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.

Keywords: Banking Crises, Crisis Prediction, Credit Booms, Macroprudential Policy

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1. Introduction

Periods of rapid credit growth, credit booms, can have diverse outcomes. Banking crises are often credit booms that have ended badly. But not all credit booms end in crisis. Many credit booms are associated with improved economic fundamentals. Such booms are likely to be beneficial sources of increased growth. In our historical data about one-quarter of credit boom episodes are followed by a systemic banking crisis. This means that policy-makers eager to avoid the debilitating effects of banking crises have to walk a fine line between the two pitfalls of failing to intervene to stop a bad boom and being too activist and choking off economic growth. Measures to dampen credit booms may reduce the risk of a banking crisis, but also reduce growth with uncertain costs for the economy (Svensson (2017); Adrian and Liang (2016)). The question that jumps from these observations is whether it is possible to distinguish the good credit booms from the bad ones that end in crisis, and whether policy-makers can identify the subset of credit booms that are dangerous, and whether they can do so with data available in real time? 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.

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 2016. 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 is based on a large number of historical sources as well as the crisis dataset compiled by Laeven and Valencia (2012). To measure cyclical variation, 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 predicted value by a country-specific threshold and identify 112 credit boom episodes in our sample of advanced economies over the past 150 years.

Adopting the perspective of policy-makers, we restrict our analysis to episodes when credit booms are underway and can be identified as such. We then turn to classification models with a wide variety of real and financial variables to examine the characteristics of booms that may help policy-makers distinguish bad booms from good booms. By design, this approach allows us to study state-dependent effects at a time when aggregate leverage in the economy is rising. Importantly, our results use a real time analysis which relies only on data available at the time to both determine whether (1) a credit boom has begun, and (2) to measure the cyclical variations of explanatory variables. The real time analysis indicates that there are 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.

The growth of credit has been of interest to economic historians, development economists and students of macro-finance for at least 30 years. Our paper connects the two important and seemingly contradictory strands in the macro-financial literature (Wachtel (2018)). 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)). There is a voluminous literature that uses post World War II panel data that has been 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 have weakened since the mid-1980s which coincides with an increase in the incidence of financial crises. There is also a small literature that uses historical data to examine the finance-growth nexus (Rousseau and Wachtel (1998)).

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)). While credit-fueled asset price bubbles can be a precursor to banking distress and crisis (Jordà *et al.* (2015)), other credit booms might represent financial deepening or be the reaction to a positive productivity shock. 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. More recently, Mian *et al.* (2017) have shown that credit booms predict bad growth outcomes in the future. We also show that there are characteristics of credit booms that make such bad growth outcomes more likely.

In the aftermath of the 2008 financial crisis there has been increased interest managing the risks emanating from credit booms. In particular, the literature explores macro-prudential and other policies to deal with the risks of credit booms (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 micro financial regulation to maintain financial stability (Bernanke and Gertler (2000)). 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)). Yet even before the financial crisis, some economists, notably at the Bank for International Settlements, 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." (p.26).

The literature on macro-prudential policies expanded rapidly after the global financial crisis (Svensson (2017), Mitra *et al.* (2011) and Adrian and Liang (2016)). Many researchers (Stein (2013)) argue that policy should intervene to contain excessive credit growth. Nevertheless, policy discussions remain concerned with the possible side effects of efforts to identify crisis situations and lean against the wind and the debate regarding policy prescriptions remains unsettled.

In particular, Svensson (2017) argues that the relationship between credit growth and crisis incidence is a reduced form correlation of many complex interactions which makes it impossible to identify a stable and consistent crisis predictor. Thus, our interest in this paper is not to predict crises outright but instead to provide information that would help policy makers determine whether an observed credit boom is likely to end badly. Only a few papers have examined booms and their outcomes, Mendoza and Terrones (2012), Dell'Ariccia *et al.* (2016) and Gorton and Ordonez (2016). These studies identify credit booms with various measures of credit and both mechanical definitions of booms and definitions based on credit detrended with a Hodrick-Prescott filter. 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.[1]

To the best of our knowledge, ours is the first paper to show that it is possible to identify markers that distinguish bad booms from good booms in real time. Our long-run historical data have the advantage that we can analyze within-country experiences as most of the sample countries have experienced both good and bad credit booms at some point in their history.

Measuring the consequences of credit booms and in particular understanding which credit booms turn into banking crises requires a methodology to identify credit booms. Our methodology using the new Hamilton (2017) filter to detrend the data is in section 2. In section 3 we examine the relationship between credit boom and crisis episodes and the characteristics of good and bad booms. In section 4, we 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 show which economic variables characterize bad booms but not good booms. The results hold up when we use the post-boom growth in real GDP as the measure of the boom outcome and when we restrict the sample to the post World War II period which includes two decades without any bad booms.

Our core results are in section 5 which sets a high bar for prediction. We put ourselves in the shoes of policy-makers and use only data that are available to them in real time. In other words, we are aiming to determine whether policy makers are able to differentiate between good and bad credit booms as they unfold. Our tests show that even using exclusively variables that are available in real time, policy makers can achieve classification with high accuracy. 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 6, we will subject our real time results to robustness tests for different boom thresholds and boom indicator variables. Our 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

[1] 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.

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.[2] Mendoza and Terrones (2008) use the HP filter to detrend 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)).[3] 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 four most 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}.[4] As Hamilton (2017) explains, the procedure is by construction forward looking (onesided) as it uses 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

[2]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.

[3]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.

