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When to Lean Against the Wind

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CROATIAN NATIONAL BANK

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 financial 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 policymakers 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: Financial Crises, Crisis Prediction, Credit Booms, Macroprudential Policy

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1. Introduction

Financial 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 financial 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 starting from 1870 to 2015. We rely on economic and financial data from the Macrohistory Database (Jordà, Schularick, and Taylor (2016)), as well as the systemic financial 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 of 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 about 144 credit boom episodes in advanced economies over the past 150 years. About one-third of the credit booms are bad and followed by a systemic financial crisis.

Using logit models with and without country-specific controls 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 compare the predictive ability, real economic variables generally do not add much predictive power relative 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 the HP filter for detrending), boom definitions (using deviations from the credit to GDP ratio instead of real credit) as well as across different subperiods and monetary regimes.

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, Tornell, and Westermann (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 suggest that financial deepening may be beneficial in early stages of financial development. The finance-growth 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 financial crisis.

Second, there is an equally large literature that associates excesses of credit growth with financial crises. Despite the potential benefits of financial deepening, many credit booms end in often debilitating financial crises with severe effects on the real economy (Jordà, Schularick, and Taylor (2013); Mian and Sufi (2016)). Put differently, credit booms can be growth enhancing but can also be a recipe for financial disaster. In the aftermath of the 2008 financial crisis, these findings have given rise to a bourgeoning literature on policies, macro-prudential and other, to deal with the risks emanating from credit booms and the appropriate policy response (Cerutti, Claessens, and Laeven (2015)). This literature emphasizes the overheating in credit markets (Stein (2013)) and argues that policy-makers should intervene to contain excessive credit growth, unlike the older consensus that central banks should not react to asset price changes (Bernanke and Gertler (2000)). Yet policy makers remain concerned about the possible side-effects of such efforts, and the net effects of policies remain the subject of much debate (Svensson (2016), Mitra, Benes, Iorgova, Lund-Jensen, Schmieder, and Severo (2011) and Adrian and Liang (2016))). While credit-fueled asset price bubbles pose some danger to the macro-economy (Jordà, Schularick, and Taylor (2015)), other credit booms might represent financial deepening or be the reaction to a positive productivity shock. Such booms are likely to be beneficial, and short-cutting such episodes might come at a high long-run cost for the economy.

An important precondition for minimizing the collateral damage of policy interventions to tame excess of 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

[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.

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. A number of 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, Igan, Laeven, and Tong (2016) and Gorton and Ordonez (2016). These papers all 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, especially in a multivariate setting.[2] Our long-run historical data have the advantage that we can analyze within-country experiences as most of the sample countries have experienced a good and a bad credit boom at some point between 1870 and today.

There is also a small literature on both the finance growth nexus and on the incidence of booms and crises with historical data. 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 (2010) 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 financial crisis. With the criteria that they adopt, about one-third of the episodes of financial deepening culminate in financial crisis. These observations suggest 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 financial 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. Our analysis in sections 4 has two steps. First, we will specify a logit binary classification model and test its ability to sort boom episodes into those associated with a financial crisies 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 financial crisis.

[2] Dell'Ariccia, Igan, Laeven, and Tong (2016) conclude that most indicators that have been suggested in the literature lose significance once one conditionsfor the existence of a credit boom.

In a second step, 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 5, 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 6.

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, Igan, Laeven, and Tong (2016) use a combination of a deviation from a 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, Schularick, and Taylor (2016)).[4] 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

[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.

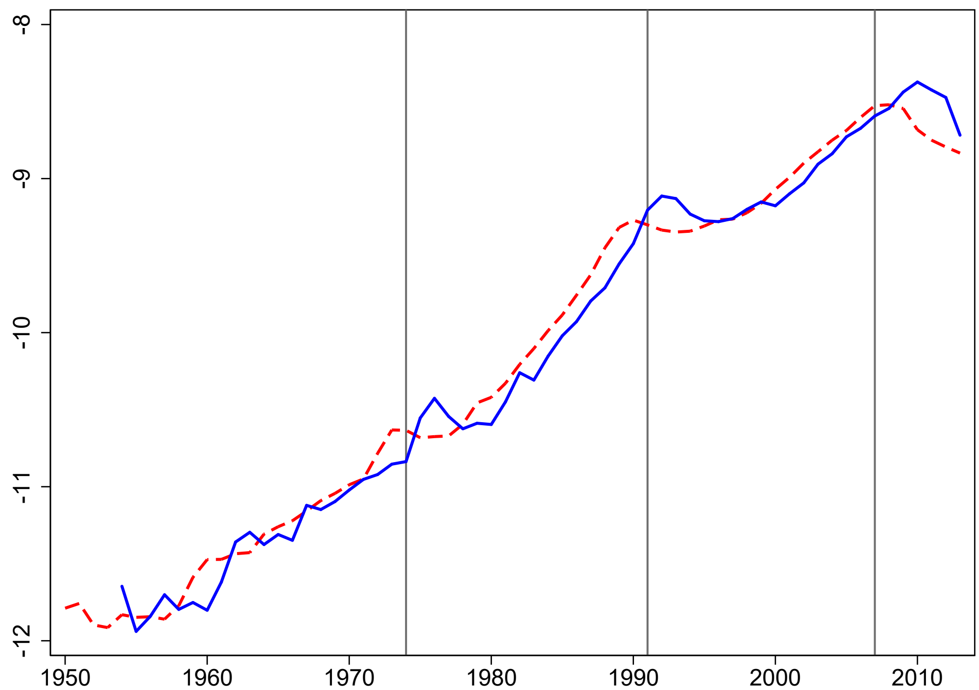
[4] We choose this credit definition as GDP data often becomes available with a significant delay and is subject to major revisions. We show however that our main results do not depend on this choice of the credit variable.

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 as we use past values for the prediction and therefore for the definition of a credit boom. This is important as a filter that smoothes using future information (e.g. a HP filter) might mechanically detect a boom prior to a crisis just because large downward adjustments in credit supply occur after a financial crisis.

Figure 1: Credit booms in Great Britain: Real private credit per capita - raw data and predicted values



Notes: This figure presents 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. Vertical lines indicate dates of financial crises.

