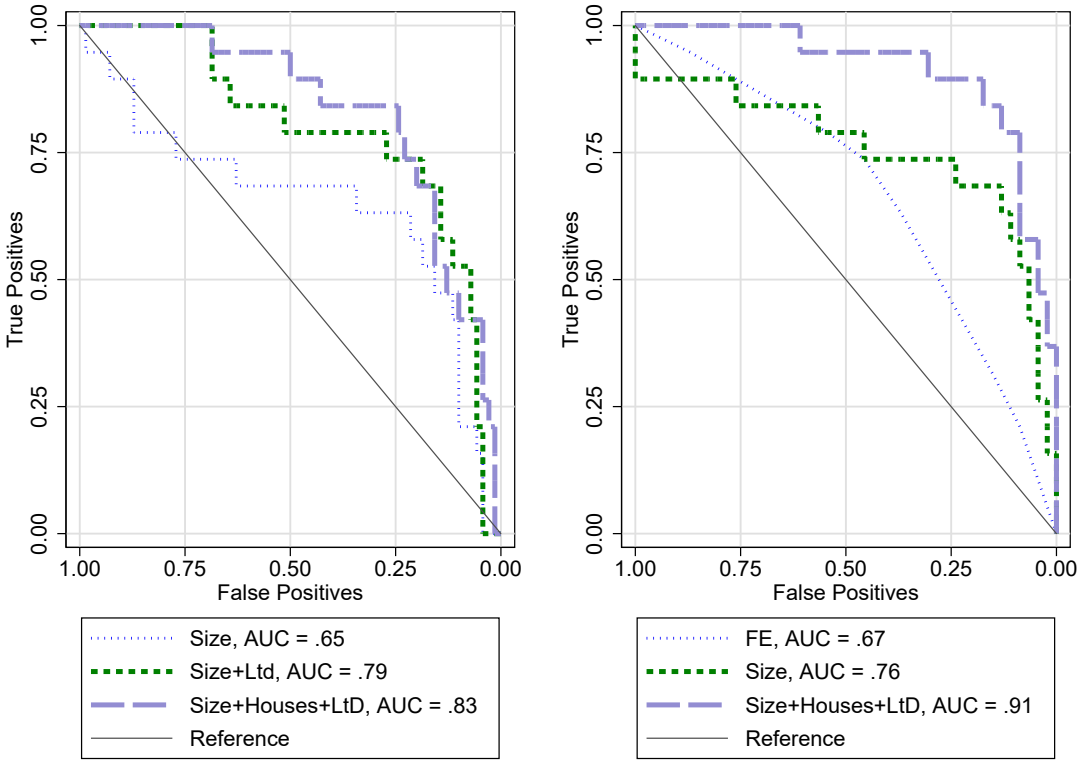
Table 9: Classification with real time information

	Baseline (1)	House prices (2)	Loan-to-deposits (3)	Both (4)
Panel A: Full sample				
Initial size of boom	2.02*	2.04	1.89	1.96
	(1.21)	(1.31)	(1.19)	(1.33)
House price index		0.57		0.56
		(0.36)		(0.43)
Loan-to-Deposits			1.16***	1.17***
			(0.33)	(0.35)
Pseudo R^2	0.059	0.101	0.188	0.224
AUC	0.65	0.74	0.79	0.83
s.e.	0.09	0.07	0.06	0.05
Observations	89	89	89	89
Panel B: Reduced sample —including country fixed effects				
Initial size of boom	2.81	3.99**	2.38	3.79**
	(1.82)	(1.93)	(1.67)	(1.72)
House price index		1.53*		1.35
		(0.88)		(0.84)
Loan-to-Deposits			1.78***	1.91**
			(0.54)	(0.89)
Pseudo R^2	0.149	0.300	0.337	0.442
AUC	0.76	0.85	0.87	0.91
s.e.	0.08	0.05	0.05	0.04
Observations	65	65	65	65

