INTERNATIONAL MONETARY FUND

Financial Inclusion, Credit Booms, and Financial Stability Risk

Adolfo Barajas, Kensuke Sakamoto, and Rasool Zandvakil

WP/26/8

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IMF Working Paper
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Financial Inclusion, Credit Booms, and Financial Stability Risk
Prepared by Adolfo Barajas, Kensuke Sakamoto, and Rasool Zandvakil*

Authorized for distribution by Selim Elekdag
January 2026

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ABSTRACT: Economic benefits of financial inclusion, meaning a broadening access of the population to financial services, have been studied extensively, but less is known about its potential effects on financial stability. We explore the complementarity between credit booms and episodes of rapid expansion of the borrower base, or "credit inclusion," and find that the confluence of both helps to predict future financial distress. Rapid credit inclusion on its own does not usually portend future instability, but it is much more likely to do so when combined with a credit boom. These results can help to enhance the policymaker's early warning toolbox.

JEL Classification Numbers:	G21, E51
Keywords:	Financial inclusion; Credit booms; Financial stability; Early warning indicators
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* The author(s) would like to thank Selim Elekdag, Luisa Zanforlin, and seminar attendees at the Institute for Capacity Development.

WORKING PAPERS

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I. Introduction

Financial inclusion, broadly defined as access to financial services and products, is a crucial aspect of financial development. The World Bank identifies it as a “key enabler to reduce extreme poverty and boost shared prosperity.”[1] While its positive effects on reducing inequality and fostering economic growth have been explored both theoretically and empirically (Dabla-Norris, et al. 2015; Sahay, et al. 2015), potential trade-offs with financial instability remain a concern for policymakers. The role subprime loans played during the global financial crisis of 2007-2009 exemplifies this trade-off: while these loans provided access to credit for households who might not have otherwise qualified, the subsequent losses that originated from them eventually triggered the global crisis[2].

Although the trade-offs of financial inclusion have been studied, findings remain mixed (e.g., Sahay, et al. 2015). One prominent gap in the literature is how financial inclusion on the credit side interacts with boom-bust cycles and what the implications are for subsequent financial instability. Given that credit booms are shown to be significant predictors of financial instability and crises (Schularick & Taylor, 2012), their interaction with financial inclusion could be key to understanding the trade-off between inclusion and stability. That is, the key question is whether the link between credit accelerations and future instability arises primarily on the intensive margin (more funds for the same borrowers) or the extensive margin (expanding the pool of borrowers, or financial inclusion).

This paper investigates the interaction between credit inclusion and credit booms[3]. Specifically, we ask two main questions: (i) to what extent does rapid growth in financial inclusion coincide with credit booms? and (ii) is a rapid increase in financial inclusion more likely to precede subsequent financial instability when accompanied by a credit boom? Hence, the goal of this paper is to assess the predictive power of these indicators rather than uncovering and describing causal relationships. To address these questions, we construct a novel country-panel dataset covering 96 countries from 2004 to 2021. This dataset matches newly accumulated supply-side financial inclusion data on credit with identified credit boom periods and various measures of financial instability.

Using this dataset, we examine changes in credit inclusion during credit booms. We find that rapid growth in credit inclusion is more common during credit booms than outside them. We then categorize credit booms as “bad” if they precede a crisis and “good” if they do not. Our findings show that rapid growth in credit inclusion is more frequent during bad credit booms than during good ones. Furthermore, we observe that within credit booms, rapid growth in credit inclusion signals a subsequent crisis that is more than twice as severe as one associated with slower growth. These results suggest a complementarity between credit inclusion growth and credit booms in predicting financial instability. We also test this complementarity using other measures of financial instability or distress, such as the non-performing loan rates (NPL) and bank z-scores.

Our empirical analysis uncovers two key patterns in the data. First, it shows that rapid growth in credit inclusion can predict subsequent credit booms. Second, it also confirms the complementarity between rapid growth in

[1] World Bank, "Financial Inclusion," World Bank, accessed January 21, 2025, https://www.worldbank.org/en/topic/financialinclusion

[2] Demyanyk and Van Hemert (2011) demonstrate that the number of subprime mortgage loans increased by a factor of 4 between 2001 and 2006, the year before the outset of the crisis.

[3] Throughout the paper we will be using the shorthand “credit inclusion,” referring to and measuring financial inclusion specifically in bank credit.

credit inclusion and credit booms as a predictor of financial instability. Specifically, we create a credit inclusion boom indicator and regress future changes in financial instability on the interactions between credit inclusion and credit booms. When financial instability is proxied by non-performing loan rates, we estimate that credit inclusion booms during credit booms increase non-performing loan rates by about 40 percent at their peak, with statistical significance. We also find that credit inclusion booms not accompanied by credit booms tend to *improve* financial stability, indicating that the trade-off between credit inclusion and instability is absent under more normal circumstances, when the economy is not in a credit boom. One reason may be that while a broadening borrower pool might include progressively riskier borrowers, this effect could be counteracted by an increasing diversification/lowering concentration of banks' loan portfolios.

Moreover, financial stability effects of credit booms alone are found to be smaller than those of credit inclusion booms during credit booms, reinforcing the complementarity between the two. We also find significant negative effects of credit inclusion booms on median GDP growth rates.

Some policy implications arise from these results. First, monitoring increases in credit inclusion along with credit growth can help complement the early warning toolbox that policymakers have at their disposal. Therefore, high-quality and real-time credit inclusion data are essential, as credit inclusion data can help to predict subsequent credit booms and help distinguish "bad" credit booms from "good" ones. Second, when promoting financial inclusion, it is critical to monitor current levels of private credit in the economy. This approach is particularly effective because promoting financial inclusion outside of credit booms is found to improve financial stability.

Our paper primarily contributes to the literature on the potential trade-offs between financial inclusion and financial stability. Several studies have investigated this trade-off, with mixed results. Han and Melecky (2013) found that financial inclusion in bank deposits can enhance stability by providing resilient funding for banks during economic turmoil. Similarly, Ahamed and Mallick (2019) reported that deposit-based financial inclusion has stabilizing effects on bank risk, particularly in banks that rely heavily on deposit funding. However, Sahay, et al. (2015) showed that the impact of various financial access measures on stability depends on the quality of supervisory practices. More recently, Ben Naceur, Candelon, and Mugrabi (2024) found that while financial inclusion in credit increases both individual and systemic bank risks, these risks are often mitigated in developing countries.

Our main contribution to this body of literature is that we qualify when the trade-off manifests, using credit boom information—a dimension that has been largely overlooked. Our findings suggest that financial inclusion in credit is associated with higher financial risks during credit booms, while it can reduce risk absent a credit boom. This novel identification is potentially informative for promoting credit inclusion, highlighting the importance of monitoring credit conditions in the economy.

We also contribute to the literature on credit cycles, where the dynamics of credit booms have been a central focus since Mendoza and Terrones (2008). Schularick and Taylor (2012) showed that credit booms are predictive of subsequent financial crises, and the literature has sought to identify factors distinguishing "bad" credit booms. For instance, credit expansions in the household sector (Mian, Sufi, and Verner 2017) and the non-trade sector (Müller and Verner 2023) have been associated with subsequent financial instability. More recently, Andrieş, Ongena, and Sprincean (2024), using bank-level data, demonstrated that credit expansions in both sectors tend to lead to subsequent systemic risk. When some studies investigate leverage buildup, often measured by the credit-to-GDP ratio, rather than credit booms directly, they find that factors like declining lending standards (Kirti 2018), loose financial conditions, and high debt levels (Barajas et al. 2021) interact with leverage buildup to increase financial instability, although macroprudential policies can mitigate these risks (Brandão-Marques et al. 2020; Barajas et al. 2021).

We complement these findings by showing that the behavior of credit inclusion can help differentiate “bad” from “good” credit booms. Specifically, we show that credit booms accompanied by rapid credit inclusion are more likely to lead to financial instability. By disaggregating credit booms into intensive and extensive margins, we provide a novel perspective on the role of credit inclusion in credit cycles. Our results suggest that more frequent and detailed credit inclusion data could be a valuable tool for designing macroprudential policies.

Our core results that concurrent credit and inclusion booms predict future financial instability raise the logical question as to the channel through which the two are interlinked. Is it simply the case that a concurrent boom is a reflection of lax credit standards or weak regulatory oversight? Or perhaps a concurrent boom results in widespread asset price inflation, which then causes a sharp credit contraction upon reversal in prices? The answer to these questions will be crucial in guiding policymakers to determine whether a concurrent credit and inclusion boom is a warning signal for future stability or not. We leave an investigation of these questions as promising avenues for future research.

