DOI: 10.1111/jmcb.12701

BJÖRN RICHTER
MORITZ SCHULARICK
PAUL WACHTEL

When to Lean against the Wind

In this paper, we show that policymakers 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 than other credit booms. We evaluate the predictive accuracy for different classification models and show that characteristics observed in real time contain valuable information for sorting the data into good and bad booms.

JEL codes: E32, E44, G01, G21
Keywords: banking crises, crisis prediction, credit booms, macroprudential policy

Periods of rapid credit growth, credit booms, can have diverse outcomes. First, there is a large literature that relates credit growth with improved economic fundamentals and argues that such financial deepening episodes are economically beneficial. Second, some credit booms end badly; they result in financial crises with severe output losses. This means that policymakers 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

This work is part of a larger project kindly supported by a research grant from the Bundesministerium für Bildung und Forschung (BMBF). We are indebted to a large number of researchers who helped with data on individual countries. Special thanks to the participants at the American Economic Association meetings in Philadelphia January 2018, the Bank of Finland seminar in June 2018, the 23rd Dubrovnik Economic Conference in June 2017, the Halle Workshop on Macroeconomics in May 2017, and the LSE SRC Conference on Financial Crises in April 2018. We are grateful to John Ducca, Evan Kraft, Olivier Jeanne, Philip Jung, and Alan M. Taylor for helpful comments. All errors are our own.

Björn Richter *is an Assistant Professor at the Department of Economics and Business, Universitat Pompeu Fabra and an Affiliated Professor at Barcelona GSE* (*E-mail*: bjorn.richter@upf.edu). Moritz Schularick *is a Professor of Economics at the Department of Economics, University of Bonn and CEPR* (*E-mail*: schularick@uni-bonn.de). Paul Wachtel *is a Professor of Economics at Stern School of Business, New York University* (*E-mail*: pwachtel@stern.nyu.edu).

Journal of Money, Credit and Banking, Vol. 53, No. 1 (February 2021)

risk of a banking crisis, but also reduce growth with uncertain costs for the economy (Svensson 2017, Adrian and Liang 2018).

Policymakers face a problem whenever they observe a period of rapid credit growth. That is, can they determine whether the boom underway will lead to a crisis? In this paper, we identify credit boom episodes and demonstrate that policymakers can distinguish good booms from bad ones and that they can do so with data available in real time. We show that there are clear markers that policymakers can use to tell apart good from bad credit booms with considerable accuracy. Financial variables such as a deteriorating liquidity position (measured by the loan-to-deposit ratio) and a house price boom are powerful classifiers to sort credit boom observations into malign and benign. Among the set of real economic variables, only changes in the current-account-to-GDP balance turn out to be a helpful classifier.

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, Schularick, and Taylor 2016), 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 data set compiled by Laeven and Valencia (2018). We use the new Hamilton (2018) filter to detrend the data and define credit booms as periods when the log of real private credit per capita exceeds its predicted value by a country-specific threshold. We identify 113 credit boom episodes and 90 systemic banking crises in our sample of advanced economies over the past 150 years.

Only a few papers have examined credit booms and their outcomes (Mendoza and Terrones 2014, Dell'Ariccia et al. 2016, Gorton and Ordoñez 2020). Yet since the time series examined are short and the country experiences are very heterogeneous, these studies often face challenges to distinguish good booms from bad booms based on observable characteristics.[1] 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.[2]

The growth of credit has been of interest to economic historians, development economists, and students of macrofinance for at least 30 years. Our paper connects two important and seemingly contradictory strands in the literature (Wachtel 2018). On the one hand, 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). There is a voluminous literature that uses post-World War II panel data that have 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. Evidence for the positive effects of financial booms is also examined by Rousseau and Wachtel (2017) who use historical data for the period 1870–1929

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.

2. However, this comes at the cost of focusing on a sample of developed, largely industrial, countries only.

and affirm the positive growth effects of financial deepening. 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.

On the other hand, there is an equally large literature that associates credit booms 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 (Schularick and Taylor 2012, Jordà, Schularick, and Taylor 2013, Mian and Sufi 2016). More recently, Mian, Sufi, and Verner (2017) have shown that household credit booms predict bad growth outcomes in more recent cross-country samples. In short, while some credit booms are a precursor to banking distress and crisis, other credit booms might represent financial deepening or be the reaction to a positive productivity shock.

There is also a large literature on crisis prediction that tries to identify crisis indicators and early warning signals (Borio and Drehmann 2009, Detken et al. 2014, Adrian, Covitz, and Liang 2015, Aldasoro, Borio, and Drehmann 2018, Kiley 2018). Since the great financial crisis there has been increased emphasis on macroprudential risks and policy and indicators based on detailed financial sector data that are now available (Cerutti, Claessens, and Laeven 2017). Crisis prediction is a daunting task because at any point in time, the probability of a financial crisis occurring is quite small and unlikely to attract the attention of policymakers.[3] The approach that we take here is very different than the crisis prediction literature. It is motivated by the idea that once a policymaker observes that a credit boom is underway and the economy is in the credit-boom state, the possibility of crisis warrants attention. For this reason, we depart from the crisis prediction literature and use the credit boom as our unit of observation. Our interest in this paper is not to predict crises but instead to provide information that would help policymakers determine whether an observed credit boom is likely to end badly. 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, an important prerequisite for the decision whether to intervene during a credit boom.

The challenge faced by the policymaker is whether a country in a credit boom can use available information to determine whether prudential or other policies should be used to deal with the risks of a credit boom turning into a crisis (Cerutti, Claessens, and Laeven 2017, Adrian and Liang 2018). The prevailing opinion prior to the recent global financial crisis was that monetary policymakers should focus on growth and inflation and rely on microfinancial regulation to maintain financial stability (Bernanke and Gertler 1999). 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 global financial crisis, some economists, notably at the Bank for International Settlements, suggested that systemic risks warranted the introduction of macroprudential

3. Svensson (2017) argues that the relationship between credit growth and crisis incidence is based on so many complex interactions that it is impossible to identify a stable and consistent crisis predictor.

policy frameworks. Interest in macroprudential policies expanded rapidly after the crisis and 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). In the U.S., Stein (2013) argued that monetary policy should intervene to contain excessive credit growth. Nevertheless, policy discussions remain concerned with the possible side effects of efforts to lean against the wind and the debate regarding policy prescriptions remains unsettled.

Here, we take a step back and ask whether it is possible to identify credit booms that deserve further attention from policymakers. Our methodology for identifying credit booms is discussed in Section 1. To measure cyclical variation, we use a recently proposed method for detrending time series (Hamilton 2018) 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). The number and distribution of credit booms depends on the specific procedure used to detrend the data and to determine when booms occur. We show that the frequency and incidence of credit booms are not dramatically different when alternative procedures are used to detrend credit series or when different credit measures (real credit per capita or the ratio of credit to GDP) are used to identify booms.

In Section 2.1, we use all available country-year observations to confirm the established relationship between credit boom indicators and crisis episodes. In Section 2.2, we present our real and financial indicators and show how they differ between good and bad booms.

Since the focus of this paper is whether an observed credit boom is likely to end badly, we turn in Section 3 to estimates which use the credit boom as the unit of observation. The specifications in this section use in-sample backward-looking information in order to make our analysis comparable with previous studies of credit booms and to utilize all the historical data for the classification exercise. In a series of specifications, we examine the influence of real and financial variables on the probability of a boom ending badly. We also confirm that the results are robust to the use of alternative procedures for defining credit booms. Finally, policymakers may be interested in growth outcomes after credit booms rather than whether or not the boom leads to crisis. Thus, we also analyze how well our bad boom markers predict medium-term GDP growth after boom episodes.