[4]Hamilton (2017) proposes $h = 2$ for business cycle variables and a longer horizon up to five years for financial variables. Since we include real and financial variables in our analysis, we chose $h = 3$, but we find similar results for $h = 5$. The choice of h affects the number of booms we identify. The result of loan-to-deposit ratios and house prices being the main predictors of bad booms however remains unchanged.

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]

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:

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

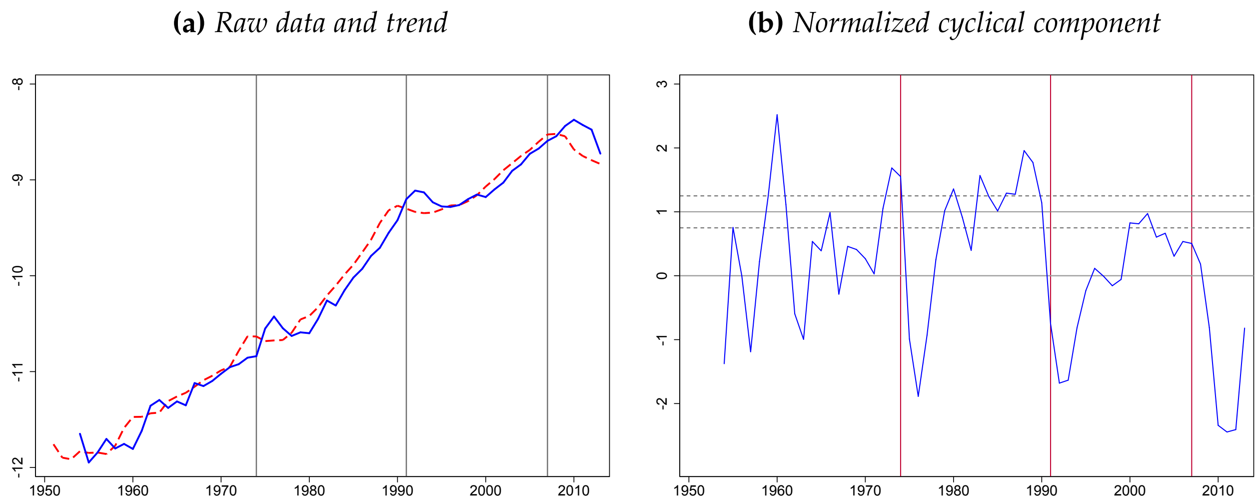
We will show that our results are robust to thresholds other than one standard deviation.[6] We furthermore refer to the local maximum value of $c_{i,t}$ during a specific boom period (i.e. conditional on Credit Boom $= 1$) as the peak of the credit boom. The normalized detrended credit measure $\frac{c_{i,t}}{\sigma(c_i)}$, 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 episodes, where the boom is already collapsing, which might take some time as our credit measures are based on stock variables (outstanding credit).

[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.

[6]We experimented with alternative thresholds of 0.5 and 0.75 and 1.25 $\sigma(c_i)$. Results are in the robustness discussions in section 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.

Figure 1: Detrended credit and cyclical component for the UK



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).

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 component 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

Table 1: Logit models with banking crises as dependent variable

	All years		Pre-WW2		Post-WW2	
	(1)	(2)	(3)	(4)	(5)	(6)
Detrended credit$_{i,t-1}$	0.61***		0.70***		0.86***	
	(0.15)		(0.18)		(0.23)	
Credit boom$_{i,t-1}$		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
	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 below is its standard error.

financial distress. [7] In particular, we estimate

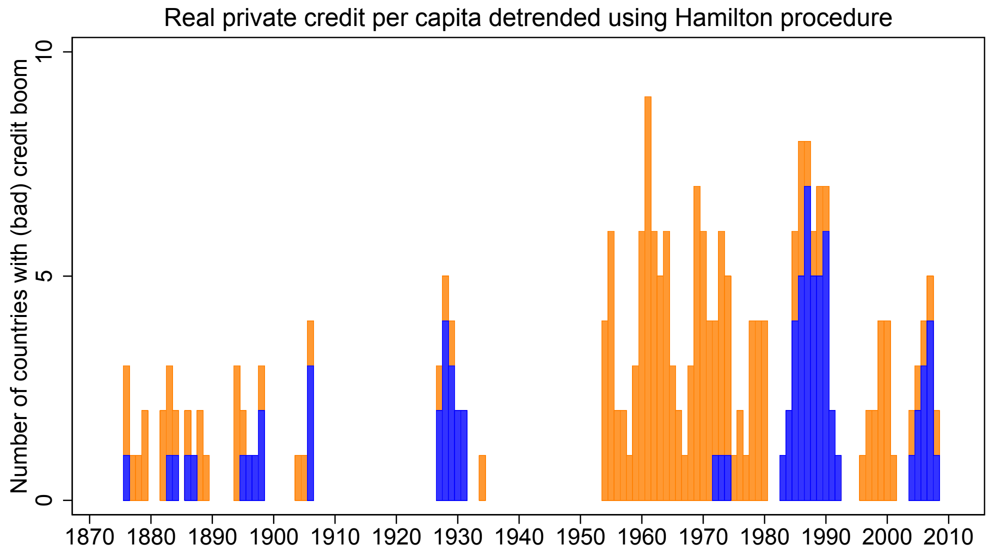
$$log\left(\frac{P[S_{i,t}=1|X_{i,t-1}]}{P[S_{i,t}=0|X_{i,t-1}]}\right)=\alpha_i+\beta X_{i,t-1}+\epsilon_{i,t}, \tag{3}$$

where α_i is a fixed effect that captures differences in the probability that a country will experience banking crises. We report results for two different choices of $X_{i,t-1}$: first, our measure of credit, the lagged normalized detrended real private credit per capita, and second, the lagged credit boom dummy as defined above (equation (2)). The first two columns of Table 1 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 $X_{i,t}$ is the credit boom indicator meaning that the probability of a banking crisis increases when a country has experienced a credit boom. 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 above results 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 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

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

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.