II. Data and Methods

We construct a country-panel dataset that contains three types of information: (i) indicators measuring credit inclusion, (ii) aggregate credit at the country level to determine boom periods, and (iii) financial instability measures sourced from several datasets, for example, the dates of financial crises or indicators of financial distress. Below, we describe the construction of our dataset and the main stylized facts that emerge.

A. Financial Inclusion

Our main data source for credit inclusion is the IMF Financial Access Survey (FAS), which covers the years 2004 to 2023 and includes more than 170 countries. It consists of supply-side information obtained from surveys of providers of financial services, and is generally compiled by the central bank in each country. An advantage of using the FAS dataset is its annual frequency, which improves the quality of matching with subsequent boom and crisis information. This consistency is not found in other, user-side, financial inclusion datasets such as the World Bank’s Enterprise Survey (WBES) and the Global Financial Index (Findex)[4]. WBES are conducted at uneven intervals and frequency for different countries, while Findex surveys have been conducted every three years since 2011.

From the FAS dataset, we use two variables related to credit inclusion: (i) the number of borrowers from commercial banks per 1,000 adults (**borrower**) and (ii) the number of loan accounts with commercial banks per 1,000 adults (**loan**). These variables capture the extent of access to bank finance, with their change reflecting the “extensive margin” aspect of credit expansion.

[4] In Annex 1, we compare WBES and Findex with our credit inclusion measure and discuss the commonalities found among them.

As expected from the definitions, these two variables of credit inclusion are closely related; if the number of borrowers increases, then the number of loan accounts must increase. Statistically, the correlation between the two variables is found to be about 0.84, which might cause unstable estimation later in the analyses section[5]. Thus, we propose the use of principal component analysis (PCA), similar to Ahamed and Mallick (2019), to create a composite indicator of borrowers and accounts, **FI**[6].

B. Credit Boom

By “credit boom,” we refer to periods experiencing a particularly rapid increase in credit provided to the private sector. We use private credit data from the IMF Global Debt Database (GDD). This private credit variable is an aggregate of private credit to nonfinancial sectors in the form of bank loans and both domestic and external securities.

To identify credit booms, we combine the methodologies of Mendoza and Terrones (2008) and Müller and Verner (2023). First, we decompose private credit-to-GDP ratio into trend and cyclical components using the Hamilton filter (Hamilton, 2018)[7]. We identify a boom as a period in which the current cyclical component, at least in one year, exceeds its long-run standard deviation by a certain multiple. Similarly, we use a smaller multiple to determine the start and end years of the boom[8].

Figure 2 illustrates how our procedure is applied to Japan during our sample period. The black solid line depicts the estimated cyclical components. Around 2019, we have a candidate for a boom episode, as the cyclical components exceed the red dashed line, which depicts the threshold of 1.75 times standard deviations of the cyclical component.

The start and end years of this boom are determined by the intersections of the cyclical components and the blue dashed line, which represents the lower threshold of one standard deviation of the cyclical component. The shaded area then defines the boom episode. Specifically, the years that fall within this shaded area are labelled as booms.

Note that the years around 2008 are not identified as a boom episode because the cyclical components fail to exceed the boom threshold. This highlights that exceeding the start/end threshold is not sufficient to be labeled as a boom.

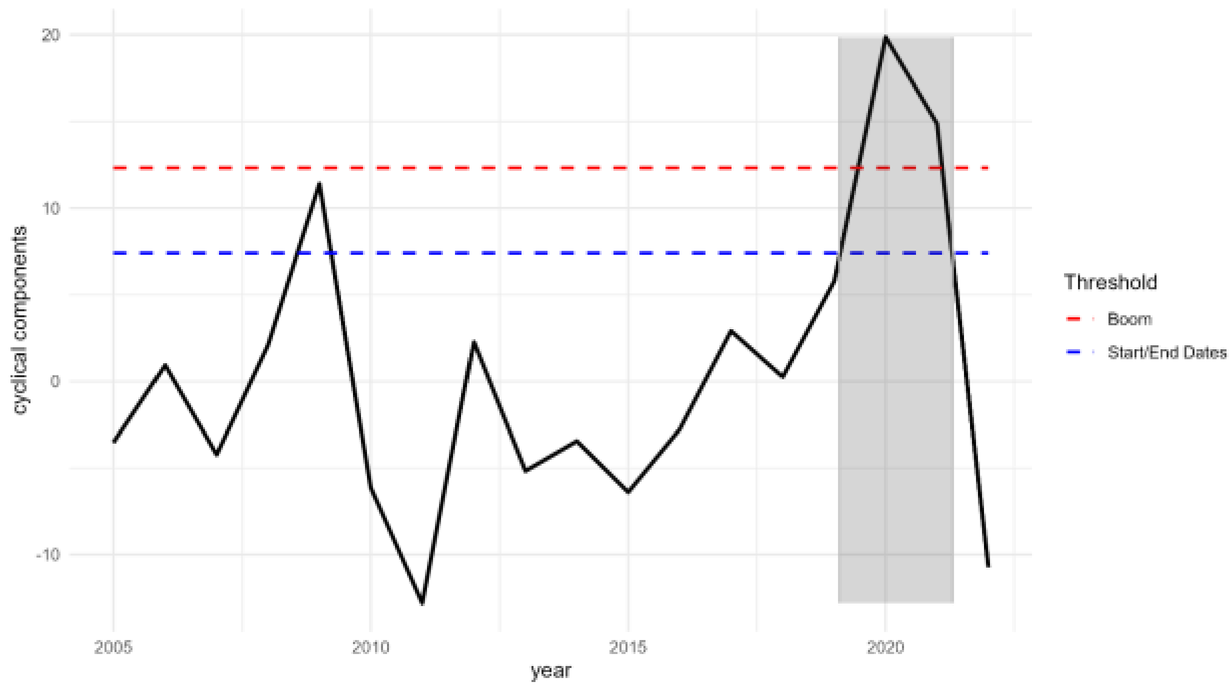
[5] Specifically, this high correlation prevents us from transforming the credit inclusion variables into binary variables, as they tend to be nearly identical, leading to perfect multicollinearity.

[6] See Annex 2 for the detailed construction of this variable.

[7] Muller and Verner (2023) also use the private credit-to-GDP ratio for boom identification and Hamilton (2018) for filtering. Alternatively, real private credit and the HP filter can be used, as in Mendoza and Terrones (2008). The identification of credit booms does not change significantly with changes in the credit indicator chosen, showing less than a 10 percent difference between them.

[8] Following Mendoza and Terrones (2008), we set the boom threshold multiple at 1.75, and the start and end-year multiples at 1.0. See Annex 3.4 for results with different boom thresholds.

Figure 1. Japan: Illustration of Credit Boom Identification



Source: Authors' calculations using IMF GDD.

C. Financial Stability

We use different measures of financial stability to explore the potential cost of rapidly expanding credit or credit inclusion. Our primary measure of financial distress is the banking crisis data from Laeven and Valencia (2020). Banking crisis dates are identified based on the following criteria: (i) significant signs of financial distress in the banking system and (ii) significant banking policy interventions in response to significant losses in the banking system. We define a dummy variable (**crises**) that equals 1 if a country is experiencing a banking crisis in a given year and 0 otherwise.

In addition to the financial crisis data, we use the bank Z-score (**zscore**) and bank nonperforming loans to gross loans (**npl**) from the World Bank Global Financial Development Database as measures of financial distress.

A bank Z-score is calculated as

$$\frac{ROA + equity/assets}{sd(ROA)}$$

, where each variable is aggregated across commercial banks in a country. Simply put, this variable captures the distance to default of a country's banking system. Specifically, since the numerator is a buffer for shocks and the denominator is the volatility of returns, a low Z-score implies a higher default probability while a higher Z-score implies a lower default probability. The ratio of nonperforming loans to gross loans reflects the health of the banking system as higher **npl** ratios result in higher levels of credit losses and erode its loss absorbing capacity.

D. Descriptive Statistics

Finally, we construct our dataset by matching the above boom and financial stability data with the credit inclusion data. When matching, we drop observations with either **borrowers** or **loan_accounts** missing during the same year, so the credit inclusion index **FI** is not missing. Our dataset covers the maximum sample of the FAS: 2004 to 2021 and 96 countries.

Table 1 presents descriptive statistics of our dataset, summarizing credit inclusion and stability variables and the frequency of booms and crises.