Figure 1 illustrates the procedure using post-WW2 data for the UK as an example: The dashed line refers to the realized values of private credit (measured as 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 financial 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 financial 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 $\sigma(c_i)$. Our credit boom condition is now that the detrended credit measure is larger than 0.75 the country specific standard deviation. This can be written as:

$$\text{Credit Boom}_{i,t} = I(c_{i,t} > 0.75\sigma(c_i)), \tag{2}$$

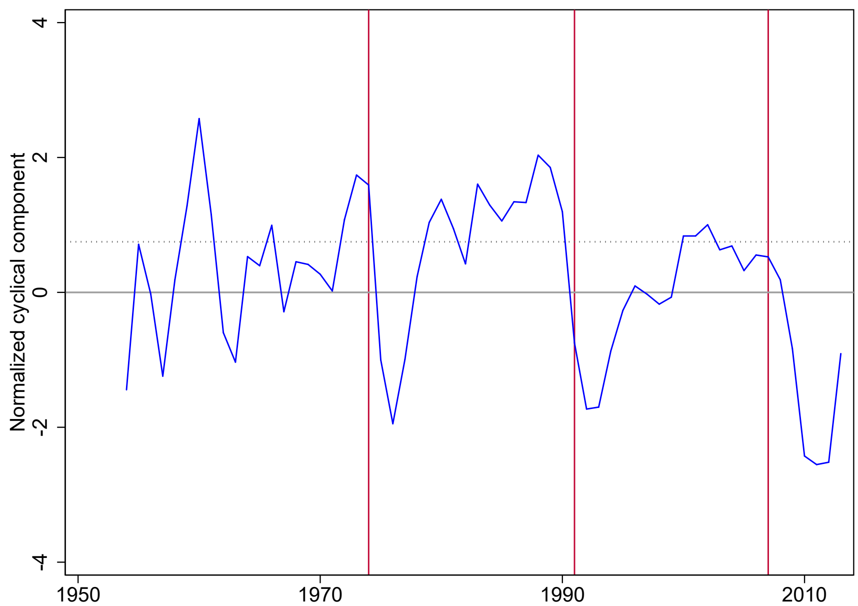
where I is the indicator function. We will show that our results are robust to thresholds other than 0.75 the standard deviation.[5] We furthermore refer to the local maximum value of $c_{i,t}$ during a specific boom period (i.e. conditional on Credit Boom $= 1$) as the peak of the credit boom. The normalized 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 0.75. The methodology is illustrated in Figure 2, which shows the normalized cyclical component for the UK for the post-WW2 period. Booms are episodes when the normalized cyclical components (the solid line) is above the dashed line that marks 0.75 standard deviations.

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 fulfil our boom criterion. Using this definition and the Hamilton procedure to detrend the credit variable yields a sample of 144 credit booms. The frequency of booms ranges from 4 in Japan to 13 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).

We will be interested in which characteristics of a credit boom determine whether it turns into

[5] We experimented with alternative thresholds of 0.5 and 1. These different thresholds clearly have an effect on 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 2: Detrended credit in the United Kingdom



Notes: This figure presents the normalized cyclical component of real private credit per capita in the UK. Red vertical lines indicate dates of systemic financial distress defined in JST2016. The dotted line marks the 0.75 boom threshold used in the paper.

a financial crisis. Crisis dates for the UK are indicated by the vertical lines in Figure 2. The UK experienced a minor credit boom in the late 1950s, unrelated to a financial crisis. The secondary banking crisis in the 1970s was preceded by a short credit boom while financial distress in 1991 was at the end of a long boom period starting at the end of the 1970s. Finally, the crisis in 2007 came after just another credit boom episode, which however ended already in 2002 according to our definition.

In the next section we distinguish between credit booms that do (bad booms) and do not result in 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 financial 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 financial crisis at time t. In particular, let

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

where α_i is a fixed effect that captures differences in countries' probabilities to experience financial crises. We report results for two different choices of $X_{i,t}$: first, the normalized detrended real private credit per capita measure and second, the 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 financial 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.

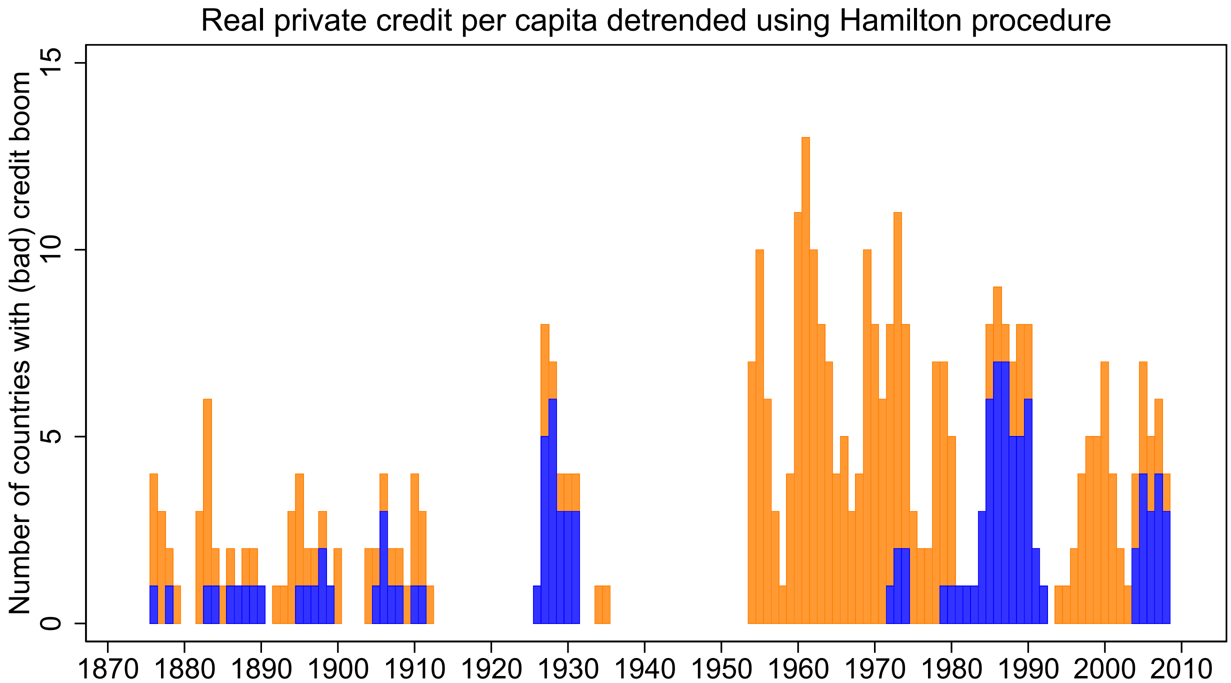
Table 1: Logit models with financial crises as dependent variables.