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. In addition, there were many booms in the late 1980s and early 1990s, and again in the early 2000s that eventually turned into crises.

The number and distribution of credit booms depends on the specific procedure used to determine when booms occur. In the Appendix, we show 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 and periods around the turn of the century where many booms ended in crisis. 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 Hamilton procedure 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 mean values in bad booms are house prices and the loan-to-deposit ratio which are both more than one standard deviation above 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.
Boom with 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
Loans-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: Macroeconomic and financial variables are detrended and normalized at the country level (except credit to GDP ratio which is the natural log of the ratio) and the values presented are lagged one-period from the peak of the credit boom. Duration is in years and size is averaged over the boom-to-peak period. Variable definitions are in Appendix B.

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

	Difference in means (Bad - Good)	
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)
Loans-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, t-statistics in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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]

We also examined the mean characteristics of the booms during the 1950s and 1960s, a period in which there were 31 credit booms in our sample countries, all of which were good (see Figure 2). The booms in this period were of similar size and duration as other booms. The mean characteristics do not differ significantly from other good and bad booms with a few notable exceptions. Detrended real GDP per capita is higher and detrended house prices and the loan-to-deposit ratio lower than in other booms with all differences significant ($p < .01$ in each case). In the good booms of the 1950s and 1960s, GDP was on average more than one standard deviation above trend while loans-to-deposits and house prices were close to their trend values.[9]

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.

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. The vector $Z_{i,b}$ contains 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. Two countries did not experience any bad booms; since the dependent variable displays no variation for these countries, it is not

[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.

[9] A table with the means for this period and the tests on the differences is available from the authors.

possible to include a fixed effect. The reduced sample with fixed effects omits the credit boom observations from these countries. The number of observations also changes due to missing data for the explanatory 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 (called the size of the boom). Together these variables can be interpreted as measuring the magnitude 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 and financial characteristics add information that helps us 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. 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.

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 power; 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 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
	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
	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. AUC is the area under the receiver operating curve, and below is its standard error. 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.

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

Table 5: Real variables

	Base (1)	GDP (2)	Cons. (3)	Invest. (4)	Current account (5)	Short-rate (6)	Long-rate (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 variables		-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
	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 variables		-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
	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 variables are in one-period-lagged normalized deviations from trend. Panel B includes additionally country-fixed effects. Clustered (by country) standard errors in parentheses. AUC is the area under the receiver operating curve, and below is its standard error.

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.

Table 6: Banking variables

	Base (1)	Credit-to-GDP (2)	Cap. Ratio (3)	Noncore (4)	Loans-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
	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
	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. Panel B includes country-fixed effects. Clustered (by country) standard errors in parentheses. AUC is the area under the receiver operating curve, and below is its standard error.

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.[10]

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

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 which 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.

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.[11]

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 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.

We noted earlier that there are some differences in the incidence of booms when alternative filters are used to detrend credit or alternative credit measures are used. We also examined the effect of such differences on the results shown here. In Appendix Table A-1 we vary the detrending procedure as well as the credit variable used to identify credit booms and estimate the full model

[11] Mian and Sufi (2018) describe the household credit demand channel that relates house prices to financial cycles. Their mechanism supports the importance of house prices in understanding boom outcomes.

Table 7: Asset prices

	Baseline (1)	House price index (2)	Stock price index (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
	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
	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. AUC is the area under the receiver operating curve, and below is its standard error.

as in Table 8, column (4) for the full sample (Panel A). In column (1) we show this result again 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, deviations of the loan-to-deposit ratio and house prices from trend signal an increasing likelihood that a credit boom ends badly. 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 while an

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	1.55**
	(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**	0.92**
		(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	0.261
AUC	0.70	0.80	0.85	0.87	0.86
	0.07	0.05	0.05	0.04	0.05
Observations	86	86	86	86	101
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
	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. AUC is the area under the receiver operating curve, and below is its standard error.

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.

Table 9: Credit Boom Characteristics and Three-Year GDP Growth

	(1)	(2)	(3)	(4)
Panel A: Pooled OLS				
Size of boom	-0.03	-0.02	-0.02	-0.02
	(0.03)	(0.03)	(0.02)	(0.02)
Duration to peak	-0.01	-0.00	0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.01)
House price index		-0.03***	-0.03***	-0.03**
		(0.01)	(0.01)	(0.01)
Loan-to-deposits			-0.02***	-0.01*
			(0.01)	(0.01)
Current account				0.02
				(0.01)
R^2	0.028	0.124	0.151	0.173
Observations	86	86	86	86
Panel B: OLS —including country-fixed effects				
Size of boom	-0.03	-0.01	-0.02	-0.02
	(0.03)	(0.04)	(0.03)	(0.03)
Duration to peak	-0.01	-0.00	0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.01)
House price index		-0.03**	-0.03*	-0.03*
		(0.01)	(0.01)	(0.01)
Loan-to-deposits			-0.02**	-0.02**
			(0.01)	(0.01)
Current account				0.02
				(0.02)
R^2	0.252	0.338	0.378	0.398
Observations	86	86	86	86

Notes: In this table the dependent variable is $\Delta_3 GDP_{i,t} = log(realGDP_{i,t+3}) - log(realGDP_{i,t})$. One observation at the peak for each credit boom, explanatory variables are in one-period-lagged normalized deviations from trend. Panel B includes country-fixed effects. Clustered (by country) standard errors in parentheses. AUC is the area under the receiver operating curve, and below is its standard error.