For the credit inclusion variable, we report the 3-year changes in **FI**, $\Delta_3 FI_{i,t} = F_{i,t} - F_{i,t-3}$, as well as **FI** itself. Note that the 3-year changes can be expressed as cumulative per-year changes:

$$\Delta_3 \mathrm{FI}_{\mathrm{i,t}} = \underbrace{\mathrm{F}_{\mathrm{i,t}} - \mathrm{F}_{\mathrm{i,t-1}}}_{=\Delta F_{\mathrm{i,t}}} + \underbrace{\mathrm{F}_{\mathrm{i,t-1}} - \mathrm{F}_{\mathrm{i,t-2}}}_{=\Delta F_{\mathrm{i,t-1}}} + \underbrace{\mathrm{F}_{\mathrm{i,t-2}} - \mathrm{F}_{\mathrm{i,t-3}}}_{=\Delta F_{\mathrm{i,t-2}}}.$$

Thus, $\Delta_3 FI$ is informative about how financial inclusion has continuously increased over the recent past. From Table 1, we can see that $\Delta_3 FI$ is distributed around its positive mean, indicating a positive trend in credit financial inclusion worldwide. At the same time, the left tail of this distribution includes negative values, which implies that some countries have experienced decreases in credit inclusion, possibly during economic downturns.

For credit booms and crises, their frequencies are about 10 percent and 5 percent, respectively. Thus, credit booms are infrequent but not extreme events, while crises are considerably rarer. Additionally, crisis dates are available only up to 2017, whereas credit booms are identified up to 2022. Table 2 shows that the global financial crisis years concentrated a substantial proportion of crises, and that crises tended to occur much more frequently in advanced economies; 17.8 percent of the time, compared to 1.6 percent in middle-income countries and zero in low-income countries.

Table 1. Changes in Credit Inclusion and Frequency of Booms and Crises

Variable	N	Countries	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
FI	1222	96	348	396	-272	46	546	3835
FI:3-year changes	936	93	31	120	-415	-5.7	51	1291
boom	942	76	0.1	0.31	0	0	0	1
bad	466	50	0.026	0.16	0	0	0	1
crises	521	54	0.052	0.22	0	0	0	1
npl	773	74	6.9	6.1	0.35	2.9	9.5	49
zscore	939	82	14	7.5	0.22	8.8	19	67

Source: Authors' calculations using IMF FAS, IMF GDD, Laeven and Valencia (2020), and WB GFD.

Table 2. Banking Crises by Income Class

	Income Class		
	Low	Middle	High
# of observations	141	624	231
# of countries	12	52	21
Years of crises	0	10	41
Frequency of crises (%)	0	1.6	17.75
Fraction of crises from 2007 to 2011 relative to all crises (%)		50.0	80.49

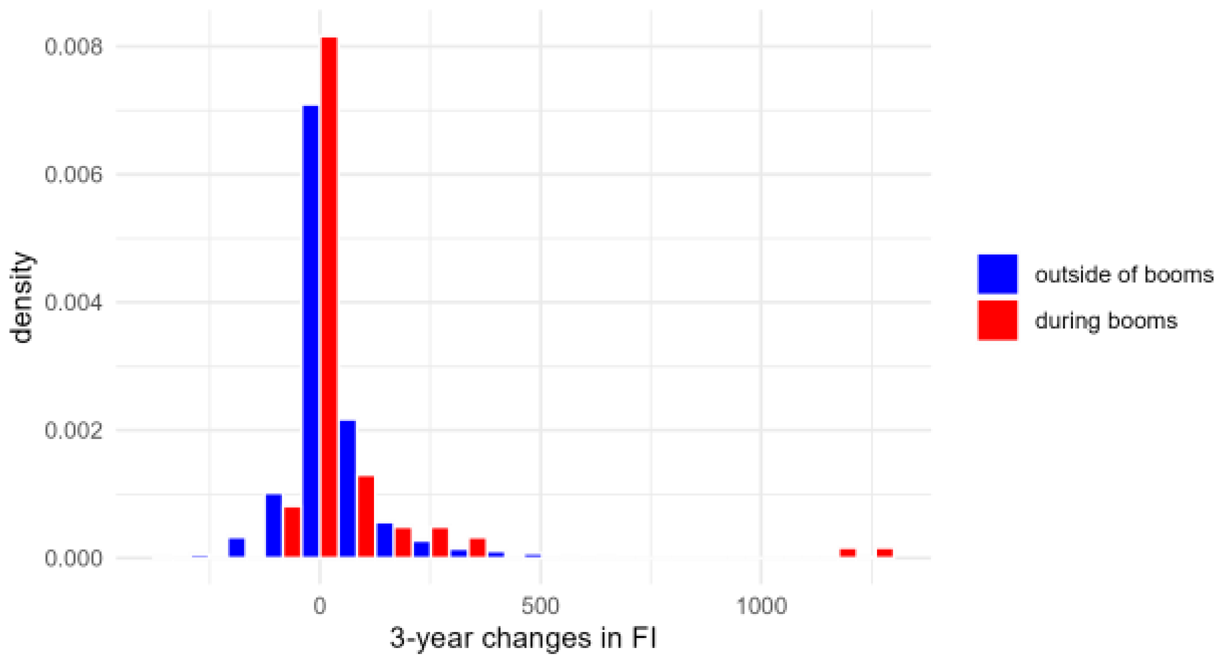
Source: Authors' calculations using Laeven and Valencia (2020).

E. Stylized Facts

Figure 3 shows the distributions of three-year changes in credit inclusion during and outside of booms. The histograms indicate that during booms, the right tails of the distributions are thicker than those outside of booms, and the opposite is true for the left tails, suggesting that increases in credit inclusion are more intensive during booms.

To confirm this, in Table 3 we show average three-year changes in **FI** depending on two types of regimes: (i) whether a boom is occurring or not—“during” or “outside”—and (ii) whether the change in credit inclusion is above or below the historical median—“low” or “high”. Average growth in **FI** is appreciably higher during credit booms, both when it is high and low. Both Figure 3 and Table 3 indicate that during booms, the distributions of changes in credit inclusion are shifted to the right.

Figure 2. Histograms of Changes in Credit Inclusion during vs outside of Booms



Source: Authors calculations using IMF FAS and IMF GDD.

Table 3. 3-year changes in credit inclusion

	Boom	
Changes in FI	outside	during
low	-10.65	9.08
high	79.45	90.48

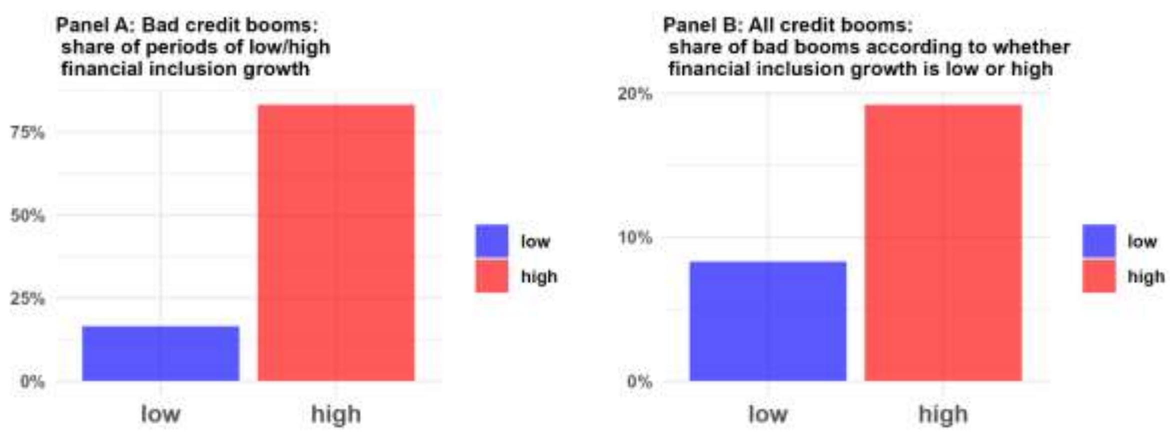
Source: Authors calculations using IMF FAS and IMF GDD.

To examine how changes in credit inclusion interact with booms and subsequent crises, we first classify booms into "bad booms" as those that are followed by a crisis within a three-year window, and "good booms" if they *are not* followed by a crisis within that same window.

Panel A of Figure 4 breaks down the types of changes observed during bad booms. We can see that high growth in credit inclusion is much more prevalent in bad booms. More than 80 percent of bad booms are characterized by rapid credit inclusion, compared to less than 20 percent that exhibit slow credit inclusion.