	All years	All years	Pre-WW2	Pre-WW2	Post-WW2	Post-WW2
Detrended credit	0.59^{***}		0.66^{***}		0.84^{***}	
	(0.15)		(0.16)		(0.22)	
Credit boom		0.67^{***}		0.90^{**}		0.89^{**}
		(0.25)		(0.37)		(0.39)
Pseudo R^2	0.054	0.029	0.078	0.048	0.078	0.037
AUC	0.69	0.63	0.71	0.66	0.73	0.66
se	0.03	0.04	0.04	0.05	0.06	0.06
Observations	1618	1618	617	617	942	942

Notes: Detrended credit is standardized at the country level. Credit boom is a dummy that is 1 if detrended credit exceeds the boom threshold, 0 else. Both variables are included as first lag. Country fixed effects included. Clustered standard errors reported in parentheses.

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 financial 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 financial crisis as "bad" booms. The financial crisis chronology comes from Jordà, Schularick, and Taylor (2016) and is based on systemic financial distress events as defined in Laeven and Valencia (2012), which focuses on systemic financial distress. The dates of these events are presented in the Appendix. We define a boom to be bad, if the financial crisis dummy is one during the boom or in the 3 years following the peak of the credit boom. With this definition, 38 of the 144 or 26% of the identified booms are "bad". This frequency is close to the ones found in Mendoza and Terrones (2012) and in Dell'Ariccia, Igan, Laeven, and Tong (2016). Two countries in our sample do not experience any bad booms – Germany and the Netherlands – and the Scandinavian countries have the most (7 in Denmark and 5 in Sweden). In the following sections the unit of observation will be a credit boom, some of them bad in the above sense, others good.

Figure 3: Number of ongoing credit booms by year



Notes: This figure presents the number of credit booms according to our definition, exclduing wars and 5-year windows around them. Dark bars refer to booms that turn into a financial crisis.

The incidence of good and bad booms is shown in Figure 3 where the dark 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 lighter shading indicates booms that will eventually end in a financial crisis. The figure shows that booms often end in financial crises, but that this has not been the case in two historical periods. First, the period from the end of WW2 to 1980 has been characterized by many credit booms, however only few of them ended in a financial crisis. The number of credit booms in this period is partly due to our boom definition as can be seen when we make a comparison with other definitions of a credit boom. For comparison, 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 financial 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, in section 6, 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, Benes, Iorgova, Lund-Jensen, Schmieder, and Severo (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 will be pooled in 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, Igan, Laeven, and Tong (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 financial crisis;
- The third set of variables relates to the financial sector itself. Here, the risk of a financial 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, Benes, Iorgova, Lund-Jensen, Schmieder, and Severo (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 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. We compare the boom observations based the value of each variable one period before the peak of the boom in order to capture vulnerabilities before the boom collapses. Summary statistics are shown in Table 2 which presents the means for the 38 bad booms and 106 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 1 standard deviation higher than the country average. This is not the case in good credit booms where the means for these variables is are only

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	38	0.00	0.00	0.00	0.00	106
Size	1.68	0.78	3.24	0.58	38	1.43	0.75	3.72	0.52	106
Duration	2.95	1.00	12.00	2.09	38	2.60	1.00	8.00	1.64	106
Duration to peak	2.16	1.00	10.00	1.67	38	1.83	1.00	7.00	1.13	106
GDP	0.55	-1.51	1.76	0.74	38	0.54	-3.65	2.71	1.01	106
Consumption	0.70	-1.16	3.06	1.03	37	0.54	-4.29	2.39	1.02	100
Current account	-0.71	-2.90	1.82	1.16	37	-0.20	-3.17	2.45	0.94	101
Investment	0.56	-0.86	3.03	0.82	36	0.45	-2.69	2.65	0.99	103
Short term rate	0.16	-1.64	4.19	1.08	35	0.19	-1.72	3.85	0.96	98
Long term rate	0.03	-1.43	1.74	0.70	38	0.14	-2.68	2.96	0.97	105
Credit-to-GDP	4.07	1.64	5.17	0.74	38	3.81	1.04	4.92	0.67	106
Capital ratio	0.10	-5.53	3.55	1.46	38	-0.20	-2.70	3.52	0.81	101
Noncore ratio	0.20	-2.61	3.89	1.34	38	0.10	-1.52	3.19	0.86	101
Loan-to-Deposits	1.04	-1.49	3.82	1.28	37	0.26	-3.13	2.63	0.92	100
House price index	1.06	-1.22	2.63	0.97	30	0.30	-2.17	2.91	0.91	89
Stock price index	0.31	-2.98	2.31	1.16	32	0.35	-3.45	2.89	1.10	92

Notes: Summary statistics for credit booms split by association with a financial crisis: Duration is in years. All other variables are detrended and normalized at the country level (except Credit-to-GDP which is in logs).

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

	Coefficient	t-stat
Boom with crisis	1.00	.
Size	0.25*	2.44
Duration	0.34	1.03
Duration to peak	0.33	1.34
GDP	0.01	0.05
Consumption	0.16	0.83
Current Account	-0.51**	-2.63
Investment	0.11	0.57
Short term rate	-0.03	-0.15
Long term rate	-0.11	-0.62
Loans-to-GDP	0.26*	2.02
Capital ratio	0.29	1.44
Noncore	-0.09	-0.43
Loan-to-Deposits	0.72***	3.64
House price index	0.76***	3.90
Stock price index	-0.04	-0.16
Observations	144	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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 (-0.71 compared to -0.20).

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, although only the size difference is 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.[6] We confirmed that these results hold when analyzing only the post-WW2 era which includes 45% of all the bad booms and 69% 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. Our basic unit of observation will be credit boom episodes. 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 financial crisis during or within a three year window after the credit boom period. 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:

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

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. In these instances the country observations are 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

[6] 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.

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 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 that have shown that larger credit booms are more likely to end in crisis (Jordà, Schularick, and Taylor (2016); Gourinchas, Valdes, and Landerretche (2001)).