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.

Ultimately, we are interested in the relationship between credit boom characteristics and their relationship with real economic outcomes. Hence, as an additional test, we ask whether the variables used to classify credit booms also explain the impact of the boom on economic activity. That is, we examine the effect on the rate of growth of real GDP in the three years after the peak of a boom. The results shown in Table 9 indicate that the size and duration of the boom are not significantly related to GDP growth after the peak. However, the house price index and loan-to-deposit ratio prior to the peak of the boom have a significant predictive effect on GDP growth in the three following years. The coefficients are negative and significant indicating that higher house prices and loan-to-deposit ratio are associated with slower GDP growth after the boom peaks. That is the factors that often lead to a crisis after a boom also impact GDP growth. Higher house prices and loan to deposit ratios are associated with a higher probability that a boom ends badly (see Table 8) and are also associated with lower GDP growth after all booms (see Table 9).

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). Our results highlight the quandary faced by policymakers. Leaning against a credit boom may come at the cost of lower GDP growth even if it does not result in crisis.

5. Real time classification

In this section, we ask whether policymakers can use available information to make useful forecasts. 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. But can policy-makers exploit information about the nature of the boom in real time and act accordingly? A strong forecast test will address the issue of crisis prediction with data available in real time. At any point in time, a policy maker would need to use available information to first determine whether a credit boom was underway and second to predict whether an observed boom will end badly. Showing that this is possible is the central contribution of this paper.

Our analysis will determine whether a boom has started and predict how it will end; in both instances, we use data available to policy-makers in real time. We show that there are strong signals available that would enable a policy maker to take offsetting action that could prevent the credit boom from ending in a crisis. The real time forecast tests in this section are effectively assessments of early warning indicators with real time information.

The first step is to detrend and normalize real private credit per capita with the same Hamilton procedure used before with regressions that roll forward adding observations year by year. In each year, a detrended and normalized estimate based on data available at the time is used to determine whether a credit boom has begun. Second, when we observe that a credit boom has started, i.e. credit growth detrended with past data is strong enough to cross the boom threshold, the Hamilton procedure is used with data up to the start of the boom to detrend and normalize the explanatory variables. Finally, we predict whether the boom will end badly on the basis of economic data available at the start of the boom.

There are a few more credit booms with the real time data than before (115 versus 112 in the entire data set) and some minor differences in dating. For the real time analysis we omit booms 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

Table 10: Classification with real time information

	(1)	(2)	(3)	(4)
Panel A: Full Sample				
Initial size of boom	0.48	0.51	0.62	0.68
	(0.61)	(0.60)	(0.77)	(0.71)
Loans-to-deposits		0.48**		0.30
		(0.20)		(0.23)
House price index			0.73***	0.68***
			(0.23)	(0.22)
Pseudo R^2	0.006	0.047	0.144	0.156
AUC	0.56	0.64	0.76	0.77
	0.09	0.08	0.06	0.07
Observations	76	76	76	76
Panel B: Reduced Sample —including country-fixed effects				
Initial size of boom	0.74	0.86	1.61	1.75
	(0.83)	(0.76)	(1.25)	(1.08)
Loans-to-deposits		0.99***		0.82*
		(0.31)		(0.45)
House price index			1.24***	1.16***
			(0.37)	(0.32)
Pseudo R^2	0.046	0.157	0.282	0.332
AUC	0.64	0.76	0.83	0.86
	0.08	0.08	0.06	0.05
Observations	58	58	58	58

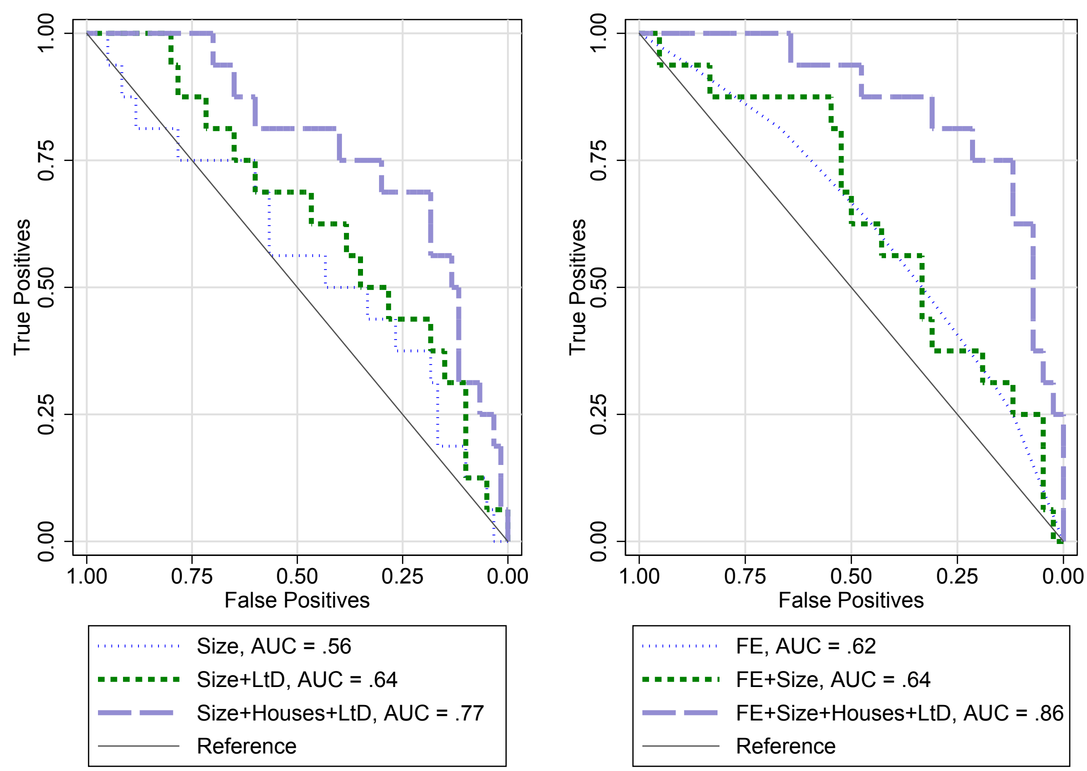
Notes: Logit classification models for systemic financial crises associated with credit booms. The dependent variable is a dummy that is 1 when a future financial crisis is associated with the credit boom, 0 otherwise. One observation for each credit boom, all variables are in country-level standardized 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. AUC is the area under the receiver operating curve, and below is its standard error.