Notes: Logit classification models for systemic banking crises associated with credit booms. The dependent variable is a dummy that is 1 when a future banking crisis is associated with the credit boom, 0 otherwise. One observation for each credit boom, all variables are in country-level standardized deviations from long-run trend in the first year the boom threshold is reached. Panel B includes country fixed effects. Clustered (by country) standard errors in parentheses.

the full sample (from Panel A) and on the right we use models with the reduced sample from Panel B. The models shown in Panel A are based on the estimates in columns (1), (2) and (4). The reduced sample results on the right include a baseline equation with just the fixed effects (AUC = 0.67 which is not shown in Table 9), and the models in columns (1) and (4). The visual impression is quite stark. The augmented model that uses information for house prices and the aggregate liquidity of the banking sector improves the predictive ability by a substantial margin and bumps up the AUC to 0.83 (without fixed effects) and 0.91 (with fixed effects) respectively. The figure confirms that even using real time indicators, policy-makers can distinguish between good and bad credit booms with considerable accuracy.

Figure 3: Correct classification frontiers with real time data



Notes: This figure presents correct classification frontiers for the models displayed in Table 9, Panel A with the full sample on the left and Panel B with the reduced sample on the right. Size is the initial size of the boom, LtD is the loan-to-deposit ratio, and House is the house price index.

In Table 10 we check the robustness of the real time results with respect to a choice of different boom thresholds as well as using the credit-to-GDP ratio in order to identify credit booms.[10] Panel A shows the results using the full sample, while Panel B shows the results using post-WW2 data only. All specifications include house prices and the loan-to-deposit ratio in addition to the initial size of the boom (not shown). We present specifications without country fixed effects in both panels, because we have very few observations when we use a 1.25 standard deviation threshold and country fixed effects. Columns (1) to (3) in panel A vary the boom threshold from 0.75 to 1.25 standard deviations. The results in column (2) correspond to the full specification in column (4) in Table 9. We see that the loan-to-deposit ratio is always significant, while the house price coefficient becomes insignificant when the number of booms drops from 106 for the 0.75 threshold to 89 observations. When we identify credit booms via the credit-to-GDP ratio instead of real private

[10]We define the credit-to-GDP variable as the log of 100 times nominal bank credit over nominal GDP. We use this measure in order to account for the increase in the credit-to-GDP ratio over our sample period. If we use the raw credit-to-GDP ratio instead, there are barely any booms in the pre-WWI period and most booms occur after the 1980's, when credit-to-GDP rose dramatically in many countries.

Table 10: Robustness of real time classification models

	Real Credit Booms			Credit-to-GDP Booms		
Boom threshold	0.75	1	1.25	0.75	1	1.25
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Full sample						
House price index	0.84**	0.56	0.47	0.60**	0.52*	0.72**
	(0.41)	(0.43)	(0.45)	(0.28)	(0.29)	(0.34)
Loan-to-Deposits	0.43*	1.17***	0.85**	0.53	0.33	0.57
	(0.25)	(0.35)	(0.33)	(0.36)	(0.30)	(0.38)
Pseudo R^2	0.121	0.224	0.169	0.101	0.078	0.198
AUC	0.76	0.83	0.80	0.71	0.69	0.80
s.e.	0.06	0.05	0.06	0.06	0.07	0.07
Observations	106	89	61	93	73	54
Panel B: Post-WW2 sample						
House price index	0.87**	0.92**	1.41**	1.11***	1.27**	1.22**
	(0.34)	(0.45)	(0.71)	(0.42)	(0.56)	(0.59)
Loan-to-Deposits	0.72**	0.75***	0.19	0.86***	1.35***	1.37***
	(0.29)	(0.28)	(0.38)	(0.29)	(0.47)	(0.48)
Pseudo R^2	0.149	0.147	0.243	0.180	0.241	0.329
AUC	0.78	0.76	0.82	0.76	0.83	0.87
s.e.	0.05	0.07	0.08	0.07	0.06	0.06
Observations	89	69	44	78	66	47

Notes: Logit classification models for systemic banking crises associated with credit booms. The dependent variable is a dummy that is 1 when a banking crisis is associated with the credit boom, 0 otherwise. One observation for each credit boom, added variables are in normalized deviations from long-run trend in the year of the start of the boom. All models include the initial size at the start of the credit boom as a control, coefficients are not shown here to conserve space. Clustered (by country) standard errors in parentheses.

credit per capita (columns (4) to (6)), the coefficients for the house price index are always significant, while the loan-to-deposit ratio is insignificant. However, in all cases, including these two variables in addition to the initial size of the credit boom improves predictive accuracy of our models.