Table 4 presents the baseline results, both for the full sample of 144 booms in 17 countries in Panel A and the reduced sample with fixed effect that includes 130 booms in 15 countries in Panel B. As expected, larger and longer booms both increase the likelihood of a bad end of the boom. However, only the size variable is statistically significant.

Table 4: Baseline specification

	Size	Duration	Both
	(1)	(2)	(3)
Panel A: Full sample			
Size of boom	0.97*		1.00**
	(0.50)		(0.51)
Duration to peak		0.18	0.20
		(0.13)	(0.12)
Pseudo R^2	0.028	0.010	0.040
AUC	0.64	0.56	0.63
se	0.06	0.05	0.06
Observations	144	144	144
Panel B: Reduced sample			
Size of boom	1.72***		1.80***
	(0.47)		(0.48)
Duration to peak		0.20	0.24
		(0.19)	(0.16)
Pseudo R^2	0.110	0.064	0.126
AUC	0.68	0.68	0.70
se	0.05	0.05	0.05
Observations	130	130	130

Notes: Logit classification models for systemic financial crises associated with credit booms. The dependent variable is a dummy that is 1 when a financial 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 between spent in boom until the peak is reached. Panel B includes country fixed effects. The fixed effects only model has an AUC of 0.65 (standard error 0.05). Clustered (by country) standard errors are presented in parentheses.

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 statistic, the area under the receiver operating curve

(ROC). The statistic measures the ability of the model to correctly sort credit booms correctly into a good and bad bin as combinations of true positive and false positive rates that result from changing the threshold variable 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. In our application, we replace the 0.5 null with the AUC from the baseline model. We then compare the classification ability of models using different additional control variables. The AUC tests for predictive ability for the different models will lend support to the view that credit booms can be sorted in good and bad variants.

We 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 0.64 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 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 financial 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 0.65. Including both size and duration increases the AUC to 0.70 (column (3) in Panel B), a small 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 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. 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 will additionally control for unobserved country specific factors driving the probability of a boom being bad.

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	1.10*	1.10*	1.06*	0.95	1.35	1.13*	1.01*
	(0.63)	(0.62)	(0.61)	(0.68)	(0.82)	(0.68)	(0.59)
Duration to peak	0.15	0.15	0.11	0.12	0.20	0.15	0.15
	(0.16)	(0.16)	(0.17)	(0.17)	(0.13)	(0.16)	(0.16)
Real variables		0.01	0.25	0.62***	-0.75***	0.07	-0.18
(see column header)		(0.22)	(0.31)	(0.20)	(0.21)	(0.27)	(0.25)
Pseudo R^2	0.037	0.037	0.042	0.070	0.120	0.038	0.042
AUC	0.65	0.65	0.64	0.69	0.74	0.65	0.65
se	0.07	0.07	0.07	0.06	0.05	0.07	0.07
Observations	110	110	110	110	110	110	110
Panel B: Reduced sample							
Size of boom	2.20***	2.20***	2.12***	2.01***	3.28***	2.30***	2.08***
	(0.65)	(0.65)	(0.65)	(0.71)	(0.89)	(0.78)	(0.67)
Duration to peak	0.21	0.21	0.17	0.19	0.37**	0.21	0.21
	(0.18)	(0.18)	(0.19)	(0.19)	(0.16)	(0.18)	(0.18)
Real variables		0.02	0.30	0.62**	-1.28***	0.17	-0.20
(see column header)		(0.27)	(0.36)	(0.24)	(0.34)	(0.41)	(0.34)
Pseudo R^2	0.118	0.118	0.123	0.143	0.259	0.120	0.122
AUC	0.71	0.71	0.72	0.74	0.80	0.71	0.71
se	0.06	0.06	0.06	0.06	0.05	0.06	0.06
Observations	92	92	92	92	92	92	92

Notes: Logit classification models for systemic financial crises associated with credit booms. The dependent variable is a dummy that is 1 when a financial crisis is associated with the credit boom, 0 otherwise. One observation for each credit boom, real 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.

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. All these variables have been detrended and normalized with the same procedure used for the credit measure. Table 5 shows the results for both the full sample (Panel A) and the reduced sample (Panel B) where the real variables in the vector $Z_{i,b}$ are entered as the first lag at the peak of the credit boom. Note that these variables are not available for all credit booms episodes so that the number of observations in Table 5 drops to 110 with the full sample and 92 with the reduced sample.

In column (1) we show re-estimates of the baseline specification from the previous table for these samples to obtain comparable AUCs. The coefficients for the baseline as well as the AUCs are similar to those obtained before. We then include the other variables one at a time in (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 0.80 in the fixed effects model. 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, but the AUC does not rise significantly when we add investment.

In Table 6 we add indicators of the capital position and 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 regression (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. The coefficient is positive, but it is insignificant and the AUC shows little improvement over the baseline specification.

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. 2017) that a higher capital ratio is no panacea against financial crises. An increase in bank capital in a credit boom can be easily offset by the increase in risk taking during the boom. The AUC however is not significantly higher than for the baseline specification. The share of non-core liabilities in the funding mix of banks seems to be unrelated to the probability of a boom being bad. However, regression (5) includes the de-trended loan-to-deposit ratio. This ratio has been identified to increase prior to financial crises (Jordà et al. 2017). The coefficient is highly significant and the AUC is also significantly higher than in the baseline specification. This measure for aggregate liquidity of the banking sector adds valuable predictive power. Higher loan-to-deposit-ratios substantially increase the risk of credit booms ending badly.