no time for a policy reaction. Similarly, the overall size and duration of the boom are unobserved and cannot be used to classify the boom.

Real time classification results are shown in Table 10, which displays our main results. The specification 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. The duration of the boom is omitted because it is unobserved when the boom starts. We also omit the real sector variables which are not as quickly available, are subject to data revision and furthermore had less impact on the predictive accuracy in our previous analysis. As before, the good-bad credit boom indicator is the dependent variable.

We start with the baseline in column (1) in Table 10. The initial size of the boom is not significant and adds little predictive power compared to a coin toss model (AUC of 0.56 compared to 0.50). As in the previous analysis, adding house prices and loan-to-deposit ratios yields strongly positive coefficient estimates, and the AUC rises substantially to 0.77 in the full sample and to 0.86 in the reduced sample with fixed effects when both are included in column (4). The coefficient on house prices is always highly significant while the coefficient for the loan-to-deposit ratio is insignificant (Panel A) or only weakly significant (Panel B) when both variables are included in column (4).

Figure 3: Correct classification frontiers with real time data



Notes: This figure presents correct classification frontiers for the models displayed in Table 10, 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 Houses is the house price index.

In Figure 3, we compare the ROC curves for real time forecasting models shown in Table 10. 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 reference line, 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 between good and bad credit booms. On the left we use models with the full sample (from Panel A of Table 10) and on the right we use models with the reduced sample from Panel B. The models shown on the left are based on the estimates in columns (1), (2) and (4). The reduced sample results on the right include a baseline with just the fixed effects (AUC = 0.62, the equation is not shown in Table 10), and the models in columns (1) and (4).

Table 11: Classification with real time information, post-WW2 booms only

	(1)	(2)	(3)	(4)
Panel A: Full sample				
Initial size of boom	0.67	0.82	0.82	0.93
	(0.69)	(0.69)	(0.91)	(0.87)
Loans-to-deposits		0.62^{**}		0.40
		(0.26)		(0.32)
House price index			0.87^{***}	0.80^{**}
			(0.31)	(0.31)
Pseudo R^2	0.014	0.082	0.201	0.220
AUC	0.56	0.69	0.80	0.83
	0.11	0.10	0.07	0.06
Observations	59	59	59	59
Panel B: Reduced sample —including country-fixed effects				
Initial size of boom	0.95	2.70^{**}	3.42	7.92^{***}
	(1.08)	(1.07)	(2.20)	(2.32)
Loans-to-deposits		2.18^{***}		3.98^{***}
		(0.70)		(1.30)
House price index			2.16^{**}	2.79^{*}
			(0.93)	(1.50)
Pseudo R^2	0.063	0.335	0.414	0.650
AUC	0.64	0.85	0.90	0.96
	0.10	0.06	0.06	0.03
Observations	39	39	39	39

Notes: Logit classification models for systemic financial crises associated with credit booms. The dependent variable is a dummy that is 1 when a future financial 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. AUC is the area under the receiver operating curve, and below is its standard error.

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. The figure confirms that even using real time indicators, policy-makers can distinguish between good and bad credit booms with considerable accuracy.

Our tests use data that extends over a long period of time to estimate the forecast relationships. Although only data available in real time are used throughout, the equation is estimated with all booms. Since other studies that predict boom outcomes use only recent data, we estimated the real time relationships with post-WW2 booms for comparison. Further, the introduction of deposit insurance and the change in the monetary regime might have changed the underlying dynamics of credit booms.

Real time results with the 59 post-WW2 booms (39 when fixed effects are included) are shown in Table 11. The coefficient estimates for loan-to-deposit ratios and house prices remain broadly stable, and the classification ability remains high. 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. It is possible that the results for the post war period are dominated by the unusual period of the 1950s and 1960s where there were many booms none of which turned out badly. In results not shown we removed these two decades and estimated the real time models with the remaining 52 booms in the entire data sample. The results are largely the same as those shown above.

Our final experiment with real time data is an out-of-sample analysis of recent booms. We ask the following: using information available from historical experiences, could a policymaker in the 2000s have known which starting credit booms would end badly? To answer this question, we estimate our real time specification with all available data up to the year 1999. We will use the coefficients from this estimation to predict the probability that each boom starting in the 2000s ends in a banking crisis. We use a 0.75 standard deviations threshold to identify booms in the 2000s in order to have a meaningful number of observations. The same threshold is used to identify pre-2000 booms for the estimation (there are 70 booms in the estimation period). There are 9 credit booms after 2000 and five of them end badly.