In Section 4, we set a higher bar for prediction. While the *ex post* markers of "bad" and "good" credit booms are interesting from an academic perspective, for policymakers the real test is whether credit booms could have successfully been classified with information available to decision makers in real time. In other words, we are aiming to determine whether policymakers are able to differentiate between good and bad credit booms as they unfold. Using expanding windows with data available to policymakers at each point in time, we (i) determine whether a credit boom has begun, (ii) measure the cyclical variations of explanatory variables, and, most importantly, (iii) ask whether these detrended variables help in classifying the boom as good or bad in the first year in which a boom is detected. Section 4.2 presents an out-of-sample forecast test for the recent booms. Classification models estimated through 1999 are used to forecast whether the booms of the early 2000s would end badly. In Section 4.3, we subject the real-time results to robustness tests for different boom thresholds and also compare our results with booms determined by detrended real credit to those based on the detrended credit to GDP ratio.

Our conclusion, discussed in Section 5 is that even using exclusively variables that are available in real time, policymakers can achieve classification with high accuracy. Credit booms are more likely to end badly when they are accompanied by deterioration in banking sector liquidity, measured by the loan-to-deposit ratio, and house price booms measured by the deviation of real house prices from country-specific trends.

1. IDENTIFYING CREDIT BOOMS

The notion of a boom implies a deviation from normal "nonboom" 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 threshold to define extraordinary credit growth.[4] Mendoza and Terrones (2014) 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 Ordoñez (2020) 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 the detrended log of real private credit per capita, where the credit data come from Schularick and Taylor (2012) and updates thereof (Jordà, Schularick, and Taylor 2016). We define real private credit per capita as total loans extended to the domestic private nonfinancial sector divided by population and deflated using the consumer price index from the same data source. We prefer real credit per capita because it avoids possible endogeneity with GDP and boom outcomes.[5] To detrend the data, we follow Hamilton (2018) who shows that the use of a HP filter introduces spurious dynamic relations 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

4. Specifically, an episode of credit deepening—a boom—occurs when the ratio of M2 to GDP increases by more than 30% over a 10-year period.

5. More specifically, the credit to GDP ratio may rise above the boom threshold when GDP is declining after a banking crisis. However, we also show results with the credit to GDP ratio; our main results do not depend on this choice of the credit variable.

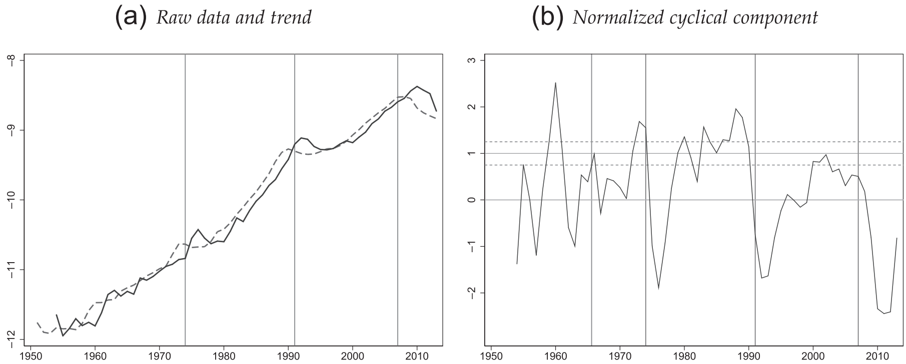

Fig 1. Detrended Credit and Cyclical Component for the UK.

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 (2018) 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 banking crises defined in Jordà, Schularick, and Taylor (2016).

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 (2018) proposes that this residual should be based on a regression of the value y at time t on the four most recent values of y at time $t-h$, that is, $y_{t-h}, y_{t-h-1}\cdots$. 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}.[6] As Hamilton (2018) explains, the procedure is by construction forward looking (one-sided) as it uses values available at time $t-h$ for the prediction.

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 3 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

6. Hamilton (2018) proposes $h=2$ for business cycle variables and a longer horizon up to 5 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. However, the results shown below regarding the main predictors of bad booms remain unchanged.

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 (Mendoza and Terrones 2014). 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 nonwar observations in country i will be denoted by $\sigma(c_i)$.[7]

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.[8] 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 $c_{i,t}/\sigma(c_i)$, that is, 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 113 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).

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

7. We exclude 4-year windows before wars from our analysis. Furthermore, when using the Hamilton (2018) filter we additionally discard 6 years after wars, so that prediction residuals are not based on wartime data.

8. We experimented with alternative thresholds of 0.75 and 1.25 $\sigma(c_i)$. Results are in the robustness discussions in Section 5. Varying the thresholds clearly affects the number and duration of booms.

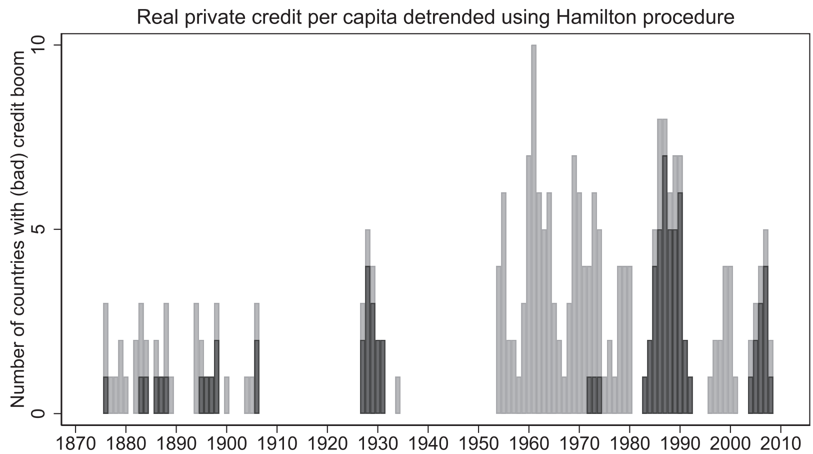

Fig 2. Number of Ongoing Credit Booms by Year.

NOTES: This figure presents the number of credit booms according to our definition. Dark bars refer to booms that turn into a banking crisis. Windows around wars are excluded from the analysis. See text.

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 solid 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 following section, we distinguish between credit booms that end in a crisis ("bad booms") and those that do not and compare one group to the other. The banking crisis chronology comes from Jordà, Schularick, and Taylor (2016) and is based on banking crisis events as defined in Laeven and Valencia (2018), which focuses on systemic financial distress.[9] Specifically, a boom is bad if a banking crisis occurs during the boom or in the 3 years following the credit boom. With this definition, 29 of the 113 or 26% of the identified booms are bad. This frequency is close to that reported in Mendoza and Terrones (2014) and in Dell'Ariccia et al. (2016). Two countries in our sample do not experience any bad booms—Germany and the Netherlands—and Denmark has the most (5). In the following sections, the unit of observation will be a credit boom, some of them bad in the above sense, others good.

The distribution 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

9. Banking crisis dates are shown in Appendix A.

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 incidence of credit booms differs when a different procedure is used to determine boom episodes or when a different credit variable is used. 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 based on 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 postwar 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.

2. GOOD AND BAD BOOMS

We start in Section 2.1 with an examination of the relationship between credit boom and crisis episodes using all available country-year observations. We confirm that boom episodes are closely associated with crisis risk. We then shift our focus to the credit boom as the unit of observation since our interest is whether an observed credit boom is likely to end badly. Our approach acknowledges that the complex relationship between credit growth and crisis probability makes it difficult to identify a stable crisis predictor (Svensson 2017). Yet when the economy is experiencing a credit boom, crisis-risk warrants particular attention from policymakers. In Section 2.2, we discuss the real and financial indicators that are potential markers to distinguish between good and bad credit booms and present descriptive statistics on how the means of these indicators differ between good and bad booms.

2.1 Relationship between 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. In particular, we estimate

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

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

TABLE 1

Logit Models with Banking Crises as Dependent Variable

	All years		Pre-WW2		Post-WW2	
	(1)	(2)	(3)	(4)	(5)	(6)
Detrended credit	0.59***		0.68***		0.84***	
	(0.15)		(0.17)		(0.23)	
Credit boom		1.16***		1.36***		1.53***
		(0.32)		(0.51)		(0.42)
FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.052	0.047	0.079	0.062	0.077	0.072
AUC	0.68	0.66	0.71	0.67	0.73	0.69
	(0.03)	(0.04)	(0.05)	(0.05)	(0.06)	(0.07)
Observations	1,541	1,541	540	540	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. AUC is the area under the receiver operating curve, and below is its standard error. Clustered (by country) standard errors in parentheses. *** $p < 0.01$.