To see whether these results hold in more recent data, in we show estimates using post-WW2 data only (also for the de-trending and normalization procedure) in Panel B. The coefficients for house prices and loan-to-deposit ratios are now highly significant (at the 5% or 1% level) in almost all specifications, only in column (3) the loan-to-deposit ratio is insignificant when the number of booms is reduced to 44 for a 1.25 threshold.

5.1. Out-of-sample classification

Our final experiment is an out-of-sample analysis of recent booms. We ask the following: using information available from historical data from the first year of credit booms, could a policymaker

Table 11: Out-of-sample test for booms starting in 2000 or later

	Start	Outcome	Initial Size (1)	Size + House Prices (2)	Full (3)
Australia	2004	good	0.161	0.914	0.914
Denmark	2002	good	0.152	0.208	0.249
Denmark	2005	bad	0.206	0.684	0.744
Finland	2000	good	0.155	0.163	0.186
Finland	2003	good	0.153	0.178	0.197
Italy	2007	bad	0.162	0.345	0.472
Norway	2005	good	0.175	0.355	0.434
Spain	2005	bad	0.195	0.508	0.572
Sweden	2005	bad	0.151	0.563	0.538
UK	2000	good	0.145	0.217	0.253
USA	2004	bad	0.159	0.533	0.533

Notes: This table presents predicted probabilities of a boom after the year 2000 being bad based on information available in the first year of the boom. Probabilities are based on coefficients from logit classification models estimated using available data until 1999. Models are including the size of the boom (1) and adding house prices (2) and additionally loan-to-deposits (3).

in the 2000s have known which starting credit booms would end badly? To answer this question, we estimate our real time logit specification with the full sample with all available data up to the year 1999. We use 0.75 standard deviations threshold for booms to arrive at meaningful number of observations for the 2000s. Afterwards, we will use the coefficients from this estimation to predict the probability that a boom starting in the 2000s ends in a banking crisis. Using the 0.75 standard deviation threshold there are 11 credit booms in this period in our data and five of them are bad.

Table 11 presents the estimated probabilities of experiencing a banking crisis for each credit boom after the year 2000 using logit estimates with data until 1999. Column (1) is based on estimates with only the initial size of the boom. We see that the size of the boom contains little information. Adding house price data in (2) and the loan-to-deposits ratio in (3) improves the accuracy of the model considerably and the resulting AUC for this model is 0.83. Inspecting the probabilities shows that the good booms, with the exception of Australia, have lower crisis probabilities than 0.45 and the bad booms have probabilities above 0.45. The model sorts the data almost correctly and only fails to predict a lower probability for Australia, where house prices increased vary rapidly in the 2000s.

6. Robustness

In this section, we report some of the results of robustness checks that we ran to test the sensitivity of our results. In Table 12 we present results of repeating the detrending procedure and the logit analysis using post-WW2 data only. Here we change the boom threshold to detrended credit being larger than 0.75 country specific standard deviations as otherwise the number of booms is too small to perform our regression analysis. In principle, the introduction of deposit insurance and the change in the monetary regime might have changed the underlying dynamics of credit booms. Yet the coefficient estimates for loan-to-deposit ratios and house prices remain broadly stable, and the