Panel B of Figure 4 shows the conditional frequencies of bad booms among all booms for high and low changes in credit inclusion. Growth in credit inclusion is more likely to signal that a given boom will end up in crisis. Specifically, Figure 4 indicates that experiencing high growth in credit inclusion and a credit boom simultaneously makes a subsequent crisis more than twice as likely compared to experiencing slow growth in credit inclusion.

Figure 3. Changes in Credit Inclusion and Bad Booms



Source: Authors calculations using IMF FAS, IMF GDD, and Laeven and Valencia (2020).
Note: In Panel A, we compute the conditional frequency of the financial growth types for observations where $bad = 1$. In Panel B, we compute the conditional frequency of bad for observations where $boom = 1$.

These facts emphasize the complementarity between credit inclusion and credit booms in predicting future crises. Let us call credit booms that occur during high credit inclusion "concurrent booms." We can directly compare how informative credit booms alone versus concurrent booms are in predicting future crises. To do this, we calculate the fraction of years in which these indicators correctly (true positives/negatives) or falsely (false positives/negatives) predict the onset of crises.

Table 4 reports the true positive/negative and false positive/negative rates. Panels A and B show these rates when credit booms and concurrent booms, respectively, are used as predictors for crises. Although there are only a few crises (only 3 crises) in a sample for which credit inclusion and aggregate credit are also available, both indicators achieve a better true positive rate than a coin toss (66% > 50%). Moreover, concurrent booms perform better than credit booms alone in reducing false positives (11% > 7.5%). The area under the ROC curve (AUC), a standard statistic for measuring the quality of a predictor, also favors concurrent booms: the AUC is 0.80 for concurrent booms and 0.78 for credit booms. Note that a benchmark of AUC is 0.5, which is attained when a prediction is based on a coin toss.

Table 4. Signal vs State Matrices

Panel A: Predictor = Credit Booms			
	State		
Signal	Crises	No Crises	Total Observations
On	0.667	0.112	38
Off	0.333	0.888	287
Outcomes	3	322	325
Panel B: Predictor = Concurrent Booms			
	State		
Signal	Crises	No Crises	Total Observations
On	0.667	0.075	26
Off	0.333	0.925	299
Outcomes	3	322	325

Source: Authors calculations using IMF FAS, IMF GDD, and Laeven and Valencia (2020).
Note: The first row reports the true and false positive rates, as well as the number of years in which each indicator equals 1. Similarly, the second row reports the corresponding negative rates and the number of years in which each indicator equals 0. The third row shows the number of crises and non-crises.

Bearing in mind the data limitations of this exercise, we find that (i) increases in credit inclusion comove with credit booms, and (ii) rapid increases in credit inclusion are observed during bad booms more frequently than during good booms, (iii) and therefore, rapid credit inclusion might have predictive power for identifying bad booms.

III. Financial Inclusion and Financial Stability

In this section, we empirically examine the relationships among credit inclusion, credit booms, and financial stability by addressing the following questions: (i) Does rapid growth in credit inclusion during credit booms predict subsequent financial instability? (ii) Does rapid growth in credit inclusion predict subsequent credit booms?

A. Identifying "Bad" Financial Inclusion

The analysis in Section 2.5 showed that bad credit booms are considerably more likely when accompanied by an above-average increase in credit inclusion. But what does this imply for financial stability? Does the expansion of credit inclusion itself lead to financial instability? If so, how does it relate to credit booms? Unfortunately, our crisis variable has serious limitations for testing our hypothesis. As shown in Table 2, during our sample periods, banking crises occurred much more frequently in advanced economies than in middle-income countries, and were nonexistent in low-income countries. However, the FAS dataset primarily covers low- to middle-income countries. This discrepancy results in severe information loss and poor matching quality. Specifically, to address financial stability beyond the advanced countries, we need measures that reflect financial distress that does not necessarily result in a full-fledged banking crisis. Therefore, we use such widely recognized measures of banking stability as the Bank Z-score and the ratio of nonperforming loans to gross loans[9].

To answer the above questions, we estimate the following local projections regression (Jorda, 2005), which is in line with the baseline specification of Jorda and Taylor (2016):

$$\Delta_{\mathrm{h}} \mathrm{y}_{\mathrm{i,t+h}} = \alpha_{\mathrm{i}}^{\mathrm{h}} + \beta^{\mathrm{h}} \mathrm{Boom}_{\mathrm{i,t}} + \gamma^{\mathrm{h}} \mathrm{FIBoom}_{\mathrm{i,t}} + \delta^{\mathrm{h}} \mathrm{Boom}_{\mathrm{i,t}} \times \mathrm{FIBoom}_{\mathrm{i,t}} + \sum_{\mathrm{j=0}}^{3} \theta_{\mathrm{j}}^{\mathrm{h}} \Delta \mathrm{y}_{\mathrm{i,t-j}} + \epsilon_{\mathrm{i,t+h}}$$

where $\Delta_{\mathrm{h}} y_{i,t+h} = y_{i,t+h} - y_{i,t}$ is the cumulative change in our measures of financial distress from year t to $t+h$, α_i^h is a horizon-specific country fixed effect, and $\mathrm{FIBoom}_{\mathrm{i,t}}$ takes a value of 1 if the three-year change in financial inclusion, $\Delta_3 \mathrm{FI}_{i,t}$, exceeds the top 25th percentile of its country-specific long-run distribution[10]. Since $\mathrm{FIBoom}_{\mathrm{i,t}}$ indicates a rapid increase in financial inclusion, it can be interpreted as an indicator of *credit inclusion booms*. The specification controls for the lags of the dependent variable in addition to the financial and inclusion boom variables, and their interaction. In the following analysis, we use Driscoll and Kraay (1998)'s robust standard errors.

Our parameter of interest is $\gamma^h + \delta^h$, which measures the predictive properties of credit inclusion booms during credit booms for future financial distress. To see why this is the case, assuming the mean independence condition, observe that $\gamma^h + \delta^h$ can be written as follows:

[9] In Annex 4, we also conduct an exercise using an alternative measure, the riskiness of credit allocation (**RCA**), which has been shown to contain predictive power for future financial stress. However, it covers a more limited sample of countries and includes only listed firms, so one would expect the association with FI to be as strong as with banking systemwide measures such as **npl** and **zscore**.

[10] Alternatively, we can choose different percentiles (e.g., top 15th percentile), but the results are similar; see Annex 3.

$$\gamma^h + \delta^h = \underbrace{E\big[y_{i,t+h} - y_{i,t-1} \big| Boom_{i,t} = FIBoom_{i,t} = 1\big] - E\big[y_{i,t+h} - y_{i,t-1} \big| Boom_{i,t} = 1, FIBoom_{i,t} = 0\big]}_{\text{effects of credit inclusion boom during credit boom}}$$

Another parameter of interest is γ^h, which measures the influence of credit inclusion booms outside of credit booms on changes in financial stability. It can be written as:

$$\gamma^h = \underbrace{E\big[y_{i,t+h} - y_{i,t-1} \big| Boom_{i,t} = 0, FIBoom_{i,t} = 1\big] - E\big[y_{i,t+h} - y_{i,t-1} \big| Boom_{i,t} = FIBoom_{i,t} = 0\big]}_{\text{effects of credit inclusion outside of credit boom}}$$

By comparing $\gamma^h + \delta^h$ and γ^h, we can identify whether and when credit inclusion booms are detrimental to financial stability.

Figure 5 shows the impulse response functions (i.e., the estimated $\gamma^h + \delta^h$ and γ^h) for horizons of $h = 1, \ldots, 4$ with outcomes being set to either **npl** (left) or **zscore** (right). Note that while a higher **npl** indicates greater financial stress, a lower **zscore** implies a higher probability of default. Thus, an increase in **npl** and a decrease in **zscore** both signal heightened financial instability. In Figure 5, the solid red line represents linearly extrapolated point estimates of $\gamma^h + \delta^h$, the blue dashed line represents those of γ^h, and shaded areas show 95 percent confidence intervals for $\gamma^h + \delta^h$.