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 the period into pre-WW2 (columns (3) and (4)) and post-WW2 ((5) and (6)) subsamples. While these results show 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 macro-economic downturn at all. In the following sections, we will use the credit boom, some good and some bad, as our unit of observation.

2.2 *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. 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 credit boom, such as its duration in years and the size of boom measured by the normalized deviation of the credit variable 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

TABLE 2

Summary Statistics

	Bad booms					Good booms				
	Mean	Min.	Max.	S.D.	Obs.	Mean	Min.	Max.	S.D.	Obs.
Size	1.78	1.01	3.11	0.48	29	1.51	1.00	3.44	0.50	84
Duration	2.69	1.00	8.00	1.79	29	1.94	1.00	8.00	1.42	84
Duration to peak	1.90	1.00	6.00	1.32	29	1.49	1.00	4.00	0.75	84
GDP	0.63	−1.47	1.77	0.73	29	0.70	−3.54	2.81	0.91	84
Consumption	0.87	−0.97	2.99	0.92	29	0.68	−2.63	2.44	0.78	82
Current account	−0.75	−2.83	1.58	1.14	28	−0.25	−2.17	2.47	0.85	80
Investment	0.72	−0.92	3.24	0.96	26	0.52	−2.42	2.64	0.92	81
Short-term rate	0.24	−1.57	4.07	1.19	26	0.24	−1.66	3.68	1.07	76
Long-term rate	0.10	−1.35	1.86	0.80	29	0.13	−2.63	3.00	0.99	83
Credit-to-GDP	4.06	2.43	5.14	0.71	29	3.82	1.04	4.72	0.68	84
Capital ratio	0.11	−2.50	3.60	1.24	27	−0.23	−2.15	3.64	0.83	79
Noncore	0.13	−2.40	3.86	1.27	26	0.01	−2.26	2.72	0.80	79
Loans-to-deposits	1.18	−1.33	3.68	1.28	26	0.28	−3.93	3.71	1.11	79
House price index	1.30	−0.46	4.18	1.10	22	0.33	−1.21	4.33	0.94	71
Stock price index	0.58	−2.40	3.70	1.32	23	0.20	−2.73	4.70	1.08	75

Notes: Macro-economic and financial variables are detrended and normalized at the country level (except Credit-to-GDP which is the natural log of the ratio in percent) 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.

literature suggests that we should expect a deteriorating current account balance to be associated with a higher risk of banking crisis (Kiley 2018);

- 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 (Mitra et al. 2011);
- A last set of variables refers to asset prices, especially in stock and housing markets.

All of these 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 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 1 year prior to 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 84 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

TABLE 3

Test of Equality of Means: Credit Booms Split by Associated Banking Crises

	Difference	t-Statistic
Size	0.26*	2.46
Duration	0.75*	2.29
Duration to peak	0.41*	2.04
GDP	−0.07	−0.36
Consumption	0.19	1.10
Current account	−0.51*	−2.49
Investment	0.20	0.95
Short-term rate	0.00	0.00
Long-term rate	−0.03	−0.14
Credit-to-GDP	0.24	1.63
Capital ratio	0.34	1.61
Noncore	0.12	0.57
Loans-to-deposits	0.90**	3.46
House price index	0.97**	4.05
Stock price index	0.38	1.40
Observations	113	

Notes: This table presents differences in the means shown in Table 2, where the difference is bad less good, and t-statistics for the null that the difference is zero. $^{*}p < 0.05$, $^{**}p < 0.01$.

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 (−0.75 compared to −0.25).

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. In addition, 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.[10]

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 ($p < 0.01$ 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.[11]

10. 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.

11. A table with the means of all variables for booms in the 1950s and 1960s and the tests on the differences from credit booms in the rest of the sample period is available from the authors.

3. CLASSIFYING BOOMS

In this section, we address the differences between good booms and bad booms in a multivariate setting. We estimate logit classification models in order to understand which real and financial variables are associated with higher odds of a boom ending in a crisis. The analysis in this section will use in-sample backward-looking information. It allows us to examine the within-country variation of credit booms and their outcomes with our full historical data set.

3.1 Classification Models

We start with a parsimonious model and then add additional variables while tracking the improvement in the classification ability that the additional variables bring. We then include in our full model the consistently significant variables and afterwards examine its robustness.

Credit booms are relatively rare events, but the long-run nature of our data set gives us multiple credit boom observations per country. We can therefore rely on the within-country variation in the data and single out the variables that distinguish good from bad booms controlling for time invariant country characteristics. This will allow us to show that the liquidity situation of the banking sector, house price developments, and the current account balance contain important information about the nature of the credit boom. This being said, banking crisis are extreme outcomes, typically associated with lower GDP growth (Cerra and Saxena 2008, Jordà, Schularick, and Taylor 2013). Yet we may alternatively think of a "bad boom" as one which ends in a recession or lower GDP growth (Mian, Sufi, and Verner 2017). We also show that the core results hold up when we use the postboom growth in real GDP as the measure of the boom outcome (and not the crisis indicator).

Formally, 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 3-year window after the credit boom. In all other boom episodes, this value will be zero. 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

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

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 possible to include a fixed effect and the reduced sample with fixed effects omits the credit boom observations from these countries. Across specifications, the number of observations also changes due to missing data for the explanatory variables. We start with a parsimonious specification that includes all boom observations and subsequently add additional controls and always use as much data as

TABLE 4

Baseline Specification

	Size (1)	Duration (2)	Both (3)
	Panel A. Full sample		
Size of boom	1.34**		1.21*
	(0.64)		(0.66)
Duration to peak		0.42**	0.34*
		(0.17)	(0.18)
Pseudo R^2	0.045	0.029	0.064
AUC	0.69	0.57	0.69
	(0.06)	(0.06)	(0.06)
Observations	113	113	113
	Panel B. Reduced sample—including country-fixed effects		
Size of boom	2.25**		2.05*
	(1.09)		(1.13)
Duration to peak		0.53**	0.37
		(0.24)	(0.23)
Pseudo R^2	0.150	0.106	0.167
AUC	0.76	0.71	0.78
	(0.06)	(0.06)	(0.06)
Observations	99	99	99

Notes: Logit classification models for systemic banking crises associated with credit booms. The unit of observation is a credit boom. 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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 (Gourinchas, Valdes, and Landerretche 2001, Jordà, Schularick, and Taylor 2016). Table 4 presents the baseline results, both for the full sample of 113 booms in 17 countries in Panel A and the reduced sample with fixed effects that includes 99 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. In other words, it yields a summary measure of predictive ability that is independent of individual cutoff values chosen by the policymaker. 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 0.69, 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).