Table 12: Full model - post WW2 data only

	Baseline (1)	Add house prices (2)	Add LtD ratio (3)	Full (4)
Panel A: Full sample				
House Price Index		1.06**	1.12**	1.11**
		(0.45)	(0.45)	(0.45)
Loan-to-Deposits			0.65*	0.65*
			(0.34)	(0.35)
Current Account				-0.03
				(0.28)
Pseudo R^2	0.240	0.361	0.400	0.400
AUC	0.80	0.88	0.89	0.89
s.e.	0.06	0.05	0.05	0.05
Observations	89	89	89	89
Panel B: Reduced sample —including country fixed effects				
House Price Index		1.75***	2.01**	2.06**
		(0.66)	(0.86)	(0.83)
Loan-to-Deposits			1.24*	1.09
			(0.70)	(0.68)
Current Account				-0.57
				(0.82)
Pseudo R^2	0.390	0.551	0.612	0.623
AUC	0.88	0.94	0.95	0.95
s.e.	0.05	0.03	0.03	0.03
Observations	80	80	80	80

Notes: Logit classification models for systemic banking crises associated with credit booms. The dependent variable is a dummy that is 1 when a banking crisis is associated with the credit boom, 0 otherwise. One observation for each credit boom, added variables are in one-period-lagged normalized deviations from long-run trend at the peak of the boom. All specifications include the size and the duration of the boom; coefficients not shown here to conserve space. Booms are defined with a 0.75 standard deviation boom threshold. Panel B includes country fixed effects. Clustered (by country) standard errors in parentheses.

classification ability remains high. When entered separately, both variables, loan-to-deposits and house prices contain valuable information. The results are very similar to the ones obtained using all available data. Elevated house prices and loan-to-deposit ratios signal higher probabilities of a boom turning into a banking crisis as indicated by the significant coefficients and high AUCs. In our sample of advanced economies, the current account balance seems to play a less important role post-WW2.

In Table 13 we vary the detrending procedure as well as the credit variable used to identify credit booms. In column (1) we report the results from Table 8 for the full sample (Panel A) and from Table 12 for the post-WW2 data (Panel B) for comparison. In column (2) we continue to use the Hamilton filter, but define boom episodes using deviations of the credit-to-GDP ratio from its trend. As before,

Table 13: Varying filter methodology

	Hamilton filter		HP filter	CF-bandpass filter
	Real Credit (1)	Credit-to-GDP (2)	Real Credit (3)	Real Credit (4)
Panel A: Full sample				
House Price Index	0.83**	0.56**	0.75**	0.42**
	(0.42)	(0.28)	(0.35)	(0.19)
Loan-to-Deposits	0.61*	0.30	0.53	0.52*
	(0.34)	(0.32)	(0.35)	(0.28)
Current Account	-0.81**	-0.49	0.05	-0.10
	(0.39)	(0.34)	(0.27)	(0.14)
Pseudo R^2	0.287	0.160	0.213	0.088
AUC	0.87	0.78	0.80	0.71
s.e.	0.04	0.05	0.05	0.08
Observations	86	77	79	91
Panel B: Post-WW2 sample				
House Price Index	1.11**	1.08***	1.23***	0.48
	(0.45)	(0.36)	(0.41)	(0.34)
Loan-to-Deposits	0.65*	1.06***	0.86**	0.51
	(0.35)	(0.30)	(0.40)	(0.40)
Current Account	-0.03	-0.23	0.17	0.06
	(0.28)	(0.45)	(0.29)	(0.10)
Pseudo R^2	0.400	0.436	0.365	0.070
AUC	0.89	0.92	0.90	0.70
s.e.	0.05	0.03	0.04	0.09
Observations	89	81	71	83

Notes: Logit classification models for systemic banking crises associated with credit booms. The dependent variable is a dummy that is 1 when a banking crisis is associated with the credit boom, 0 otherwise. One observation for each credit boom, added variables are in one-period-lagged normalized deviations from long-run trend at the peak of the boom. All specifications include the size and the duration of the boom; coefficients not shown here to conserve space. Full sample results are based on a boom threshold of one standard deviation. Post-WW2 results in Panel B are based on a 0.75 standard deviations threshold. Clustered (by country) standard errors in parentheses.