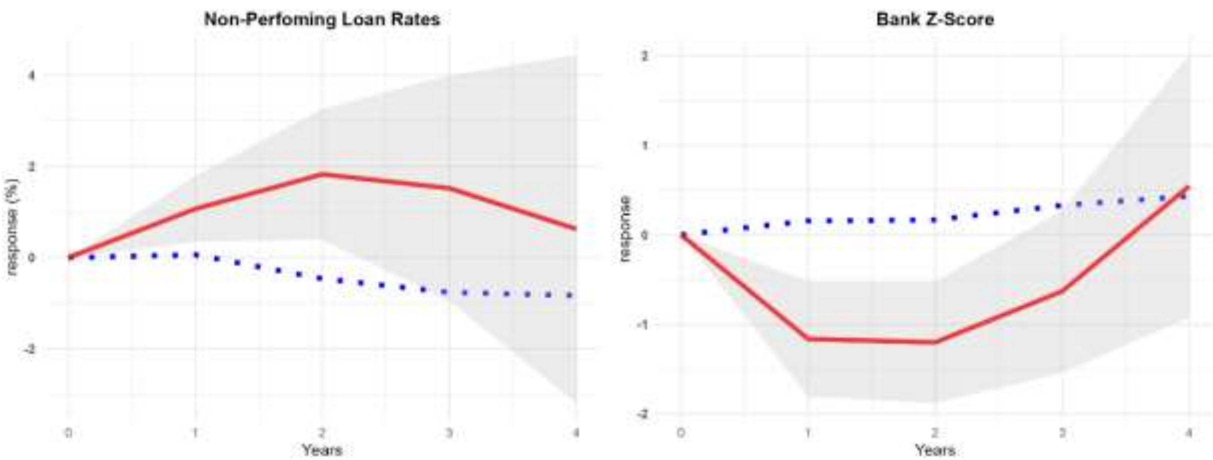
Figure 5 provides strong evidence that credit inclusion booms during credit booms predict financial instability, as measured by the non-performing loan rates and the bank Z-score. The effects are economically large: simultaneous credit inclusion and credit boom predicts nonperforming loan rates to increase by as much as 2 percent compared to the baseline. Interestingly, the estimates for γ^h are negative and move in the opposite direction to those of $\gamma^h + \delta^h$, suggesting that credit inclusion booms can be beneficial for financial stability during non-boom episodes.

Similarly, we can look at the predictive power of credit booms for financial instability by examining β^h (credit boom effects outside of credit inclusion booms) and $\beta^h + \delta^h$ (credit boom effects during credit inclusion booms), rather than γ^h and $\gamma^h + \delta^h$. Figure 6 shows the impulse response functions for the credit boom effects. The results indicate that credit booms during credit inclusion booms predict financial instability, with a similar magnitude to the one found for inclusion booms during credit booms. The baseline credit boom effects, β^h, are smaller than or opposite to the simultaneous boom effects, $\beta^h + \delta^h$, confirming the complementarity between credit inclusion and credit booms in predicting future financial distress.

To further validate the complementarity between these two booms, we run the regression excluding the interaction term $Boom_{i,t} \times FIBoom_{i,t}$. Panel B of Table 5 presents the results of this regression. A comparison of Panels A and B of Table 5 reveals that the interaction effects largely dominate the individual effects of credit booms and credit inclusion booms when complementarity is not considered. This result reinforces our hypothesis that credit inclusion booms, when combined with credit booms, serve as significant indicators of future financial distress. Indeed, in the regressions without the interaction term, one would conclude that inclusion booms do not have any explanatory power for predicting changes to NPLs or Z-scores, as opposed to when the interaction term is included. This may explain the common mixed results in the literature regarding the effect of inclusion booms on financial instability. Furthermore, the R-squared is significantly higher in the regression including the interaction term compared to the one without it.

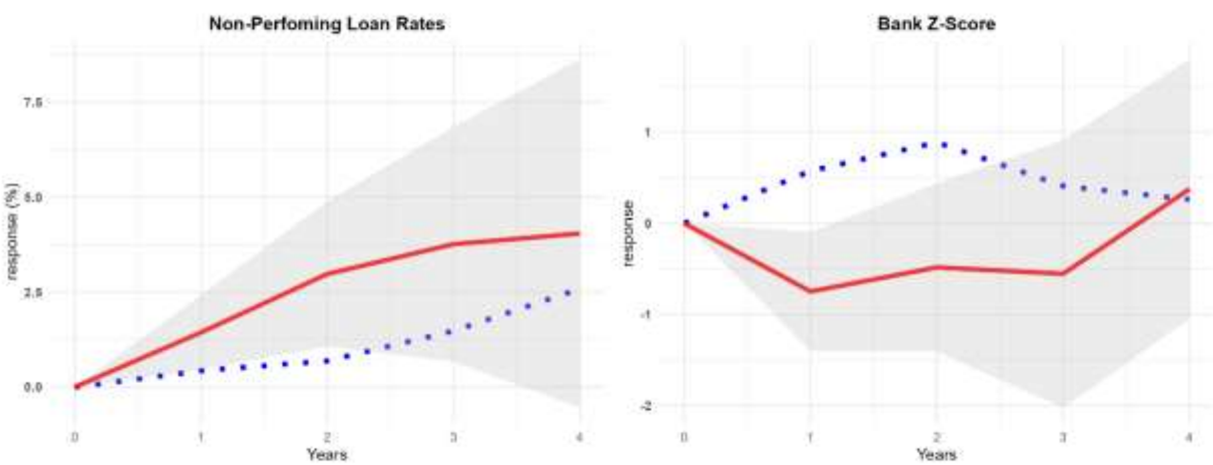
In summary, our findings show that credit inclusion and credit booms are complementary in predicting subsequent financial instability. This allows us to identify potentially harmful credit inclusion booms by examining whether the economy is in a credit boom. Likewise, the presence of a credit inclusion boom can also help predict whether a credit boom will be problematic. This result has important policy implications: policymakers should be doubly vigilant of financial stability issues if a credit boom is taking place concurrently with a credit inclusion boom.

Figure 4. Impulse response functions from credit inclusion boom shocks



Note: The red real line depicts the estimated $\gamma^h + \delta^h$, and the blue dashed line depicts the estimated γ^h. The shaded area represents 95% confidence interval for $\gamma^h + \delta^h$, computed from Driscoll and Kraay (1998)'s robust standard error.

Figure 5. Impulse response functions from credit boom shocks



Note: The red real line depicts the estimated $\beta^h + \delta^h$, and the blue dashed line depicts the estimated β^h. The shaded area represents 95% confidence interval for $\beta^h + \delta^h$, computed from Driscoll and Kraay (1998)'s robust standard error.

Table 5. Effects of credit inclusion and credit booms on financial instability

Panel A: Model with Interaction

	Dependent variable: Non-Perfoming Loan Rates				Dependent variable: Bank Z-Score			
Variable	t+1	t+2	t+3	t+4	t+1	t+2	t+3	t+4
Boom	0.43 (0.35)	0.69 (0.66)	1.48 (1.18)	2.58 (2.26)	0.57 (0.36)	0.89+ (0.45)	0.41 (0.44)	0.26 (0.66)
FIBoom	0.06 (0.25)	-0.46 (0.37)	-0.76 (0.67)	-0.83 (0.73)	0.16 (0.20)	0.17 (0.26)	0.33 (0.31)	0.43 (0.27)
Boom*FIBoom	1.01* (0.51)	2.29** (0.71)	2.28** (0.80)	1.46 (0.91)	-1.32** (0.50)	-1.37** (0.49)	-0.96 (0.66)	0.11 (0.37)
Observations	349	299	250	203	445	390	338	292
Countries	52	50	47	42	59	55	50	49
R2	0.032	0.059	0.077	0.093	0.156	0.239	0.202	0.341