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 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 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 69 with the reduced (fixed effects) sample. In column (1), we show reestimates of the baseline specification for these samples in order to obtain comparable AUCs. The coefficients and the AUCs are similar to those obtained before. We then include the other variables one at a time in columns (2)–(7). Most of the real sector measures are neither significant nor do they add predictive accuracy to the baseline model with the exception of the current account. 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, Schularick, and Taylor 2011, Kiley 2018) and the AUC reaches 0.82 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

TABLE 5

REAL VARIABLES

	Base (1)	GDP (2)	Consumption (3)	Investment (4)	Current account (5)	Short rate (6)	Long rate (7)
Panel A. Full sample							
Size of boom	1.18	1.18	1.18	1.08	1.25	1.08	1.13
	(0.83)	(0.83)	(0.84)	(0.92)	(0.91)	(0.75)	(0.77)
Duration to peak	0.42*	0.41*	0.41*	0.38*	0.38*	0.45**	0.43**
	(0.21)	(0.22)	(0.21)	(0.22)	(0.22)	(0.23)	(0.21)
Real variable		0.05	0.01	0.42*	−0.70*	−0.31	−0.17
		(0.27)	(0.33)	(0.25)	(0.37)	(0.40)	(0.28)
Pseudo R^2	0.077	0.077	0.077	0.089	0.122	0.085	0.081
AUC	0.68	0.68	0.68	0.73	0.75	0.71	0.68
	(0.07)	(0.07)	(0.07)	(0.07)	(0.06)	(0.06)	(0.07)
Observations	90	90	90	90	90	90	90
Panel B. Reduced sample—including country-fixed effects							
Size of boom	2.24	2.25	2.30	2.21	2.54	1.76	2.00
	(1.54)	(1.49)	(1.49)	(1.58)	(1.55)	(1.45)	(1.38)
Duration to peak	0.53*	0.60**	0.65**	0.53*	0.60*	0.64*	0.59**
	(0.29)	(0.29)	(0.29)	(0.29)	(0.35)	(0.38)	(0.29)
Real variable		−0.31	−0.48	0.07	−1.21**	−0.70	−0.38
		(0.42)	(0.54)	(0.27)	(0.50)	(0.81)	(0.43)
Pseudo R^2	0.195	0.200	0.206	0.195	0.270	0.219	0.209
AUC	0.79	0.79	0.79	0.79	0.82	0.81	0.78
	(0.07)	(0.07)	(0.07)	(0.07)	(0.05)	(0.06)	(0.07)
Observations	69	69	69	69	69	69	69

NOTES: Logit classification models for systemic banking crises associated with credit booms. The unit of observation is a credit boom. The dependent variable is a dummy that is 1 when a banking crisis is associated with the credit boom, 0 otherwise. Real variables are in one-period-lagged normalized deviations from trend at the peak of the boom. Panel B includes additionally country-fixed effects. AUC is the area under the receiver operating curve, and below is its standard error. Clustered (by country) standard errors in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

TABLE 6
Banking Variables

	Base (1)	Credit-to-GDP (2)	Capital ratio (3)	Noncore ratio (4)	Loans-to-deposits (5)
Panel A. Full sample					
Size of boom	1.12	1.15	1.22*	1.12	1.07
	(0.71)	(0.73)	(0.72)	(0.71)	(0.75)
Duration to peak	0.38**	0.32*	0.37**	0.34	0.26
	(0.18)	(0.19)	(0.16)	(0.21)	(0.20)
Banking variable		0.56	0.44	0.09	0.42**
		(0.61)	(0.34)	(0.18)	(0.19)
Pseudo R^2	0.067	0.080	0.100	0.068	0.098
AUC	0.68	0.67	0.69	0.69	0.72
	(0.06)	(0.07)	(0.08)	(0.06)	(0.06)
Observations	100	100	100	100	100
Panel B. Reduced sample—including country-fixed effects					
Size of boom	2.35	2.31	2.39	2.38	2.40
	(1.64)	(1.64)	(1.67)	(1.66)	(1.66)
Duration to peak	0.50*	0.45*	0.48*	0.43	0.30
	(0.28)	(0.27)	(0.26)	(0.28)	(0.28)
Banking variable		0.45	0.32	0.16	0.55*
		(0.78)	(0.38)	(0.22)	(0.32)
Pseudo R^2	0.200	0.204	0.218	0.202	0.230
AUC	0.81	0.81	0.81	0.81	0.82
	(0.06)	(0.06)	(0.05)	(0.06)	(0.05)
Observations	81	81	81	81	81

Notes: Logit classification models for systemic banking crises associated with credit booms. The unit of observation is a credit boom. The dependent variable is a dummy that is 1 when a banking crisis is associated with the credit boom, 0 otherwise. Banking variables are in one-period-lagged normalized deviations from trend (except credit-to-GDP) at the peak of the boom. Panel B includes country-fixed effects. AUC is the area under the receiver operating curve, and below is its standard error. Clustered (by country) standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

sample, but this relationship disappears once we include fixed effects in the reduced sample.

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 log of 100 times 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.[12]

12. However, the coefficient becomes significant when looking at post-WW2 data only.

TABLE 7

Asset Prices

	Baseline (1)	House price index (2)	Stock price index (3)	Both (4)
	Panel A. Full sample			
Size of boom	1.41	1.45	1.57	1.78*
	(0.96)	(1.06)	(0.96)	(1.05)
Duration to peak	0.52**	0.45	0.55**	0.50
	(0.23)	(0.28)	(0.24)	(0.30)
House price index		0.85**		0.91**
		(0.39)		(0.38)
Stock price index			−0.18	−0.37
			(0.27)	(0.33)
Pseudo R^2	0.108	0.206	0.112	0.221
AUC	0.71	0.82	0.72	0.82
	(0.07)	(0.05)	(0.07)	(0.05)
Observations	84	84	84	84
	Panel B. Reduced sample—including country-fixed effects			
Size of boom	2.37	2.61	3.76**	6.17**
	(1.75)	(1.66)	(1.79)	(2.46)
Duration to peak	0.74**	0.71	0.91**	0.97
	(0.35)	(0.46)	(0.40)	(0.68)
House price index		1.44**		2.15***
		(0.58)		(0.65)
Stock price index			−0.95**	−1.86***
			(0.41)	(0.68)
Pseudo R^2	0.233	0.383	0.284	0.502
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 unit of observation is a credit boom. The dependent variable is a dummy that is 1 when a banking crisis is associated with the credit boom, 0 otherwise. Asset price variables are in one-period-lagged normalized deviations from trend at the peak of the boom. Panel B includes country-fixed effects. AUC is the area under the receiver operating curve, and below is its standard error. Clustered (by country) standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Turning to the capital ratio in column (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. (Forthcoming). The share of noncore 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., forthcoming). The coefficient is highly significant and the AUC is also higher than in the baseline specification. 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 reduced sample.

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 0.11 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, Schularick, and Taylor 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.[13]

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 reestimate 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), the current account balance. All variables remain statistically significant at least at the 10% level in column (4). The joint inclusion of the three conditioning variables in column (4) increases the predictive power considerably from 0.68 with the baseline to 0.87 in the full sample (with 85 boom observations available) and from 0.77 to 0.93 for the reduced sample with fixed effects which includes 62 observations.

3.2 Extended Results

We explore the robustness of these findings by looking at results with alternative filters used to detrend our credit measure, results with alternative credit measures and results which are restricted to the post-World War 2 period. It is important to examine these issues because we saw earlier (Appendix Figure A1) that there are some differences in the incidence of booms when alternative filters are used to detrend credit or alternative credit measures are used.

In Appendix Table A1, we start with estimates of the full model for the postwar period in columns (1) and (2) which correspond to the full sample results in Table 8, columns (3) and (4). The results for the shorter time period are stronger, especially for the loans-to-deposits ratio, and house prices remain highly significant. The current account is insignificant in post-WW2 data and adds little predictive accuracy. The last four columns of the table show results that use the credit to GDP ratio to define credit booms. Only the house price index is significant in the full sample estimates

13. 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 8
FULL MODEL

	Baseline (1)	+ House prices (2)	+ LtD ratio (3)	Full (4)
Panel A. Full sample				
Size of boom	1.22	1.12	1.03	1.26
	(0.96)	(1.01)	(1.05)	(1.03)
Duration to peak	0.47**	0.41	0.21	0.22
	(0.22)	(0.27)	(0.31)	(0.29)
House price index		0.87**	0.82**	0.86**
		(0.40)	(0.40)	(0.43)
Loan-to-deposits			0.71**	0.62*
			(0.28)	(0.32)
Current account				−0.80**
				(0.39)
Pseudo R^2	0.086	0.186	0.245	0.289
AUC	0.68	0.80	0.85	0.87
	(0.07)	(0.05)	(0.05)	(0.04)
Observations	85	85	85	85
Panel B. Reduced sample—including country-fixed effects				
Size of boom	1.55	1.44	1.46	2.02
	(1.59)	(1.61)	(1.74)	(2.17)
Duration to peak	0.72**	0.61	0.35	0.85
	(0.32)	(0.51)	(0.47)	(1.02)
House price index		1.19*	1.28*	1.58***
		(0.65)	(0.73)	(0.61)
Loan-to-deposits			0.98***	0.89*
			(0.33)	(0.48)
Current account				−2.45**
				(0.96)
Pseudo R^2	0.191	0.315	0.389	0.509
AUC	0.77	0.86	0.89	0.93
	(0.07)	(0.05)	(0.05)	(0.03)
Observations	62	62	62	62

NOTES: Logit classification models for systemic banking crises associated with credit booms. The unit of observation is a credit boom. The dependent variable is a dummy that is 1 when a banking crisis is associated with the credit boom, 0 otherwise. Added variables are in one-period-lagged normalized deviations from trend at the peak of the boom. AUC is the area under the receiver operating curve, and below is its standard error. Clustered (by country) standard errors in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

while both house prices and the loan-to-deposit ratio are highly significant once we restrict the sample to the postwar period in columns (5) and (6). The current account is not significant and the AUCs are smaller when credit to GDP is used to define booms.