deviations of the loan-to-deposit ratio and house prices from trend signal an increasing likelihood that a credit boom ends badly. These results are even stronger in the post-WW2 data. In column (3) we use a two-sided HP-filter with a smoothing parameter of $\lambda = 100$, in line with some of the previous literature, to identify the cyclical component of the variables. The results using the HP-filter are broadly similar, albeit the loan-to-deposit ratio loses statistical significance in the full sample, while an increase in house prices continues to send precisely estimated warning signals. In column (4) we use a bandpass filter as proposed by Christiano and Fitzgerald (2003) to determine the trend in real credit and specify our cyclical component to capture variation at frequencies between 2 and 8 years. Using the full sample we again find that there is a statistically significant relationship between

adverse funding conditions measured by an elevated loan-to-deposit ratio as well as high house prices and the probability of a boom ending in a banking crisis. The post-WW2 results are similar in size, but insignificant.

7. Conclusion

In modern economic history, about one-quarter of credit booms are followed by a systemic banking crisis. This means that policy-makers eager to avoid the debilitating economic consequences of banking crises have to walk a fine line between the two pitfalls of failing to intervene in time to stop bad booms and being overly activist and intervening at the wrong time with potentially severe costs for the economy. The findings presented in this paper mark a first step towards informing and eventually alleviating this trade-off. We showed, on the basis of a dataset that covers the near universe of credit cycles and crises in the modern economic history of advanced economies, that there are discernible economic features of some credit booms that make them more likely than others to end in a crisis. Importantly, policy-makers are able to use information available to them in real time to make well-informed decisions about the nature of the credit boom developing before their eyes.

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Appendices

A. Systemic banking crises

The crisis prediction classification models in the paper employ data on all systemic banking crises from 1870 to 2008. Dates of systemic banking crises are based on Jordà *et al.* (2017b).