Panel B: Model without Interaction

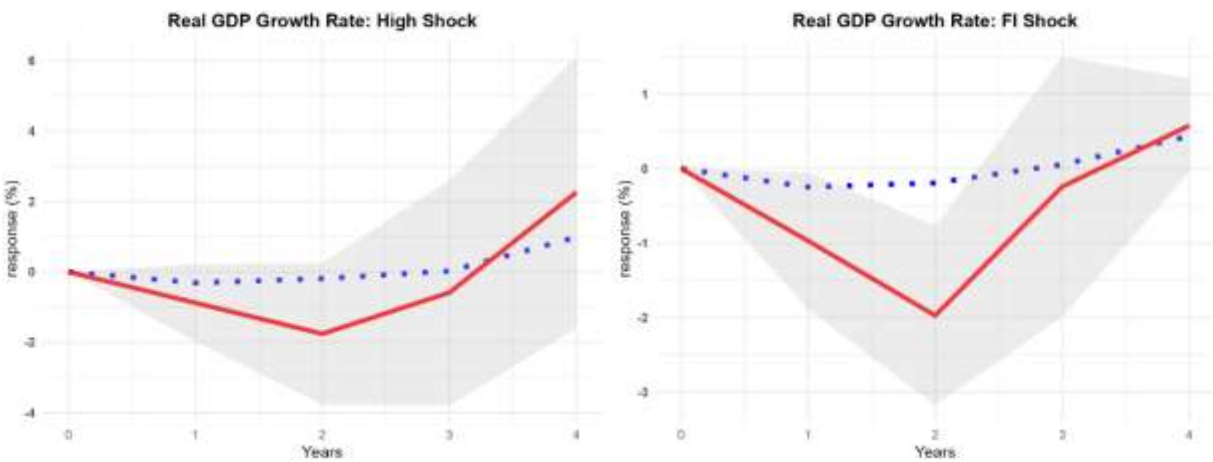
	Dependent variable: Non-Perfoming Loan Rates				Dependent variable: Bank Z-Score			
Variable	t+1	t+2	t+3	t+4	t+1	t+2	t+3	t+4
Boom	0.83** (0.33)	1.54* (0.67)	2.28+ (1.22)	3.15 (2.18)	0.07 (0.25)	0.38 (0.33)	0.08 (0.46)	0.30 (0.65)
FIBoom	0.15 (0.23)	-0.24 (0.37)	-0.53 (0.63)	-0.67 (0.69)	-0.01 (0.18)	-0.01 (0.25)	0.20 (0.27)	0.45+ (0.24)
Observations	349	299	250	203	445	390	338	292
Countries	52	50	47	42	59	55	50	49
R2	0.025	0.041	0.063	0.087	0.143	0.228	0.196	0.341

Note: +, *, and ** denote significance at the 10%, 5%, 1% level, respectively. The outcomes are transformed so the presented estimates are read in %. The standard errors are based on Driscoll and Kraay (1998).

Since the non-performing loan rates and bank z-scores are indirect measures of financial stability, it is still not clear whether concurrent inclusion and credit booms can predict significant economic downturns. To fill this gap, we can complement our analysis by replacing these variables with the real GDP growth rates. Here, in addition to the binary $FIBoom$ variable, we also consider a model that features the changes in financial inclusion, $\Delta_3 FI$, as a regressor.

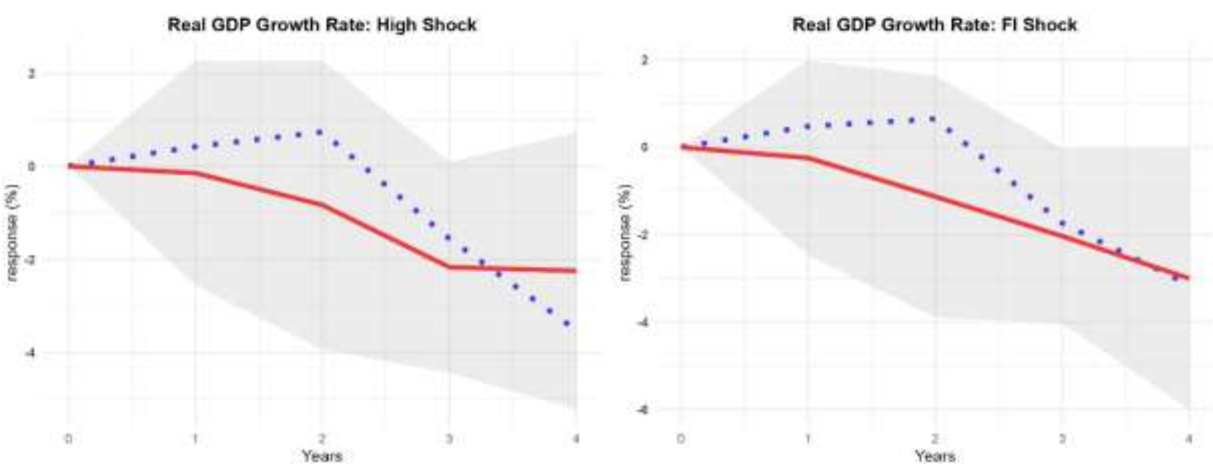
Similar to the previous analysis, Figures 7 and 8 present the impulse response functions for the effects of credit inclusion booms and credit booms, respectively. Although the estimates are noisier than before, we find that concurrent inclusion and credit booms have short-term negative effects on economic growth, reaching as much as -2%. We also find that credit inclusion booms alone have smaller impacts on economic growth compared to concurrent booms. These results suggest that credit inclusion and credit booms are complementary in predicting severe financial instability accompanied by sharp economic downturns, thereby reinforcing the usefulness of concurrent booms as key economic indicators.

Figure 6. Impulse response functions from credit inclusion boom shocks: Real GDP Growth



Note: The red real line depicts the estimated $\gamma^h + \delta^h$, and the blue dashed line depicts the estimated γ^h. The shaded area represents 95% confidence interval for $\gamma^h + \delta^h$, computed from Driscoll and Kraay (1998)'s robust standard error. The left and right figures show the IRFs when $High$ and $\Delta_3 FI$ are used as regressors, respectively.

Figure 7. Impulse response functions from credit boom shocks: Real GDP Growth



Note: The red real line depicts the estimated $\beta^h + \delta^h$, and the blue dashed line depicts the estimated β^h. The shaded area represents 95% confidence interval for $\beta^h + \delta^h$, computed from Driscoll and Kraay (1998)'s robust standard error. The left and right figures show the IRFs when $FIBoom$ and $\Delta_3 FI$ are used as regressors, respectively

Table 6. Effects of credit inclusion and credit booms on real GDP growth rates

Panel A: Model with FIBoom

	Dependent variable: Real GDP Growth Rates			
Variable	t+1	t+2	t+3	t+4
Boom	0.42 (0.82)	0.74 (1.42)	-1.56 (1.94)	-3.52 (2.47)
FIBoom	-0.31 (0.42)	-0.19 (0.74)	0.02 (0.96)	0.98 (1.31)
Boom*FIBoom	-0.57 (1.24)	-1.57 (1.62)	-0.61 (1.72)	1.28 (2.12)
Observations	592	530	465	401
Countries	69	68	65	61
R2	0.004	0.006	0.01	0.021

Panel B: Model with FI

	Dependent variable: Real GDP Growth Rates			
Variable	t+1	t+2	t+3	t+4
Boom	0.48 (0.67)	0.65 (1.21)	-1.74 (1.79)	-3.15 (2.39)
FI	-0.25 (0.17)	-0.19 (0.35)	0.05 (0.48)	0.43 (0.59)
Boom*FI	-0.72 (0.54)	-1.78** (0.64)	-0.30 (0.98)	0.14 (1.00)
Observations	592	530	465	401
Countries	69	68	65	61
R2	0.008	0.014	0.01	0.019

Note: : +, *, and ** denote significance at the 10%, 5%, 1% level, respectively. The outcomes are transformed so the presented estimates are read in %. The standard errors are based on Driscoll and Kraay (1998).

B. Credit Booms Fueled by Credit Inclusion

The stylized facts presented in Section 2 highlight the co-movement between financial inclusion growth and credit booms. This co-movement may be driven by the mechanism in which financial inclusion growth contributes to credit growth along the extensive margin. If this mechanism is strong enough to trigger a credit boom, we can hypothesize that rapid growth may serve as a predictor of a subsequent credit boom.

To test this hypothesis, we run the following predictive regression, similar to the specification of Greenwood, et al. (2022):

$$\mathrm{Boom}_{i,t\rightarrow t+h} = \alpha_i^h + \beta^h \mathrm{FIBoom}_{\mathrm{i,t}} + \sum_{\mathrm{j=1}}^{3} \theta_{\mathrm{j}}^{\mathrm{h}} \mathrm{Boom}_{\mathrm{i,t-j}} + \epsilon_{i,t+h}$$

where $Boom_{i,t\rightarrow t+h} = max\{Boom_{i,t}, Boom_{i,t+1}, \dots, Boom_{i,t+h}\}$ is a dummy variable equal to 1 if a credit boom begins between year t and $t+h$ (here $Boom_{i,t}$ refers to the start year of a boom, not the entire boom episode), α_i^h is a horizon-specific country fixed effect, and $FIBoom_{i,t}$ is a dummy variable equal to 1 if a country experiences a rapid increase in financial inclusion. We also control for the lags of $Boom_{i,t}$. Our primary interest is in β^h, which measures the added probability of experiencing a credit boom following financial inclusion booms.

Table 7, Panel A, presents the results of this regression using $FIBoom_{i,t}$ as an explanatory variable for horizons of $h = 0,1, \dots, 3$. The point estimates suggest that credit inclusion booms can increase the probability of entering a credit boom by up to 5 percent, with statistical significance. This result is notable given that the unconditional probability of experiencing a credit boom is approximately 10 percent, as shown in Table 1. The effect peaks one year after a credit inclusion boom, with the added probability decreasing over time. Note that in this regression, both the outcome and the independent variable are binary, which results in a reduction of variation in data and noisy estimates.