In Appendix Table A2, we vary the detrending procedure as well as the credit variable used to identify credit booms and estimate the full model as in Table 8, column (4) for the full sample (Panel A). In columns (1) and (2), we show results using the Hamilton filter for comparison. 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. In column (4), we use this filter and credit-to-GDP to define credit booms. Specifications (2) and (3) again indicate a

TABLE 9

Credit Boom Characteristics and 3-Year GDP Growth

	Baseline (1)	+ House prices (2)	+ LtD ratio (3)	Full (4)
Panel A. Pooled OLS				
Size of boom	−0.01	−0.00	0.00	0.00
	(0.04)	(0.03)	(0.03)	(0.03)
Duration to peak	−0.02**	−0.01**	−0.01	−0.01
	(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				0.01
				(0.01)
R^2	0.067	0.256	0.330	0.334
Observations	71	71	71	71
Panel B. OLS—including country-fixed effects				
Size of boom	−0.03	−0.01	−0.01	−0.01
	(0.04)	(0.04)	(0.03)	(0.03)
Duration to peak	−0.02**	−0.01	−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				0.00
				(0.01)
R^2	0.279	0.431	0.482	0.482
Observations	71	71	71	71

Notes: 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. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

statistically significant relationship between elevated house prices and the probability of a boom ending in a banking crisis. An elevated loan-to-deposit ratio signals a higher crisis probability in model (4), while the current account loses significance in all these models.

Ultimately, we are interested in the relationship between credit boom characteristics and 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 their relationship with the rate of growth of real GDP in the 3 years after the peak of a boom.[14] The results presented 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 3

14. The 3-year growth window was chosen because it is consistent with the results shown in Mian, Sufi, and Verner (2017).

following years. The coefficients are negative and significant indicating that elevated house prices and loan-to-deposit ratios 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). Appendix Table A3 shows that these relationships also hold when we widen the window and look at the 5 years after observing the peak of a credit boom.

These results indicate that looking back at almost 150 years of macro-economic 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 to a lesser extent the inflow of foreign capital (as measured by the current account balance). Our results highlight the quandary faced by policymakers. Credit booms that are associated with high illiquidity and house prices may come at the cost of lower GDP growth even if they do not result in crisis.

4. 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 policymakers 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 policymaker 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.

4.1 Classification with Real-Time Data

We use real-time data to determine whether a boom has started and predict how it will end. The results show that there are strong signals available that would enable a policymaker to take offsetting action that could prevent the credit boom from ending in a crisis. The 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 so that coefficients in this regression are solely based on past data.[15] In each year, a detrended and normalized estimate based on data available at

15. Although only past data are used to identify booms and explain their end, the data may not be the exact information available at the time, so-called vintage data. For much of the historical period, such data would not be available.

TABLE 10

Classification with Real-Time Information

	(1)	(2)	(3)	(4)	(5)
Panel A. Full sample					
Initial size of boom	0.73	0.76	0.78	0.77	0.83
	(0.61)	(0.58)	(0.74)	(0.64)	(0.67)
Loans-to-deposits		0.46**			0.25
		(0.21)			(0.25)
House price index			0.73***		0.67***
			(0.24)		(0.23)
Current account				0.11	0.04
				(0.25)	(0.23)
Pseudo R^2	0.015	0.055	0.143	0.017	0.152
AUC	0.59	0.65	0.76	0.60	0.76
	(0.09)	(0.08)	(0.07)	(0.08)	(0.07)
Observations	68	68	68	68	68
Panel B. Reduced sample—including country-fixed effects					
Initial size of boom	0.92	1.00	2.10	0.93	2.00*
	(0.86)	(0.74)	(1.29)	(0.88)	(1.07)
Loans-to-deposits		0.96***			0.74*
		(0.32)			(0.39)
House price index			1.46***		1.36***
			(0.32)		(0.30)
Current account				0.04	−0.32
				(0.27)	(0.36)
Pseudo R^2	0.053	0.162	0.307	0.053	0.354
AUC	0.66	0.76	0.84	0.66	0.87
	(0.08)	(0.08)	(0.06)	(0.08)	(0.06)
Observations	54	54	54	54	54

Notes: Logit classification models for systemic banking crises associated with credit booms. The unit of observation is a credit boom. The dependent variable is a dummy that is 1 when a subsequent banking crisis is associated with the credit boom, 0 otherwise. All variables are in country-level standardized deviations from trend in the first year the boom threshold is reached. Panel B includes country-fixed effects. AUC is the area under the receiver operating curve, and below is its standard error. Clustered (by country) standard errors in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

the time is used to determine whether a credit boom has begun. This also means that only past observations are used to compute the country-specific standard deviation of the cyclical component. If the detrended log of real private credit per capita is above this country-specific standard deviation, the boom threshold is reached. The real-time Hamilton procedure is also used to detrend and normalize the explanatory variables. We again group consecutive boom observations into one episode, but now the focus is on the first year of this episode and information readily available at this point in time. Finally, we predict whether a boom will end badly on the basis of the detrended and normalized explanatory variables in the first year the boom threshold is reached.

There are a few more credit booms with the real-time data than before (115 versus 113) and some minor differences in dating. For the real-time analysis, we omit booms where the country is in a banking crisis in the same year that the boom threshold is passed. It would make no sense to try to forecast a bad boom that has already turned into a full-blown banking crisis; there is no time for a policy reaction. Similarly, the

TABLE 11

CLASSIFICATION WITH REAL-TIME INFORMATION, POST-WW2 BOOMS ONLY

	(1)	(2)	(3)	(4)	(5)
			Panel A. Full sample		
Initial size of boom	0.75	0.84	0.87	0.79	0.98
	(0.69)	(0.68)	(0.89)	(0.70)	(0.79)
Loans-to-deposits		0.57**			0.39
		(0.26)			(0.31)
House price index			0.85***		0.78**
			(0.32)		(0.34)
Current account				0.21	0.07
				(0.43)	(0.41)
Pseudo R^2	0.018	0.081	0.195	0.026	0.216
AUC	0.58	0.69	0.81	0.61	0.83
	(0.12)	(0.09)	(0.07)	(0.11)	(0.07)
Observations	54	54	54	54	54
			Panel B. Reduced sample—including country-fixed effects		
Initial size of boom	1.17	2.98**	3.65	1.19	10.42***
	(1.23)	(1.23)	(2.25)	(1.28)	(2.80)
Loans-to-deposits		2.27***			5.53***
		(0.77)			(1.18)
House price index			2.14***		3.02***
			(0.83)		(0.89)
Current account				0.11	−1.61
				(0.66)	(1.19)
Pseudo R^2	0.068	0.361	0.417	0.069	0.696
AUC	0.65	0.86	0.89	0.65	0.99
	(0.10)	(0.07)	(0.06)	(0.10)	(0.01)
Observations	36	36	36	36	36

NOTES: Logit classification models for systemic banking crises associated with credit booms. The unit of observation is a credit boom. The dependent variable is a dummy that is 1 when a subsequent banking crisis is associated with the credit boom, 0 otherwise. All variables are in country-level standardized deviations from trend in the first year the boom threshold is reached. Panel B includes country-fixed effects. AUC is the area under the receiver operating curve, and below is its standard error. Clustered (by country) standard errors in parentheses. $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

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	0.184	0.258	0.291
Denmark	2005	bad	0.257	0.603	0.680
Spain	2005	bad	0.225	0.377	0.430
Finland	2000	good	0.189	0.222	0.238
Finland	2003	good	0.188	0.246	0.268
Italy	2007	bad	0.175	0.194	0.284
Norway	2005	good	0.224	0.456	0.493
Sweden	2005	bad	0.186	0.617	0.553
U.S.	2004	bad	0.179	0.480	0.441

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.