In our next set of experiments in Table 7, we investigate the role of asset prices (Mitra, Benes, Iorgova, Lund-Jensen, Schmieder, and Severo (2011)). 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. Higher equity prices are not related to the probability of credit booms ending in a systemic financial crisis, but house price booms are. Including the house price index increases the AUC significantly by 0.12 in Panel A and 0.08 in Panel B – substantial improvements in the predictive ability of the model. By contrast, the inclusion of share prices barely changes the AUC of

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	0.91**	0.93**	1.04**	0.90**	1.01**
	(0.44)	(0.46)	(0.51)	(0.45)	(0.47)
Duration to peak	0.15	0.09	0.09	0.13	0.05
	(0.14)	(0.17)	(0.15)	(0.15)	(0.17)
Banking variable		0.53	0.42**	0.06	0.65***
(see column header)		(0.45)	(0.20)	(0.15)	(0.18)
Pseudo R^2	0.029	0.043	0.060	0.029	0.089
AUC	0.62	0.63	0.63	0.62	0.71
se	0.06	0.06	0.06	0.06	0.05
Observations	130	130	130	130	130
Panel B: Reduced sample					
Size of boom	1.88***	1.89***	2.04***	1.85***	2.01***
	(0.57)	(0.59)	(0.63)	(0.60)	(0.57)
Duration to peak	0.18	0.13	0.12	0.16	0.10
	(0.16)	(0.18)	(0.17)	(0.17)	(0.18)
Banking variable		0.47	0.41	0.11	0.75***
(see column header)		(0.48)	(0.26)	(0.18)	(0.20)
Pseudo R^2	0.107	0.115	0.131	0.108	0.173
AUC	0.69	0.71	0.72	0.70	0.75
se	0.05	0.05	0.05	0.05	0.05
Observations	117	117	117	117	117

Notes: Logit classification models for systemic financial crises associated with credit booms. The dependent variable is a dummy that is 1 when a financial 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 long-run trend at the peak of the boom Panel B includes country fixed effects. Clustered (by country) standard errors in parentheses.

Table 7: Asset prices.

	Baseline (1)	House prices (2)	Stock prices (3)	Both (4)
Panel A: Full sample				
Size of boom	1.28***	1.37***	1.20***	1.29***
	(0.40)	(0.31)	(0.38)	(0.31)
Duration to peak	0.23	0.14	0.21	0.13
	(0.16)	(0.17)	(0.16)	(0.17)
House Price Index		0.96***		0.95***
		(0.26)		(0.26)
Stock Price Index			0.12	0.10
			(0.19)	(0.15)
Pseudo R^2	0.052	0.158	0.054	0.159
AUC	0.64	0.76	0.63	0.77
se	0.07	0.06	0.07	0.06
Observations	110	110	110	110
Panel B: Reduced sample				
Size of boom	2.10***	1.97***	2.13***	2.03***
	(0.53)	(0.42)	(0.54)	(0.44)
Duration to peak	0.29	0.22	0.30	0.23
	(0.19)	(0.21)	(0.19)	(0.20)
House Price Index		1.11***		1.11***
		(0.41)		(0.41)
Stock Price Index			-0.03	-0.07
			(0.31)	(0.28)
Pseudo R^2	0.138	0.247	0.138	0.248
AUC	0.73	0.81	0.73	0.81
se	0.06	0.05	0.06	0.05
Observations	89	89	89	89

Notes: Logit classification models for systemic financial crises associated with credit booms. The dependent variable is a dummy that is 1 when a financial 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 parantheses.

the model.

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 2016). This literature supports the idea that unleveraged "irrational exuberance" asset 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, the current account balance and, marginally, the investment ratio. 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 financial variables, the loan-to-deposit-ratio and the house price index, and in column (3), the real sector measures, the current account balance and investment. In column (5), we include all variables jointly. All variables remain statistically significant at least at the 5% level in the models with all variables. The joint inclusion of the four conditioning variables increases the predictive power considerably from 0.66 with the baseline to 0.89 in the full sample (with 105 boom observations available) and from 0.72 to 0.94 for the reduced sample with fixed effects which includes 85 observations. In both samples, the inclusion of financial variables in column (2) has a significantly stronger effect than the inclusion of the real variables in column (3).

These results indicate that looking back at the 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 in real time, 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

Table 8: Full model

	Baseline	Financial variables	Real variables	All
	(1)	(2)	(3)	(4)
Panel A: Full sample				
Size of boom	1.44**	1.70***	1.54**	1.85**
	(0.62)	(0.63)	(0.76)	(0.73)
Duration to peak	0.17	-0.01	0.21	0.04
	(0.17)	(0.30)	(0.16)	(0.19)
Loan-to-Deposits		0.94***		0.90***
		(0.26)		(0.29)
House Price Index		1.01***		1.07***
		(0.37)		(0.38)
Investment			0.61**	0.56*
			(0.27)	(0.33)
Current Account			-0.89***	-1.02**
			(0.31)	(0.42)
Pseudo R^2	0.051	0.258	0.151	0.342
AUC	0.66	0.84	0.78	0.89
se	0.07	0.04	0.05	0.03
Observations	105	105	105	105
Panel B: Reduced sample				
Size of boom	2.19***	2.70***	2.78***	4.21***
	(0.70)	(0.92)	(0.93)	(1.45)
Duration to peak	0.25	0.08	0.37*	0.40*
	(0.19)	(0.28)	(0.20)	(0.22)
Loan-to-Deposits		1.36***		1.64**
		(0.45)		(0.66)
House Price Index		1.40**		2.08*
		(0.65)		(1.10)
Investment			0.76**	0.88*
			(0.31)	(0.49)
Current Account			-1.41***	-2.69***
			(0.50)	(0.98)
Pseudo R^2	0.122	0.377	0.263	0.549
AUC	0.72	0.88	0.80	0.94
se	0.07	0.04	0.05	0.02
Observations	85	85	85	85

Notes: Logit classification models for systemic financial crises associated with credit booms. The dependent variable is a dummy that is 1 when a financial 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. Panel B includes country fixed effects. Clustered (by country) standard errors in parantheses.

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 financial crisis as soon as the boom threshold is passed. It would make no sense to try to forecast a bad boom that has already occurred; 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. All variables are again 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 insignificant and does not add much predictive power compared to a coin toss model. 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 to 0.78 in the full sample and to 0.87 in the reduced sample with fixed effects. Accounting for these three variables that are observable in real time leads to a considerable improvement in predictive ability. However, the loan to deposit ratio is not significant when it is included jointly with the house price index in (4).