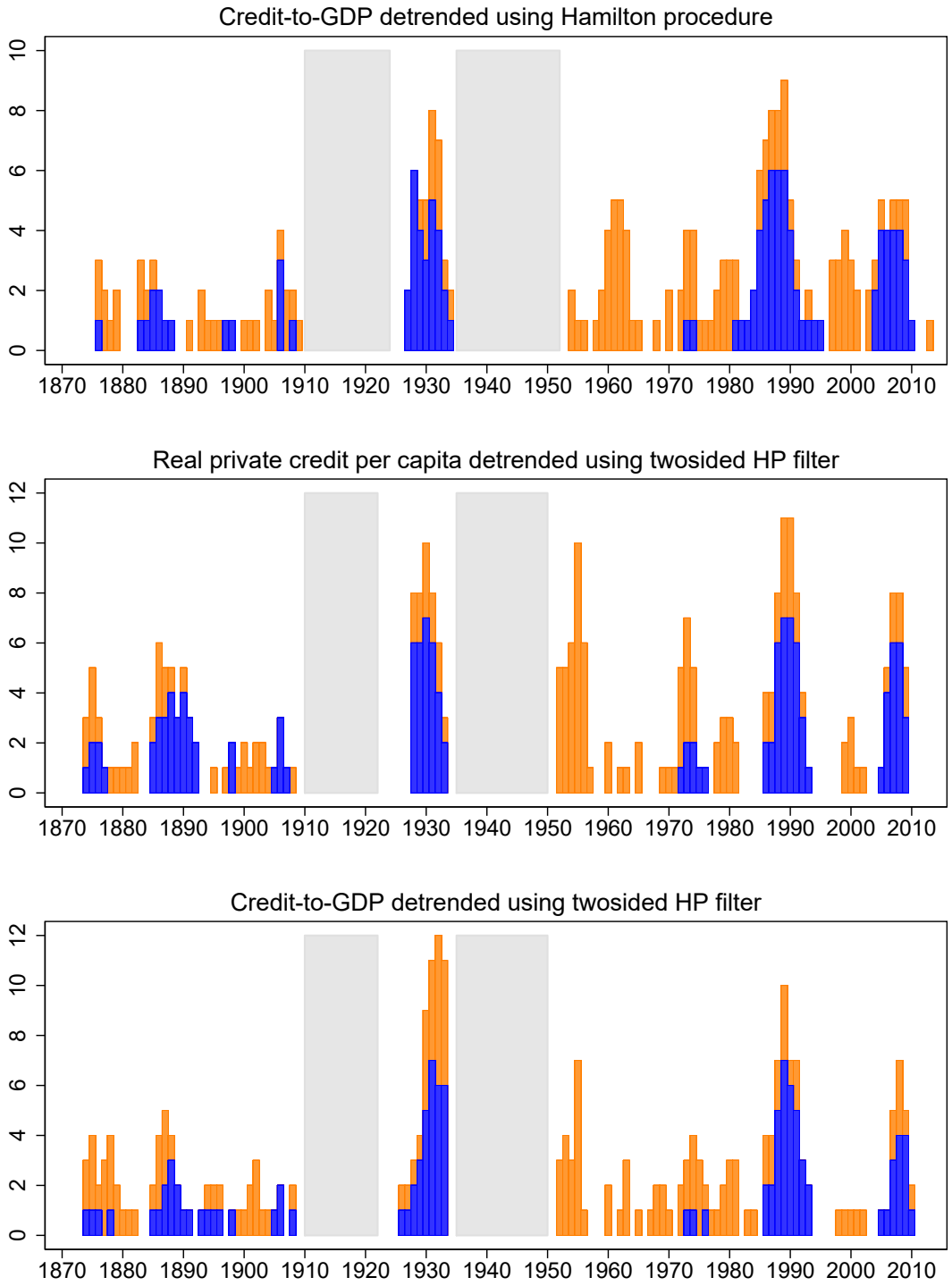
AUS:	1893, 1989.
BEL:	1870, 1885, 1925, 1931, 1934, 1939, 2008.
CAN:	1907.
CHE:	1870, 1910, 1931, 1991, 2008.
DEU:	1873, 1891, 1901, 1907, 1931, 2008.
DNK:	1877, 1885, 1908, 1921, 1931, 1987, 2008.
ESP:	1883, 1890, 1913, 1920, 1924, 1931, 1978, 2008.
FIN:	1878, 1900, 1921, 1931, 1991.
FRA:	1882, 1889, 1930, 2008.
GBR:	1890, 1974, 1991, 2007.
ITA:	1873, 1887, 1893, 1907, 1921, 1930, 1935, 1990, 2008.
JPN:	1871, 1890, 1907, 1920, 1927, 1997.
NLD:	1893, 1907, 1921, 1939, 2008.
NOR:	1899, 1922, 1931, 1988.
PRT:	1890, 1920, 1923, 1931, 2008.
SWE:	1878, 1907, 1922, 1931, 1991, 2008.
USA:	1873, 1893, 1907, 1929, 1984, 2007.

B. Variable definitions

Variable	Description
Bad boom	Dummy variable - equals 1 if there is a banking crisis during a boom or up to three years after the peak of a boom
Duration	Duration of boom until peak in years
GDP	Real GDP per capita
Consumption	Real consumption per capita (2006=100)
Investment	Gross fixed capital formation in % of GDP
Current account/GDP	Current account balance in % of GDP
Real share price	Share price index deflated, (1990=100)
Real house price	House price index deflated, (1990=100)
Short term rate	Short term interest rate in %
Long term rate	Long term interest rate in %
Real private credit per capita	Bank credit to private per capita deflated with CPI
Credit-to-GDP	log(Bank credit to private in % of nominal GDP)
Noncore share	Non-deposit bank debt/Total bank debt
Capital ratio	Bank capital/bank assets
Loans-to-Deposits	Bank credit to private/bank deposits

Notes: Data are based on the Macrohistory Database (Jordà *et al.* (2017b)), Knoll *et al.* (2017) and Jordà *et al.* (2017a).

Appendix Figure A1: Number of countries with ongoing credit booms by year using different credit measures and detrending procedures.



Notes: This figure presents the number of credit booms using different filters and credit variables. Dark bars refer to booms that turn into a banking crisis. Shaded areas mark windows around wars that we exclude from our analysis. These are 2 years longer for the Hamilton filter. See text.