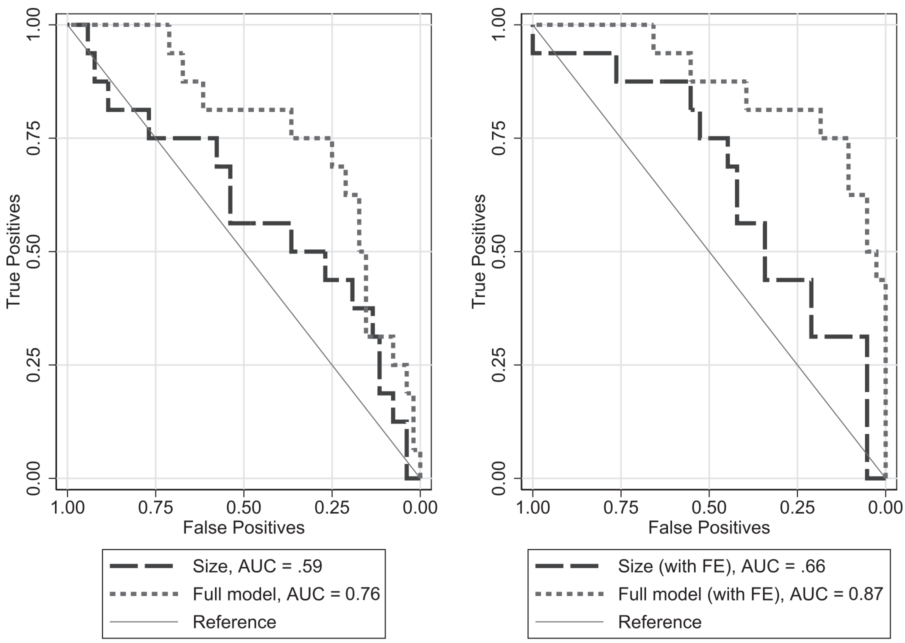

Fig 3. Correct Classification Frontiers with Real-Time Data.

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 model in column (1) including the initial size of the boom, and full model corresponds to the specification in column (5) of Table 10, including additionally the normalized deviation from trend of the house price index, the loans-to-deposits ratio, and the current account.

overall size and duration of the boom are unobserved in the first year of the boom and cannot be used to classify the boom, we instead include the initial size of the boom, that is, the normalized cyclical component in the first year of the boom.

Real-time classification results are shown in Table 10. As before, the good–bad credit boom indicator is the dependent variable. We include in the specifications the variables we identified as helpful predictors in the previous section. These were the size of the boom (now the initial size), the loan-to-deposit ratio, the house price index, and in some specifications the current account balance.

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 0.59 compared to 0.50). As in the previous analysis, adding house prices and loan-to-deposit ratios separately yields significant coefficient estimates and considerable improvements in predictive accuracy. The current account, which was not consistently significant earlier, is insignificant in real time and adds no predictive accuracy. The results in the reduced sample with fixed effects are very similar. Loans-to-deposits and house prices are again highly significant with considerable improvements in the AUC. Specification (5) includes all four variables jointly and

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	1.49**	0.83	1.95**	−0.21	−0.29	0.81
	(0.76)	(0.67)	(0.83)	(0.82)	(1.05)	(1.81)
House price index	0.85***	0.67***	0.79**	0.39**	0.61**	0.97**
	(0.29)	(0.23)	(0.37)	(0.17)	(0.29)	(0.42)
Loans-to-deposits	0.60*	0.25	0.51	0.43	0.76***	0.89**
	(0.36)	(0.25)	(0.38)	(0.29)	(0.24)	(0.39)
Pseudo R^2	0.211	0.152	0.236	0.085	0.175	0.319
AUC	0.80	0.76	0.83	0.71	0.79	0.85
	(0.07)	(0.07)	(0.06)	(0.07)	(0.06)	(0.06)
Observations	70	68	52	71	59	44
Panel B. Reduced sample—including country-fixed effects						
Initial size of boom	3.22**	2.00*	4.90**	−0.46	2.63	1.54
	(1.48)	(1.07)	(2.50)	(1.24)	(2.81)	(2.83)
House price index	1.40*	1.36***	1.75*	0.52**	1.28*	1.17*
	(0.75)	(0.30)	(0.96)	(0.27)	(0.73)	(0.63)
Loans-to-deposits	1.16	0.74*	1.05**	0.78	1.96***	1.27*
	(0.77)	(0.39)	(0.53)	(0.55)	(0.65)	(0.73)
Pseudo R^2	0.377	0.354	0.484	0.163	0.453	0.415
AUC	0.88	0.87	0.92	0.75	0.89	0.90
	(0.05)	(0.06)	(0.05)	(0.08)	(0.05)	(0.06)
Observations	58	54	32	60	39	30

NOTES: Logit classification models for systemic banking crises associated with credit booms. The unit of observation is a credit boom. The dependent variable is a dummy that is 1 when a subsequent banking crisis is associated with the credit boom, 0 otherwise. Added variables are in normalized deviations from trend in the year of the start of the boom. AUC is the area under the receiver operating curve, and below is its standard error. Clustered (by country) standard errors in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

yields high improvements in predictive accuracy with house prices being always significant and loans-to-deposits being significant once including fixed effects.

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 trade-off 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 are based on the estimates in columns (1) and (5). The visual impression is quite stark in the full and in the reduced sample with fixed effects. The augmented model in column (5) of Table 10 that uses information for house prices, the aggregate liquidity of the banking sector and the current account improves the predictive ability by a substantial margin. The figure confirms that even using real-time indicators, policymakers can distinguish between good and bad credit booms with considerable accuracy.

Our tests use data that extend 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. Furthermore, 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 54 post-WW2 booms (36 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.[16]

4.2 *Out-of-Sample Forecasts*

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 nine credit booms after 2000 and five of them end badly.

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 71 pre-2000 booms is 0.70. 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 0.284 with the full model in

16. It is possible that the results for the postwar 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 booms in the entire data sample. The results are largely the same as those shown above.

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 0.493 with the full model.

4.3 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. All specifications include house prices and the loan-to-deposit ratio in addition to the initial size of the boom, while we do not include the current account, which was never significant in real-time data. As before estimates with country-fixed effects are shown in Panel B.

We see that the results do not vary noticeably as the boom threshold changes. House prices are significant across all specifications, varying the boom thresholds as well as the credit variable used to define booms. Similar to the results presented in Tables 10 and 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. Furthermore, as expected the AUCs are somewhat higher when there is a larger boom threshold and fewer booms in the sample.

5. CONCLUSION

The findings presented in this paper mark a first step toward 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 data set 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, policymakers 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.

It is important to note that our paper does not present a crisis prediction model; indeed there are more than a few crises that are completely unrelated to credit booms. There are many such efforts in the literature including (Kiley 2018) using the same long-run data base. In addition, Adrian, Covitz, and Liang (2015) describe the framework adopted by American regulators to monitor crisis risks which includes some of the variables in our study. Our paper is based on the hypothesis that periods of credit boom are likely to draw intense interest from forecasters and policymakers and we attempt to show that there are markers that can usefully help them distinguish those booms that are likely to end badly from those that are not.

APPENDIX

A: SYSTEMIC BANKING CRISES DATES

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, Schularick, and Taylor (2016).