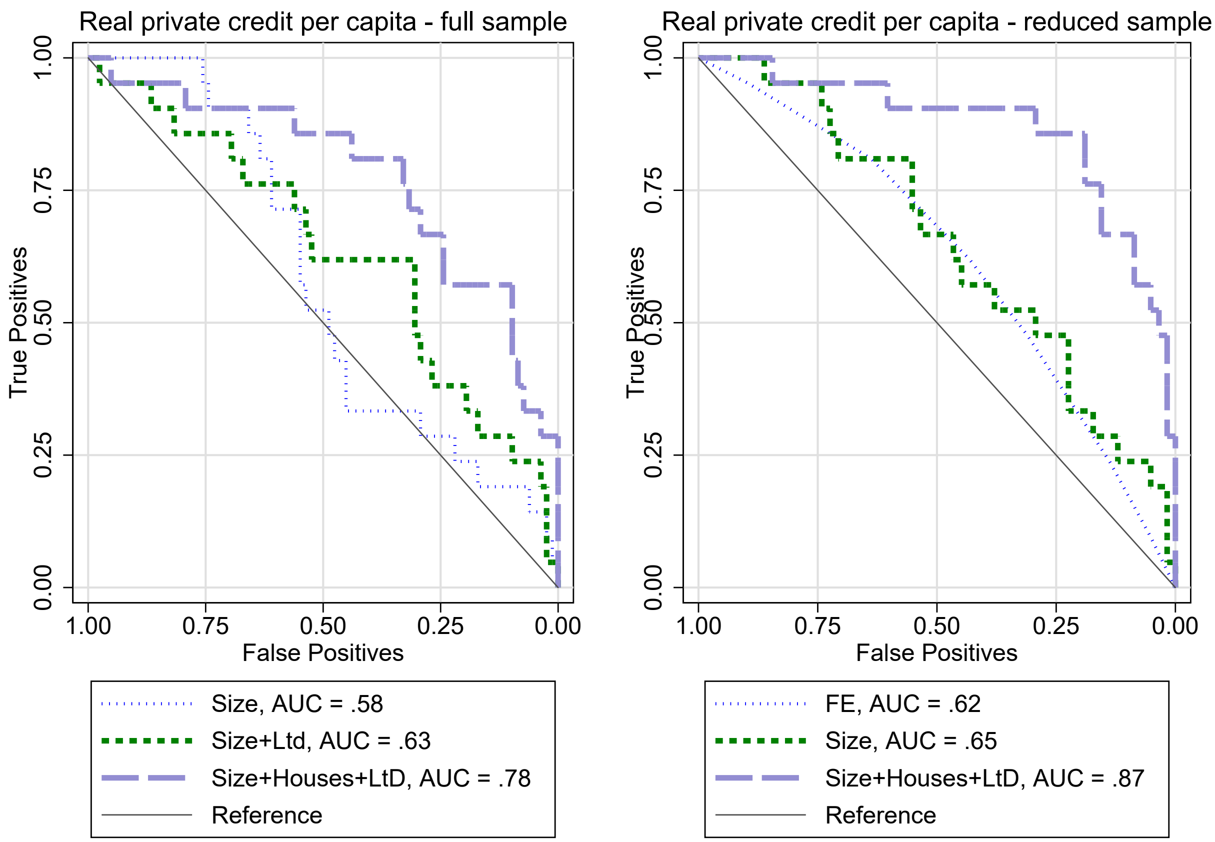
In Figure 4, we compare the ROC curves for several real time forecasting models. The figure graphically compares the AUCs for the different models with real time data and displays the tradeoff between true and false calls of the classification technology. The larger the area between the respective line 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 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 columns (1), (2) and (4). The reduced sample results on the right include a baseline equation with just the fixed effects (AUC = 0.62 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 0.78 (without fixed effects) and 0.88 (with fixed effects) respectively. The chart confirms that even using real time indicators, policy-makers can distinguish between good and bad credit booms with considerable accuracy.

Table 9: Classification with real time information

	Baseline (1)	Loan-to-deposits (2)	House prices (3)	Full (4)
Panel A: Full sample				
Initial size of boom	1.19	1.20	1.95**	2.01***
	(0.91)	(0.90)	(0.79)	(0.78)
Loan-to-Deposits		0.44*		0.48
		(0.23)		(0.30)
House price index			1.08***	1.12***
			(0.21)	(0.24)
Pseudo R^2	0.022	0.045	0.145	0.168
AUC	0.58	0.63	0.74	0.78
se	0.07	0.07	0.06	0.06
Observations	103	103	103	103
Panel B: Reduced sample				
Initial size of boom	1.53	1.72	3.89**	4.22**
	(1.18)	(1.19)	(1.97)	(2.11)
Loan-to-Deposits		0.70***		0.75
		(0.25)		(0.61)
House price index			2.22***	2.15***
			(0.72)	(0.74)
Pseudo R^2	0.063	0.111	0.302	0.330
AUC	0.65	0.71	0.85	0.87
se	0.07	0.07	0.05	0.05
Observations	79	79	79	79

Notes: Logit classification models for systemic financial crises associated with credit booms that startedin the respective year. 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. Panel B includes country fixed effects. Clustered (by country) standard errors in parantheses.

Figure 4: Correct classification frontiers.



Notes: This figure presents correct classification frontiers for the models displayed in Table 9, panel A on the left and Panel B on the right.

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 in the 2000s have known which starting credit boom ends badly? To answer this question, we will run our real time logit specification explained above for all available data up to the year 1999. Afterwards, we will use the coefficients from this estimation to predict the probability that a boom starting in the 2000s ends in a financial crisis. Based on our definition, there are 11 credit booms starting in this period, for which we are able to predict probabilities for the boom turning bad. There are two credit booms, in the US starting in 2004 and in Italy in 2007, for which we are unable to predict probabilities including a country fixed effect, as these countries experienced before only bad booms turning into a crisis as soon as they started.

We show fixed effects models in columns (1) to (3) and a pooled model including these two booms in column (4). The first column shows probabilities of the boom being bad based on a

Table 10: Out-of-sample test for booms starting in 2000 or later.