Table 12: Out-of-sample test for booms starting in 2000 or later

	Start	Outcome	(1) Initial Size	(2) Size + House Prices	(3) Size+ House Prices + LtD
Denmark	2000	good	0.185	0.251	0.284
Denmark	2005	bad	0.267	0.558	0.642
Spain	2005	bad	0.231	0.358	0.412
Finland	2000	good	0.190	0.221	0.237
Finland	2003	good	0.189	0.241	0.265
Italy	2007	bad	0.176	0.195	0.279
Norway	2005	good	0.229	0.425	0.464
Sweden	2005	bad	0.188	0.559	0.493
USA	2004	bad	0.182	0.459	0.416

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. Data are detrended using an expanding window. Models are including the initial size of the boom (1), adding house prices (2) and additionally loans-to-deposits (3). The boom threshold is set at 0.75 country-specific standard deviations of real private credit per capita.

Table 12 presents the estimated probabilities of experiencing a banking crisis for each of the credit booms after the year 2000 using logit estimates with real time data until 1999. The AUC from estimating the full model without fixed effects for the 70 pre-2000 booms is 0.72. The coefficients of these estimations are used to compute crisis probabilities for the post-2000 booms that were not used in the estimation stage. Column (1) shows the probabilities based on coefficient estimates with only the initial size of the boom. The initial size is not very informative, all booms have a similarly low probability of turning out bad. Adding house price data in column (2) and additionally the loan-to-deposit ratio in column (3) improves the accuracy of the model considerably. Using 0.40 as a cutoff for a boom being bad, the model in column (3) sorts all but two of the booms correctly; one good boom and one bad boom seem to be misclassified. The model misses the bad boom in Italy that started in 2007 (estimated probability is only 0.279 with the full model in column (3)) probably because Italy did not experience a house price boom. The good boom in Norway in 2005 would have been misclassified as well, it had an estimated probability of being bad of 0.464 with the full model.

6. Robustness

In this section, we report results of robustness checks that we ran to test the sensitivity of our results with real time data. In Table 13 we check the robustness of the real time results with respect to the choice of boom thresholds as well as using the credit-to-GDP ratio in order to identify credit booms.[12] All specifications include house prices and the loan-to-deposit ratio in addition to the initial size of the boom. As before estimates with country-fixed effects are shown in Panel B.

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 10. We see that the results do not vary noticeably as the boom threshold changes; the coefficient sizes and significance are similar across columns (1) to (3). The one exception is the fixed effect result with a boom threshold of 1.25 standard deviations where the sample size is just 35 booms. When we identify credit booms via the credit-to-GDP ratio instead of real private credit per capita (columns (4) to (6)), the coefficients for the house price index are always significant. Similar to the results presented in Table 10 and Table 11, the loan-to-deposit ratio is significant when added to the baseline, but not always significant when it is entered jointly with the house price index. The models using the credit-to-GDP ratio for the identification of credit booms are similar to those based on real credit. Further, as expected the AUCs are somewhat higher when there is a larger boom threshold and fewer booms in the sample.

7. Conclusion

The findings presented in this paper mark a first step towards informing and eventually alleviating the trade-off between 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. 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.

[12] We define the credit-to-GDP variable again as the log of 100 times nominal bank credit over nominal GDP.

Table 13: 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						
Initial size of boom	0.90*	0.68	2.20**	0.19	0.19	0.53
	(0.54)	(0.71)	(0.89)	(0.58)	(0.97)	(1.39)
House price index	0.74***	0.68***	0.79***	0.48***	0.54***	0.77***
	(0.21)	(0.22)	(0.28)	(0.17)	(0.21)	(0.27)
Loans-to-deposits	0.42	0.30	0.58	0.32	0.70***	0.58
	(0.33)	(0.23)	(0.37)	(0.32)	(0.25)	(0.37)
Pseudo R^2	0.155	0.156	0.261	0.072	0.147	0.228
AUC	0.76	0.77	0.85	0.70	0.76	0.80
	0.07	0.07	0.06	0.07	0.07	0.07
Observations	79	76	57	82	68	54
Panel B: Reduced sample —including country-fixed effects						
Initial size of boom	1.33*	1.75	3.80*	0.48	3.60	3.51
	(0.75)	(1.08)	(2.11)	(0.88)	(2.85)	(2.97)
House price index	0.82**	1.16***	1.53*	0.70**	1.03**	1.25**
	(0.38)	(0.32)	(0.91)	(0.30)	(0.46)	(0.59)
Loans-to-deposits	0.91*	0.82*	0.71	0.89	1.70***	1.26**
	(0.52)	(0.45)	(0.51)	(0.62)	(0.51)	(0.54)
Pseudo R^2	0.248	0.332	0.417	0.183	0.363	0.377
AUC	0.82	0.86	0.89	0.75	0.85	0.86
	0.06	0.05	0.05	0.07	0.06	0.06
Observations	65	58	35	72	46	36

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. Clustered (by country) standard errors in parentheses. AUC is the area under the receiver operating curve, and below is its standard error.

References

Adrian, Tobias, and Liang, Nellie. 2016. *Monetary Policy, Financial Conditions, and Financial Stability*. Federal Reserve Bank of New York – Staff Reports, No. 690.

Bernanke, Ben, and Gertler, Mark. 2000. *Monetary Policy and Asset Price Volatility*. NBER Working Paper (7559).

Borio, Claudio, and White, William. 2014. *Whither monetary and financial stability? The implications of evolving policy regime*. BIS Working Papers No. 147.

Cerutti, Eugenio, Claessens, Stijn, and Laeven, Luc. 2015. The Use and Effectiveness of Macroprudential Policies: New Evidence. *IMF Working Paper*.