Australia:	1893, 1989.
Belgium:	1870, 1885, 1925, 1931, 1934, 1939, 2008.
Canada:	1907.
Denmark:	1877, 1885, 1908, 1921, 1931, 1987, 2008.
Germany:	1873, 1891, 1901, 1907, 1931, 2008.
Finland:	1877, 1900, 1921, 1931, 1991.
France:	1882, 1889, 1930, 2008.
Great Britain:	1890, 1974, 1991, 2007.
Italy:	1873, 1887, 1893, 1907, 1921, 1930, 1935, 1990, 2008.
Japan:	1871, 1890, 1907, 1920, 1927, 1997.
Netherlands:	1893, 1907, 1921, 1939, 2008.
Norway:	1899, 1922, 1931, 1988.
Portugal:	1890, 1920, 1923, 1931, 2008.
Spain:	1883, 1890, 1913, 1920, 1924, 1931, 1977, 2008.
Sweden:	1878, 1907, 1922, 1931, 1991, 2008.
Switzerland:	1870, 1910, 1931, 1991, 2008.
United States:	1873, 1893, 1907, 1929, 1984, 2007.

B: VARIABLE DEFINITIONS

Variable	Description
Real private credit per capita	Bank credit to the private non-financial sector per capita deflated with CPI
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
Size	Average of the detrended and normalized credit variable between the start and peak of the boom
Duration	Duration of boom in years
Duration to peak	Duration of boom until peak in years
GDP	log (real GDP per capita)
Consumption	log (real consumption per capita (2006=100))
Current account/GDP	Current account balance in % of GDP
Investment	Gross fixed capital formation in % of GDP
Short term rate	Short term interest rate in %
Long term rate	Long term interest rate in %
Credit-to-GDP	log(bank credit to private sector in % of nominal GDP)
Capital ratio	Bank capital/bank assets
Noncore share	Non-deposit bank debt/total bank debt
Loans-to-Deposits	Bank credit to private non-financial sector/bank deposits
House price index	House price index deflated, (1990=100)
Stock price index	Share price index deflated, (1990=100)

Notes: Data are based on the Macrohistory Database (Jordà, Schularick, and Taylor (2016), Knoll, Schularick, and Steger (2017) and Jordà et al. (2017)).

C: TABLES

TABLE A1

Robustness of Table 8. Post-WW2 Samples and Credit-to-GDP Booms

	Real private credit		Credit/GDP			
	Post	Post	Full	Full	Post	Post
	(1)	(2)	(3)	(4)	(5)	(6)
Loan-to-Deposits	0.99**	0.90**	0.38	0.37	0.69*	0.67*
	(0.27)	(0.29)	(0.26)	(0.29)	(0.28)	(0.30)
House price index	0.95*	0.97*	0.46+	0.50+	0.66*	0.64*
	(0.38)	(0.41)	(0.27)	(0.27)	(0.30)	(0.29)
Current account		−0.70		−0.55		−0.20
		(0.43)		(0.34)		(0.36)
Pseudo R^2	0.385	0.416	0.154	0.190	0.287	0.290
AUC	0.91	0.92	0.74	0.79	0.83	0.83
	(0.04)	(0.03)	(0.06)	(0.05)	(0.06)	(0.06)
Observations	71	71	76	76	56	56

Notes: Models presented in this table correspond to columns (3) and (4) in Table 8 − Panel A of the paper. Columns (1) and (2) show results for a post−WW2 sample instead of using the full sample. Columns (3) and (4) show results for the full sample with boom definitions based on the credit-to-GDP ratio (instead of real credit per capita) and columns (5) and (6) show results for the post-WW2 sample with this credit boom definition. All models include the duration and the size of the boom as additional regressors (not presented). AUC is the area under the receiver operating curve, and below is its standard error. Clustered (by country) standard errors in parentheses.
$^+p < 0.1$ * $p < 0.05$ ** $p < 0.01$

TABLE A2

Varying Filter Methodology

	Hamilton filter		HP filter	
	Real credit	Credit-to-GDP	Real credit	Credit-to-GDP
	(1)	(2)	(3)	(4)
Loan-to-Deposits	0.62+	0.37	0.62	0.79**
	(0.32)	(0.29)	(0.44)	(0.25)
House price index	0.86*	0.50+	0.65*	0.47
	(0.43)	(0.27)	(0.26)	(0.32)
Current account	−0.80*	−0.55	0.12	0.14
	(0.39)	(0.34)	(0.25)	(0.24)
Pseudo R^2	0.289	0.190	0.212	0.213
AUC	0.87	0.79	0.82	0.78
	(0.04)	(0.05)	(0.05)	(0.06)
Observations	85	76	73	78

Notes: Logit classification models for systemic banking crises associated with credit booms. The unit of observation is a credit boom. The dependent variable is a dummy that is 1 when a banking crisis is associated with the credit boom, 0 otherwise. Data is detrended using the Hamilton filter in (1) and (2) and a HP filter in (3) and (4). Boom definitions are based on real private credit per capita in (1) and (3) and credit-to-GDP in (2) and (4). Added variables are in one-period-lagged normalized deviations from trend at the peak of the boom. All specifications include the size and the duration of the boom (not shown here). AUC is the area under the receiver operating curve, and below is its standard error. Clustered (by country) standard errors in parentheses.
$+p < 0.1$ * $p < 0.05$ ** $p < 0.01$

TABLE A3

Robustness of Table 9. Credit Boom Characteristics and Five-Year GDP Growth

	Baseline (1)	+ House prices (2)	+ LtD ratio (3)	Full (4)
Panel A: Pooled OLS				
Size of boom	0.00	0.01	0.02	0.02
	(0.05)	(0.05)	(0.04)	(0.04)
Duration to peak	-0.02^{*}	-0.01^{+}	-0.00	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)
House price index		-0.04^{**}	-0.04^{**}	-0.04^{**}
		(0.01)	(0.01)	(0.01)
Loan-to-Deposits			-0.03^{*}	-0.03^{*}
			(0.01)	(0.01)
Current account				0.01
				(0.01)
R^2	0.043	0.241	0.331	0.340
Observations	71	71	71	71
Panel B: OLS **—including country fixed effects**				
Size of boom	-0.02	-0.00	0.00	0.00
	(0.05)	(0.05)	(0.04)	(0.04)
Duration to peak	-0.02^{*}	-0.02^{+}	-0.00	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)
House price index		-0.05^{**}	-0.04^{**}	-0.04^{**}
		(0.01)	(0.01)	(0.01)
Loan-to-Deposits			-0.03^{*}	-0.03^{*}
			(0.02)	(0.02)
Current account				0.01
				(0.02)
R^2	0.268	0.448	0.535	0.537
Observations	71	71	71	71

Notes: The dependent variable is $\Delta_5 GDP_{i,t} = log(realGDP_{i,t+5}) - log(realGDP_{i,t})$. 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. AUC is the area under the receiver operating curve, and below is its standard error. Clustered (by country) standard errors in parentheses.
$^{+}$ $p < 0.1$ * $p < 0.05$ ** $p < 0.01$