To measure the signaling quality of credit inclusion booms in predicting credit booms, we report the area under the ROC curve (AUC) in Table 7. We find that the AUC values derived from our regression models are substantially higher than the benchmark of 0.5, indicating that credit inclusion booms are highly informative in predicting future credit booms.

To retain more variation in data, we replace $FIBoom_{i,t}$ with the standardized $\Delta_3 FI_{i,t}$ where the mean is 0 and the standard deviation is 1. In this case, β^h represents the added probability of a credit boom when the three-year change in the financial inclusion index increases by one standard deviation. Although this no longer directly indicates a credit inclusion boom, it still captures a rapid growth in financial inclusion.

Table 7, Panel B, reports the result from this regression with $\Delta_3 FI_{i,t}$ as the explanatory variable. The point estimates remain similar to those in the previous specification but with greater precision due to the increased variability in the independent variable. Also, similar magnitudes of AUCs are reported as before. This strengthens the evidence that a rapid increase in financial inclusion can signal the heightened probability of a credit boom in the near future.

In addition, we run the following regression, replacing credit booms as the dependent variable with credit inclusion booms:

$$\mathrm{FIBoom}_{\mathrm{i,t\to t+h}} = \alpha_i^h + \beta^h \mathrm{Boom}_{\mathrm{i,t}} + \sum_{\mathrm{j=1}}^{3} \theta_{\mathrm{j}}^{\mathrm{h}}\, \mathrm{FIBoom}_{i,t-j} + \epsilon_{i,t+h}.$$

The objective is to determine whether credit inclusion booms can predict credit booms. If they cannot, it would suggest that credit inclusion booms indeed precede the onset of credit booms.

Table 8 presents the results of this regression. Although the point estimates are substantially larger, they are also considerably noisier than the previous estimates. The implied AUC values are notably lower than those obtained when predicting credit booms from credit inclusion booms, indicating that credit booms weakly signal the onset of credit inclusion booms in the near future. Consequently, these findings support the idea that credit inclusion booms precede credit booms and may serve as a useful predictor of them.

The findings from these regressions support our hypotheses that a financial inclusion boom can signal a subsequent credit boom. Thus, monitoring financial inclusion can be an effective tool for predicting future credit booms.

Table 7. Predictive Regression: Credit Inclusion Booms Preceding Credit Booms

Panel A: Model with FIBoom

	Dependent Variable: Credit Booms within...			
Variable	1 year	2 years	3 years	4 years
FIBoom	2.93* (1.48)	5.47+ (2.90)	2.37 (3.45)	0.22 (3.48)
Observations	699	633	503	322
Countries	70	68	65	52
R2	0.039	0.077	0.112	0.293
AUC	0.873	0.884	0.854	0.84

Panel B: Model with FI

	Dependent Variable: Credit Booms within...			
Variable	1 year	2 years	3 years	4 years
FI	1.25* (0.59)	2.52* (1.18)	4.07* (1.89)	3.95* (2.00)
Observations	699	633	503	322
Countries	70	68	65	52
R2	0.038	0.077	0.131	0.309
AUC	0.896	0.899	0.846	0.846

Note: +, *, and ** denote significance at the 10%, 5%, 1% level, respectively. The outcomes are multiplied by 100 so the presented estimates are read in %. The standard errors are based on Driscoll and Kraay (1998).

Table 8. Predictive Regression: Credit Booms Preceding Credit Inclusion Booms

	Dependent Variable: Credit Inclusion Booms within...			
Variable	1 year	2 years	3 years	4 years
Boom	6.41 (5.04)	8.19 (8.52)	1.58 (9.73)	8.35 (12.21)
Observations	490	438	325	176
Countries	64	61	54	40
R2	0.067	0.154	0.255	0.346
AUC	0.746	0.769	0.726	0.751

Note: +, *, and ** denote significance at the 10%, 5%, 1% level, respectively. The outcomes are multiplied by 100 so the presented estimates are read in %. The standard errors are based on Driscoll and Kraay (1998).

IV. Conclusion

The trade-off between financial inclusion on the credit side—credit inclusion—and financial instability has long been a concern for policymakers. Although it is well known that financial instability often follows periods of credit booms, the link between credit inclusion and financial stability has been less clear. Our paper contributes to this topic by showing that credit inclusion that takes place during a credit boom has significant predictive power for future financial instability using different measures of financial distress and financial crisis. Our results indicate that credit booms that are not accompanied by credit inclusion booms do not predict future instability, thus placing credit inclusion at the center of the relationship between credit booms and financial instability.

In addition, our findings show that during credit booms, credit inclusion increases more sharply than during non-boom periods. In addition, rapid financial inclusion growth is found to predict subsequent credit booms, while the opposite does not seem to hold: credit booms do not tend to predict subsequent rapid increases in credit inclusion. These results together point to the importance of the extensive margin of credit booms in planting the seeds of financial instability.

Several policy implications arise from our findings. First, when promoting financial inclusion, it is critical to monitor the current levels of private credit in the economy[11]. If the economy is in the midst of a credit boom, promoting financial inclusion may heighten the risk of financial instability and crisis. Second, financial inclusion data can be a valuable tool for identifying bad booms and predicting future credit booms. Therefore, timely and comprehensive data on financial inclusion in general, and credit inclusion in particular, are highly desirable for effective policymaking. For example, while the FAS dataset has been valuable in helping to uncover the results, its annual frequency is still a limitation. Therefore, countries could usefully make efforts to collect and monitor financial inclusion indicators at a higher frequency.

The results of our paper call for more research to be done to better understand the channel through which concurrent credit and inclusion booms lead to financial stability. Is it simply the case of lower credit extension standards that makes the financial system more vulnerable and simultaneously drives a boom in credit and in inclusion? Do concurrent credit and inclusion booms lead to higher and more widespread asset price increases that end up in crisis? Furthermore, are there specific sectors in which concurrent booms are more likely to endanger financial stability? The answers to such questions will give us better insights into the channels through which credit and inclusion booms signal instability and help policymakers identify problematic credit booms better in real time. We leave the study of such questions to future research.

[11] These policy implications are consistent with the IMF GFSR study "Loose Financial Conditions, Rising Leverage and Risks to Macrofinancial Stability" (Global Financial Stability Report, April 2021: Preempting a Legacy of Vulnerabilities).

Annex

Annex 1. Credit Inclusion and Indicators from the WBES and Findex

Some financial inclusion measures on the credit side are found in WBES and Findex datasets, but have very few time observations (particularly Findex) and/or are available at highly irregular time intervals (particularly WBES). For this reason, they are not suited to use in time series regressions. However, we sought to draw comparisons with the FAS indicators used in our empirical analysis and these user-side indicators. From WBES, we took the (i) share of firms using banks to finance investments (**fbankinv1**), (ii) share of firms using banks to finance working capitals (**fbankwk1**), (iii) share of investments financed by banks (**fbankinv2**), (iv) share of working capitals financed by banks (**fbankwk2**), (v) share of firms identifying access to finance as a non-major constraint (**fcredobst**), (vi) share of firms with a bank loan or credit line (**fbankln**), and (vii) share of small firms with a bank loan or credit line (**fsmbankln**). From Findex, we took the (i) share of adults who borrowed from a formal financial institution in the past year (**bor**) and (ii) share of adults who borrowed money from any source in the past year (**borany**).

Annex: Table 1 reports the comparison of our supplier-side financial inclusion measure with the above user-side financial inclusion variables. We can see that there is little correlation between our measure and the others. However, the conditional shares of increases in our financial inclusion measure, given increases in the other financial inclusion measures, are close to 100 percent, indicating that both types of variables tend to coincide in tracking increases in credit financial inclusion.

Since our analysis focuses on what happens when there is a rapid increase in our financial inclusion measure, one can expect that similar results would be obtained if WBES and Findex data were available for a longer time period, and at a greater and more regular frequency.