	Start	Outcome	(1) Baseline	(2) Baseline + HP	(3) Full	(4) Full, no FE
			Predicted probabilities for a boom ending badly			
Australia	2004	Good	0.204	0.550	0.525	0.441
Denmark	2000	Good	0.240	0.293	0.414	0.146
Denmark	2005	Bad	0.626	0.975	0.990	0.691
Spain	2004	Bad	0.174	0.400	0.581	0.322
Finland	2000	Good	0.286	0.368	0.383	0.204
Finland	2003	Good	0.261	0.314	0.287	0.169
UK	2000	Good	0.306	0.458	0.523	0.160
Italy	2007	Bad	-	-	-	0.290
Norway	2005	Good	0.143	0.390	0.390	0.372
Sweden	2005	Bad	0.194	0.865	0.820	0.323
USA	2004	Bad	-	-	-	0.412

Notes: This table presents predicted probabilities of a boom 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. Columns (1) to (3) are based on fixed effects models including the size of the boom (1) and adding house prices (2) and additionally loan-to-deposits (3). Column (4) presents probabilities from pooled models including size, house prices and the loan-to-deposit ratio.

country fixed effect and on the size of the boom in the first year. In the second column we add house price information and in the third column additionally the loan-to-deposit ratio. Of the 9 booms in the fixed effects setup, 3 are bad booms by our definition. Using model (3) including house prices and the loan-to-deposit ratio, the booms are sorted correctly. In descending order by probability, the booms in Denmark (start 2005), Sweden (start 2005) and Spain (start 2004) end badly, 3 or 4 years later. The predicted probabilities for these booms are higher than for the UK, Australia, Denmark (2000), Norway and the two booms in Finland which do not end in a financial crisis. As we saw before, the credit boom in the UK is not classified as a bad boom in our setup, because the detrended credit component falls below the threshold more than 3 years before the crisis. Still, among the booms not ending badly according to our definition, the model assigns the highest probability of a crisis to this observation, slightly above 50%. Importantly, from columns (1) and (2) can be seen that house prices and loan-to-deposits improve the accuracy. Using a country FE and size of the boom, the model attaches very low probabilities to the booms in Spain and Sweden that however end badly. Including house prices partly changes this ordering in column (2). Finally, the estimated probability for Spain further increases when adding the loan-to-deposit ratio. The results from the pooled model are not as clear. However, looking at the two booms in Denmark, the model correctly attaches a very high probability to the 2005 boom, while assigning a very low probability to the previous (start in 2000) boom.

6. Robustness

In this section, we report the results of extensive robustness checks that we ran to test the sensitivity of our results to i) defining credit booms episodes using changes in the credit-to-GDP ratio (instead

Table 11: Robustness of classification models

	Hamilton filter		HP filter	
	Post-WW2	All years	All years	All years
Boom variable	Real Credit (1)	Credit-to-GDP (2)	Real Credit (3)	Credit-to-GDP (4)
Panel A: Full sample				
Size of boom	2.08**	2.24***	1.51***	0.80
	(0.89)	(0.82)	(0.42)	(0.49)
Duration to peak	0.19	0.06	0.05	0.30
	(0.24)	(0.32)	(0.31)	(0.30)
Loan-to-Deposits	0.98***	0.63**	0.45	0.57***
	(0.25)	(0.25)	(0.30)	(0.19)
House Price Index	0.95*	0.69**	0.54**	0.29
	(0.51)	(0.33)	(0.27)	(0.21)
Pseudo R^2	0.319	0.251	0.194	0.186
AUC	0.88	0.81	0.78	0.79
se	0.04	0.05	0.05	0.05
Observations	82	106	106	109
Panel B: Reduced sample Including fixed effects				
Size of boom	3.74***	3.27**	1.90***	0.77
	(1.16)	(1.42)	(0.58)	(0.75)
Duration to peak	0.32	0.21	0.15	0.35
	(0.26)	(0.38)	(0.41)	(0.46)
Loan-to-Deposits	1.90***	1.22***	0.43	0.68***
	(0.61)	(0.43)	(0.34)	(0.25)
House Price Index	1.78	1.51***	0.65	0.21
	(1.25)	(0.51)	(0.42)	(0.25)
Pseudo R^2	0.523	0.472	0.318	0.249
AUC	0.93	0.90	0.85	0.81
se	0.03	0.04	0.04	0.05
Observations	60	93	97	86

Notes: Logit classification models for systemic financial crises associated with credit booms. The dependent variable is a dummy that is 1 when a financial 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. Panel B includes country fixed effects. Clustered (by country) standard errors in parantheses.

of changes in real credit per capita), and ii) detrending the variables using the HP-filter instead of using the forecast residuals. We will show that none of this affects the validity of our overall results with respect to the classification ability of the models and their predictive ability using real time data.

Table 11 reports the robustness of the logit classification model in various dimensions. We again start by using information available at the peak of the credit boom so the results are comparable to those discussed earlier in Table 8. The first regression employs the Hamilton detrending method but limits the sample to the post-WW2 period. In principle, the introduction of deposit insurance and the change in the monetary regime might have change the underlying dynamics of the boom. Yet the coefficient estimates remain broadly stable, and the classification ability remains high. When entered separately, both variables, loan-to-deposits and house prices contain valuable information. In the second column, we continue to use the Hamilton filter, but define boom episodes using deviations of the credit-to-GDP ratio from its trend.[7] As before, the size variable as well as the deviation of the loan-to-deposit ratio and house prices from trend signal an increasing likelihood that the credit boom ends badly. The last two regressions use a two-sided HP-filter, in line with some of the previous literature, to identify the cyclical component of the variables. Moreover, we provide additional detail by first turning to real credit per capita and then to the credit-to-GDP to define credit boom episodes. The results using the HP-filter are broadly similar, albeit the house price index loses statistical significance, while a deteriorating funding situation continues to send precisely estimated warning signals. The AUC of the regression using real credit per capita as the boom indicator are somewhat higher, potentially because GDP fluctuations introduce some noise.

In Table 12, we subject the real time estimations discussed above in Table 9 to additional checks. We first test if our results remain valid if we limit the observation period to the post-WW2 era. From the perspective of policy makers today this is certainly the most relevant comparison as the regulatory environment is close to the one they operate under today. Importantly, we still have 83 boom observations for the post-WW2 period. The first column in Table 12 displays only marginal differences compared to the full sample results discussed above. The initial size of the boom as well as the deviation of house prices from their country-specific trends remains strongly significant with similar coefficient estimates. The AUC too remains at a high level of 0.80 compared to 0.78 for all years.

The two remaining specifications shown in Table 11 use the credit-to-GDP ratio to define credit booms, using the Hamilton method and only data available in real time. Once more we find our overall results robust to this modification. For all observation years we have 88 credit boom observations and 61 observations for the post-WW2 period. As in the regressions using real credit per capita to identify boom episodes, simultaneous house price booms make it more likely that credit booms end in a systemic crisis. The significance of the house price variable weakens somewhat for the post-WW2 period, but the liquidity variable turns significant again and the AUC remains solid.