Christiano, Lawrence J., and Fitzgerald, Terry J. 2003. The Band Pass Filter. *International Economic Review*, **44**(2), 435–465.

Dell'Ariccia, Giovanni, Igan, Deniz, Laeven, Luc, and Tong, Hui. 2016. Credit Booms and Macrofinancial Stability. *Economic Policy*, **31**(86), 299–355.

Gorton, Gary, and Ordonez, Guillermo. 2016. *Good Booms, Bad Booms*. NBER Working Paper (22008).

Gourinchas, Pierre-Olivier, Valdes, Rodrigo, and Landerretche, Oscar. 2001. Lending Booms: Latin America and the World. *Economia*, 47–99.

Greenspan, Alan. 1999. Testimony of Chairman Alan Greenspan Before the Committee on Banking and Financial Services, U. S. House of Representatives, July 22, 1999. https://www.federalreserve.gov/boarddocs/hh/1999/July/testimony.htm.

Hamilton, James D. 2017. Why You Should Never Use the Hodrick-Prescott Filter. *Review of Economics and Statistics*. Forthcoming.

Hodrick, Robert E., and Prescott, Edward C. 1997. Postwar U.S. Business Cycles: An Empirical Investigation. *Journal of Money, Credit and Banking*, **29**(1), 1–16.

Jordà, Oscar, and Taylor, Alan M. 2011. *Performance Evaluation of Zero Net-Investment Strategies*. NBER Working Paper (17150).

Jordà, Òscar, Schularick, Moritz, and Taylor, Alan M. 2011. Financial Crises, Credit Booms and External Imbalances. *IMF Economic Review*, **59**(2).

Jordà, Òscar, Schularick, Moritz, and Taylor, Alan M. 2013. When Credit Bites Back. *Journal of Money, Credit and Banking*, **45**(2).

Jordà, Òscar, Schularick, Moritz, and Taylor, Alan M. 2015. Leveraged Bubbles. *Journal of Monetary Economics*, **76**(February), 1–20.

Jordà, Òscar, Richter, Björn, Schularick, Moritz, and Taylor, Alan M. 2017a. *Bank Capital Redux: Solvency, Liquidity and Crisis*. NBER Working Paper (23287).

Jordà, Òscar, Schularick, Moritz, and Taylor, Alan M. 2017b. Macrofinancial History and the New Business Cycle Facts. *NBER Macroannual 2016*.

King, Robert, and Levine, Ross. 1993. Finance and Growth: Schumpeter Might Be Right. *Quarterly Journal of Economics*, **153**(3), 717–738.

Knoll, Katharina, Schularick, Moritz, and Steger, Thomas. 2017. No Price Like Home: Global House Prices, 18702012. *American Economic Review*, **107**(2), 331–353.

Laeven, Luc, and Valencia, Fabian. 2012. Systemic Banking Crises Database: An Update. *IMF Working Paper*, **12/163**.

Levine, Ross. 2005. Finance and Growth: Theory, Evidence, and Mechanisms. *In:* Aghion, Philippe, and Durlauf, Steve (eds), *The Handbook of Economic Growth*. Netherlands: North-Holland.

Mendoza, Enrique G., and Terrones, Marco E. 2008. *An Anatomy of Credit Booms: Evidence from Macro Aggregates and Micro Data*. NBER Working Paper (14049).

Mendoza, Enrique G., and Terrones, Marco E. 2012. *An Anatomy of Credit Booms and their Demise*. NBER Working Paper (18379).

Mian, Atif, and Sufi, Amir. 2016. *Who Bears the Cost of Recessions? The Role of House Prices and Household Debt*. NBER Working Paper (22256).

Mian, Atif, and Sufi, Amir. 2018. *Finance and Business Cycles: The Credit-Driven Household Demand Chanel*. Unpublished Manuscript.

Mian, Atif, Sufi, Amir, and Verner, Emil. 2017. Household Debt and Business Cycles Worldwide*. *The Quarterly Journal of Economics*, **132**(4), 1755–1817.

Mitra, Srobona, Benes, Jaromir, Iorgova, Silvia, Lund-Jensen, Kasper, Schmieder, Christian, and Severo, Thiago. 2011. *Toward Operationalizing Macroprudential Policies: When to Act?* Chapter 3 in Global Financial Stability Report, September, Washington, DC, International Monetary Fund.

Rancière, Romain, Tornell, Aaron, and Westermann, Frank. 2008. Systemic Crises and Growth. *Quarterly Journal of Economics*, **123**(3), 359–406.

Reinhart, Carmen M., and Rogoff, Kenneth S. 2009. *This Time is Different: Eight Centuries of Financial Folly*. Princeton University Press, Princeton, N.J.

Rousseau, Peter L., and Wachtel, Paul. 1998. Financial Intermediation and Economic Performance: Historical Evidence from Five Industrialized Countries. *Journal of Money, Credit and Banking*, **30**(4), 657–678.

Rousseau, Peter L., and Wachtel, Paul. 2009. What is Happening to the Impact of Financial Deepening on Economic Growth. *Economic Inquiry*, **49**(1), 276–288.

Rousseau, Peter L., and Wachtel, Paul. 2017. Episodes of financial deepening: Credit booms or growth generators? *In:* Rousseau, Peter L., and Wachtel, Paul (eds), *Financial Systems and Economic Growth*. Cambridge, UK: Cambridge University Press.

Schularick, Moritz, and Taylor, Alan M. 2012. Credit Booms Gone Bust: Monetary Policy, Leverage Cycles, and Financial Crises, 1870-2008. *American Economic Review*, **102**(2), 1029–61.