D: FIGURES

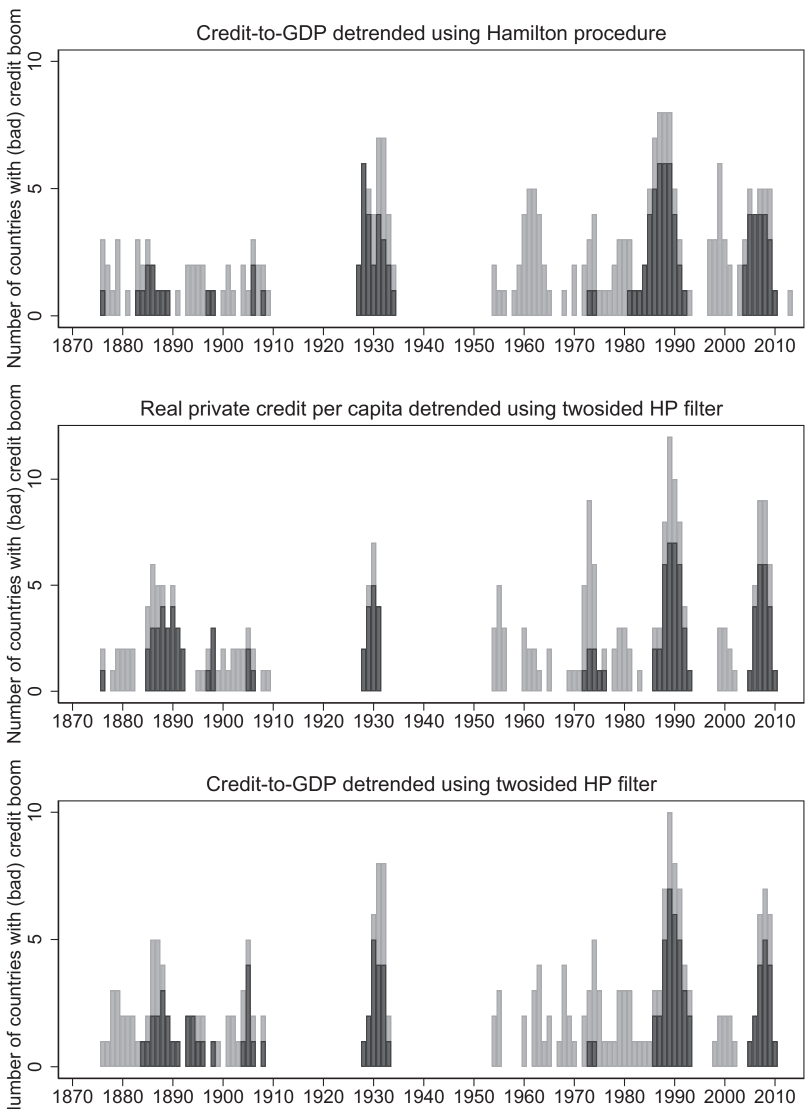

Fig D1. Number of Countries with Ongoing Credit Booms by Year Using Different Credit Measures and Detrending Procedures.

Notes: This figure presents the number of credit booms using different filters and credit variables. Dark bars refer to subset of booms that are associated with a banking crisis. Windows around wars are excluded from the analysis.

LITERATURE CITED

Adrian, Tobias, Daniel Covitz, and Nellie Liang. (2015) "Financial Stability Monitoring." *Annual Review of Financial Economics*, 7, 357–95.

Adrian, Tobias, and Nellie Liang. (2018) "Monetary Policy, Financial Conditions, and Financial Stability." *International Journal of Central Banking*, 14, 73–131.

Aldasoro, Inaki, Claudio Borio, and Mathias Drehmann. (2018) "Early Warning Indicators of Banking Crises: Expanding the Family." *BIS Quarterly Review*, 29–45.

Bernanke, Ben, and Mark Gertler. (1999) "Monetary Policy and Asset Price Volatility." *Economic Review*, 84, 17–51.

Borio, Claudio, and Mathias Drehmann. (2009) "Assessing the Risk of Banking Crises - Revisited." *BIS Quarterly Review*, 29–46.

Borio, Claudio, and William White. (2014) "Whither Monetary and Financial Stability? The Implications of Evolving Policy Regime." BIS Working Papers No. 147.

Cerra, Valerie, and Sweta Chaman Saxena. (2008) "Growth Dynamics: The Myth of Economic Recovery." *American Economic Review*, 98, 439–57.

Cerutti, Eugenio, Stijn Claessens, and Luc Laeven. (2017) "The Use and Effectiveness of Macroprudential Policies: New Evidence." *Journal of Financial Stability*, 28, 203–24.

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

Detken, Carsten, Olaf Weeken, Lucia Alessi, Diana Diana Bonfim, Miguel M. Boucinha, Christian Castro, Sebastian Frontczak, Gaston Giordana, Julia Giese, Nadya Jahn, Jan Kakes, Benjamin Klaus, Jan H. Lang, Natalia Puzanova, and Peter Welz. (2014) "Operationalising the countercyclical capital buffer: indicator selection, threshold identification and calibration options." ESRB Occasional Paper Series No. 5.

Gorton, Gary, and Guillermo Ordoñez. (2020) "Good Booms, Bad Booms." *Journal of the European Economic Association*, 18, 618–65.

Gourinchas, Pierre-Olivier, Rodrigo Valdes, and Oscar Landerretche. (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. https://www.federalreserve.gov/boarddocs/hh/1999/July/testimony.htm.

Hamilton, James D. (2018) "Why You Should Never Use the Hodrick-Prescott Filter." *Review of Economics and Statistics*, 100, 831–43.

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

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

Jordà, Òscar, Björn Richter, Moritz Schularick, and Alan M. Taylor. Forthcoming "Bank Capital Redux: Solvency, Liquidity and Crisis." *Review of Economic Studies*.

Jordà, Òscar, Moritz Schularick, and Alan M. Taylor. (2011) "Financial Crises, Credit Booms and External Imbalances." *IMF Economic Review*, 59, 340–78.

Jordà, Òscar, Moritz Schularick, and Alan M. Taylor. (2013) "When Credit Bites Back." *Journal of Money, Credit and Banking*, 45, 3–28.

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

Jordà, Òscar, Moritz Schularick, and Alan M. Taylor. (2016) "Macrofinancial History and the New Business Cycle Facts." In *NBER Macroeconomics Annual 2016*, Volume 31, NBER Chapters, pp. 213–263. National Bureau of Economic Research, Inc. https://ideas.repec.org/h/nbr/nberch/13776.html.

Kiley, Michael T. (2018) "What Macroeconomic Conditions Lead Financial Crises?" Finance and Economics Discussion Series 2018-038, Board of Governors of the Federal Reserve System (US).

King, Robert, and Ross Levine. (1993) "Finance and Growth: Schumpeter might be Right." *Quarterly Journal of Economics*, 153, 717–38.

Knoll, Katharina, Moritz Schularick, and Thomas Steger (2017). "No Price Like Home: Global House Prices, 1870–2012." *American Economic Review*, 107, 331–353.

Laeven, Luc, and Fabian Valencia. (2018) "Systemic Banking Crises Database: An Update." IMF Working Paper, 18/206.

Levine, Ross. (2005) "Finance and Growth: Theory and Evidence." In *Handbook of Economic Growth*, edited by Philippe Aghion and Steven Durlauf, Vol. 1, pp. 865–934. Amsterdam: Elsevier.

Mendoza, Enrique G., and Marco E. Terrones. (2014) "An Anatomy of Credit Booms and their Demise." In *Capital Mobility and Monetary Policy*, edited by Miguel Fuentes D., Claudio E. Raddatz, and Carmen M. Reinhart, Vol. 18 of Central Banking, Analysis, and Economic Policies Book Series, pp. 165–204. Santiago, Chile: Central Bank of Chile.

Mian, Atif, and A. Sufi. (2016) "Who Bears the Cost of Recessions? The Role of House Prices and Household Debt." In *Handbook of Macroeconomics*, Vol. 2, pp. 255–96. Amsterdam: Elsevier.

Mian, Atif, and Amir Sufi. (2018) "Finance and Business Cycles: The Credit-Driven Household Demand Channel." *Journal of Economic Perspectives*, 32, 31–58.

Mian, Atif, Amir Sufi, and Emil Verner. (2017) "Household Debt and Business Cycles Worldwide." *Quarterly Journal of Economics*, 132, 1755–817.

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

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

Rousseau, Peter L., and Paul Wachtel. (2009) "What is Happening to the Impact of Financial Deepening on Economic Growth." *Economic Inquiry*, 49, 276–88.

Rousseau, Peter L., and Paul Wachtel. (2017) "Episodes of Financial Deepening: Credit Booms or Growth Generators?" In *Financial Systems and Economic Growth*, edited by Peter L. Rousseau and Paul Wachtel, pp. 52–75. Cambridge, UK: Cambridge University Press.

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