In all previously presented specifications, the boom threshold was set to 0.75 times the normalized and detrended credit measure. Tables 12 and 13 in the Appendix report the results for the real time specification reported in Table 9, when we use alternative thresholds for defining a boom (1

[7] 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 12: Robustness of real time classification models

	Real Credit Booms	Credit-to-GDP Booms	
	Post-WW2	All years	Post-WW2
	(1)	(2)	(3)
Panel A: Full sample			
Initial size of boom	2.48**	1.84***	0.46
	(1.12)	(0.65)	(0.91)
House price index	1.27***	0.90***	0.92**
	(0.41)	(0.26)	(0.42)
Loan-to-Deposits	0.74**	0.45*	0.81**
	(0.30)	(0.27)	(0.38)
Pseudo R^2	0.212	0.138	0.135
AUC	0.80	0.74	0.76
se	0.07	0.05	0.06
Observations	83	93	69
Panel B: Reduced sample			
Initial size of boom	7.54**	2.46**	1.14
	(3.66)	(1.01)	(1.42)
House price index	3.81***	1.28***	1.03*
	(1.27)	(0.43)	(0.58)
Loan-to-Deposits	2.66*	0.82**	1.54*
	(1.48)	(0.41)	(0.93)
Pseudo R^2	0.466	0.290	0.245
AUC	0.90	0.82	0.82
se	0.04	0.05	0.07
Observations	58	76	51

Notes: Logit classification models for systemic financial crises associated with credit booms. The dependent variable is a dummy that is 1 when a financial 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. Panel B includes country fixed effects. Clustered (by country) standard errors in parantheses.

and 0.5 instead of 0.75). The number of booms shrinks to 93 (full sample) and 69 (reduced sample), when we increase the threshold to 1. Entered separately, both variables are significant and improve the AUCs. Including both variables further improves the AUC, although the significance of the coefficient for house prices weakens. When we decrease the boom threshold to 0.5, the number of booms increases. In this case the significance of both coefficients increases. The AUCs are lower than in the previous setup, but the two variables still contain helpful information to classify booms into the two bins.

The overall insights we get from these additional tests are reassuring. Across a variety of indicators, methods and sub-periods, it appears possible for policy makers to judge the risk of credit booms ending badly. This ability to classify credit booms is an important precondition for targeted measures to intervene in situations where the risk of financial instability appears high without inflicting damage on the economy by short-cutting beneficial financial deepening episodes.

7. Conclusion

In modern economic history, about one-third of the credit booms are followed by a systemic financial crisis. This means that policy-makers eager to avoid the debilitating economic consequences of financial 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 at 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 financial crises from 1870 to 2008. Dates of systemic financial crises are based on Jordà, Schularick, and Taylor (2016).

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.

Appendix Table A1: Variable definitions

Variable	Description
Boom with crisis	Dummy variable - equals 1 if there is a financial 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 from Barro
Consumption	Real consumption per capita from Barro (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/bank deposits

Table 12: Classification with real time information – boom threshold is normalized detrended credit measure larger 1

	Baseline (1)	Loan-to-deposits (2)	House prices (3)	Full (4)
Panel A: Full sample				
Initial size of boom	1.53	1.51	1.44	1.41
	(0.95)	(0.99)	(1.12)	(1.19)
Loan-to-Deposits		0.75^{**}		0.72^{**}
		(0.30)		(0.33)
House price index			0.66^{**}	0.65^{*}
			(0.29)	(0.37)
Pseudo R^2	0.036	0.103	0.084	0.143
AUC	0.57	0.70	0.70	0.78
se	0.09	0.07	0.07	0.06
Observations	93	93	93	93
Panel B: Reduced sample				
Initial size of boom	2.44^{**}	2.30	3.36^{**}	3.50
	(1.20)	(1.48)	(1.47)	(2.16)
Loan-to-Deposits		1.21^{***}		1.23^{**}
		(0.41)		(0.57)
House price index			1.51^{**}	1.48
			(0.72)	(0.97)
Pseudo R^2	0.106	0.225	0.235	0.322
AUC	0.70	0.80	0.82	0.86
se	0.08	0.06	0.06	0.06
Observations	69	69	69	69

Notes: Logit classification models for systemic financial crises associated with credit booms that started in the respective year. The dependent variable is a dummy that is 1 when a future financial crisis is associated with the credit boom, 0 otherwise. Booms are classified using an alternative threshold of 1 in terms of the normalized detrended credit variable. One observation for each credit boom, all variables are in country-level standardized deviations from long-run trend. Panel B includes country fixed effects. Clustered (by country) standard errors in parantheses.

Table 13: Classification with real time information – boom threshold is normalized detrended credit measure larger 0.5

	Baseline (1)	Loan-to-deposits (2)	House prices (3)	Full (4)
Panel A: Full sample				
Initial size of boom	0.15	0.16	0.24	0.25
	(0.72)	(0.69)	(0.72)	(0.69)
Loan-to-Deposits		0.49**		0.46**
		(0.21)		(0.21)
House price index			0.65***	0.62***
			(0.22)	(0.21)
Pseudo R^2	0.000	0.032	0.051	0.076
AUC	0.48	0.65	0.66	0.68
se	0.06	0.06	0.06	0.06
Observations	124	124	124	124
Panel B: Reduced sample				
Initial size of boom	0.09	0.22	0.30	0.39
	(0.94)	(0.94)	(1.00)	(1.00)
Loan-to-Deposits		0.66***		0.61**
		(0.24)		(0.24)
House price index			0.83***	0.77***
			(0.30)	(0.28)
Pseudo R^2	0.041	0.090	0.108	0.144
AUC	0.64	0.68	0.71	0.73
se	0.06	0.06	0.06	0.06
Observations	109	109	109	109

Notes: Logit classification models for systemic financial crises associated with credit booms that started in the respective year. The dependent variable is a dummy that is 1 when a future financial crisis is associated with the credit boom, 0 otherwise. Booms are classified using an alternative threshold of 0.5 in terms of the normalized detrended credit variable. One observation for each credit boom, all variables are in country-level standardized deviations from long-run trend. Panel B includes country fixed effects. Clustered (by country) standard errors in parantheses.

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