Stein, Jeremy C. 2013. *Overheating in Credit Markets: Origins, Measurement, and Policy Responses*. Remarks at Restoring Household Financial Stability after the Great Recession: Why Household Balance Sheets Matter A Research Symposium sponsored by the Federal Reserve Bank of St. Louis.

Svensson, Lars E.O. 2017. Cost-benefit analysis of leaning against the wind. *Journal of Monetary Economics*, **90**, 193 – 213.

Wachtel, Paul. 2018. Credit Deepening: Precursor to Growth or Crisis? *Comparative Economic Studies*, **50**, 34–43.

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

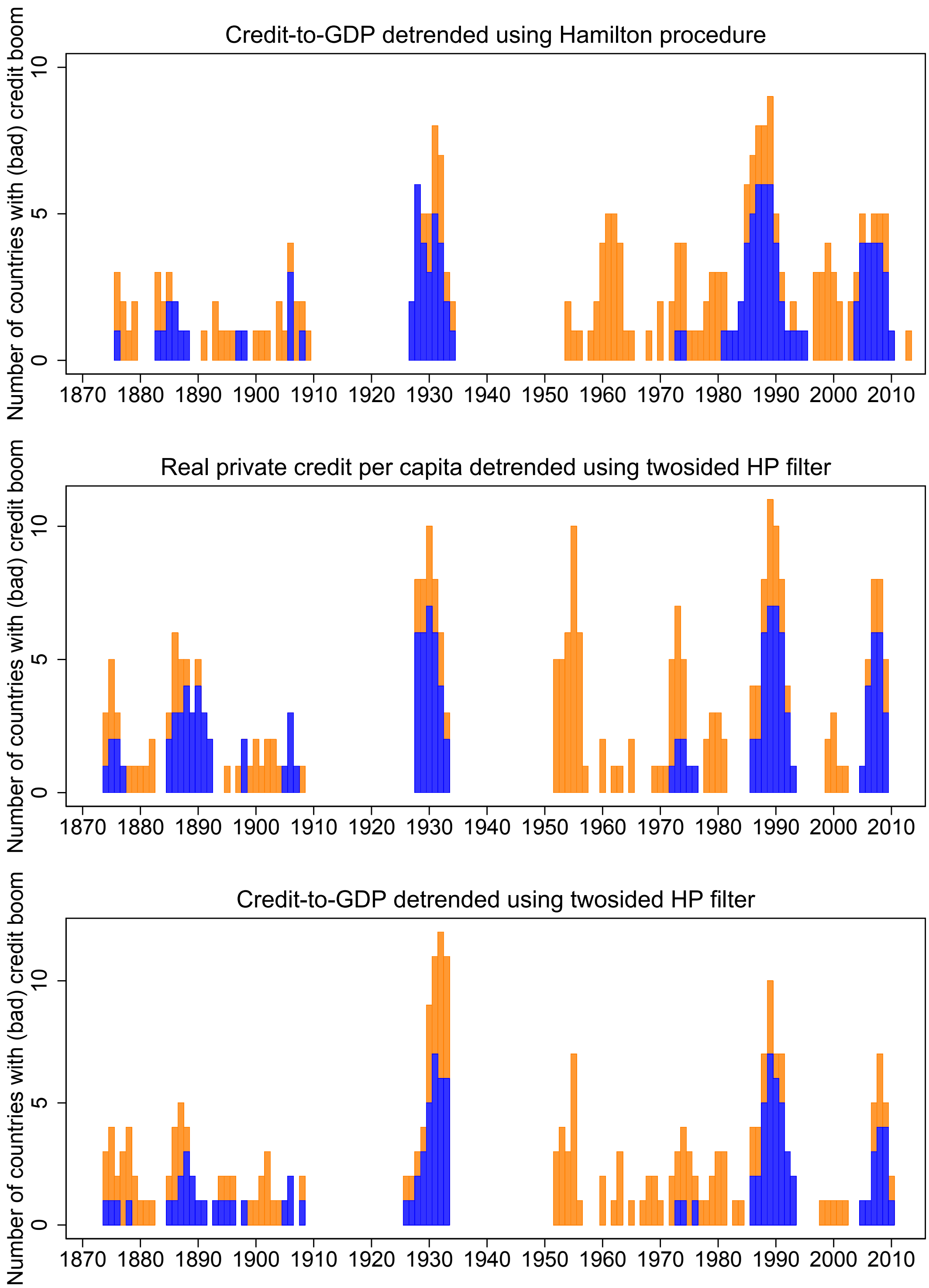
Notes: Data are based on the Macrohistory Database (Jordà *et al.* (2017b)), Knoll *et al.* (2017) and Jordà *et al.* (2017a).

Appendix Table A1: Varying filter methodology.

	Hamilton filter		HP filter	CF-bandpass filter
	Real Credit	Credit-to-GDP	Real Credit	Real Credit
	(1)	(2)	(3)	(4)
Panel A: Full sample				
Loan-to-deposits	0.61*	0.30	0.52	0.50*
	(0.34)	(0.32)	(0.35)	(0.26)
House price index	0.83**	0.56**	0.75**	0.41**
	(0.42)	(0.28)	(0.35)	(0.19)
Current account	-0.81**	-0.49	0.05	-0.09
	(0.39)	(0.34)	(0.27)	(0.14)
Pseudo R^2	0.287	0.160	0.208	0.092
AUC	0.87	0.78	0.80	0.71
	0.04	0.05	0.05	0.08
Observations	86	77	78	90

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. Clustered (by country) standard errors in parentheses. AUC is the area under the receiver operating curve, and below is its standard error.

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.