Annex Table 1. Comparing WBES/Findex with FI

			fbankinv1	fbankwk1	fbankinv2	fbankwk2	fcredobst	fbankln	fsmbankln	bor	borany
		# of observations	78	65	78	65	78	77	77	176	116
		# of countries	53	53	53	53	53	52	52	73	69
Financial Inclusion Measure		# of common observations	78	65	78	65	78	77	77	176	116
		Correlation	-0.22	-0.08	-0.15	-0.01	0.06	-0.13	-0.12	0.28	0.12
	Share in total common observations (%)	Simultaneous increases	61.54	55.38	46.15	52.31	30.77	42.86	44.16	62.50	46.55
		Simultaneous decreases	0.00	0.00	0.00	1.54	1.28	0.00	0.00	0.57	0.86
	Share in total # of increases or decreases in ES financial inclusion (%)	Simultaneous increases	97.96	97.30	97.30	100.00	100.00	97.06	97.14	99.10	98.18
		Simultaneous decreases	0.00	0.00	0.00	3.23	1.85	0.00	0.00	1.54	1.64

Source: Authors calculations using IMF FAS, WB ES, and WB Findex

Annex 2. Construction of the Composite FI Measure

The idea is to find country-specific weights w_i such that[12]:

$$FI_{i,t} = w_{b,i}\text{borrower}_{i,t} + \mathrm{w_{l,i}loan_{i,t}}.$$

Technically, the weights $\left(w_{b.i}, w_{l,i}\right)$ are the eigenvector corresponding to the largest eigenvalue of the correlation matrix computed from $borrower_{i,t}$ and $loan_{i,t}$ for country i's time horizon. Intuitively, these weights measure how important each variable is for explaining variations in the data. We find that in virtually all countries the two weights are similar, $w_{b,i} \sim w_{l,i} \sim 0.71$, for each country i, reflecting the fact that these variables have strong correlations and similar importance[13].

Furthermore, as described in Annex 1, we compare changes in **FI** with changes in measures based on the two surveys described above of users of financial system credit. These measures tend to be more detailed and target specific users (firms or households) and, in some cases, different uses (for example, working capital or investment). However, as mentioned above, the frequency of observations is much lower and, for some measures, is not consistent across countries, so they are less useful than **FI** for the purposes of our analysis. We find that, although there is low correlation between **FI** and these other measures, they tend to be quite consistent directionally; when **FI** signals an increase in credit inclusion, this signal is shared by the other indicators as well.

Annex 3. Robustness Checks

3.1 Credit inclusion booms with different thresholds

In Section 3.1-3.2, we defined $FIBoom_{i,t}$ as a dummy variable equal to 1 if $\Delta_3 FI_{i,t}$ exceeds the top 25th percentile of its long-run distribution. Alternatively, we can select different quantiles for this definition.

As an illustration, we present the results when the top 15th percentile is used for $FIBoom_{i,t}$ in both the predictive and local projections regression. In both cases, the estimates become noisier compared to the top 25th percentile case, due to the reduction in variation in $FIBoom_{i,t}$. However, the results are qualitatively similar to those found in Section 3.1-3.2, as shown in Panel A of Annex Table 2, Annex Table 3, and Annex Figures 1 and 2 below.

[12] Through this procedure, we are forced to drop observations where either the borrower or loan data is missing. The borrower and loan variables have 1,650 and 1,786 observations, respectively, but only 1,222 observations in common.

[13] In Annex 3, we confirm that there is no significant information loss when using the composite FI measure by comparing results with those obtained using **borrower** and loan separately.

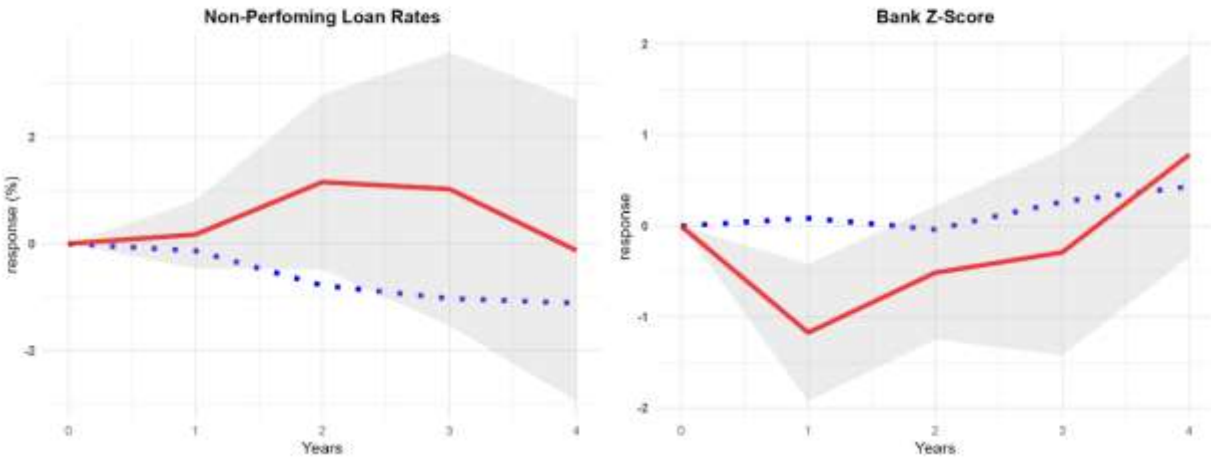
Annex Table 2. Predictive regression with credit inclusion booms based on the top 15th percentile

Panel A: Model with FIBoom				
	Dependent Variable: Credit Booms within...			
Variable	1 year	2 years	3 years	4 years
FIBoom	2.68 (1.78)	5.46 (3.35)	2.85 (3.63)	0.75 (3.79)
Observations	699	633	503	322
Countries	70	68	65	52
R2	0.037	0.074	0.113	0.293
AUC	0.876	0.878	0.854	0.846

Panel B: Model with FI				
	Dependent Variable: Credit Booms within...			
Variable	1 year	2 years	3 years	4 years
FI	1.25* (0.59)	2.52* (1.18)	4.07* (1.89)	3.95* (2.00)
Observations	699	633	503	322
Countries	70	68	65	52
R2	0.038	0.077	0.131	0.309
AUC	0.896	0.899	0.846	0.846

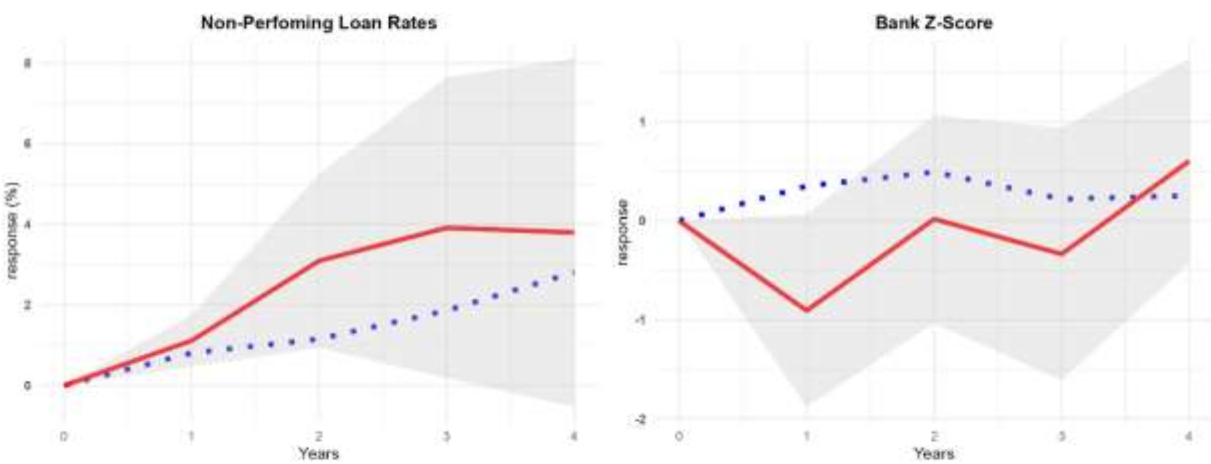
Note: +, *, and ** denote significance at the 10%, 5%, 1% level, respectively. The outcomes are multiplied by 100 so the presented estimates are read in %. The standard errors are based on Driscoll and Kraay (1998).

Annex Figure 1. Impulse response functions from credit inclusion boom shocks with $FIBoom_{i,t}$ based on the top 15th percentile



Note: The red real line depicts the estimated $\gamma^h + \delta^h$, and the blue dashed line depicts the estimated γ^h. The shaded area represents 95% confidence interval for $\gamma^h + \delta^h$, computed from Driscoll and Kraay (1998)'s robust standard error.

Annex Figure 2. Impulse response functions from credit boom shocks with $FIBoom_{i,t}$ based on the top 15th percentile



Note: The red real line depicts the estimated $\beta^h + \delta^h$, and the blue dashed line depicts the estimated β^h. The shaded area represents 95% confidence interval for $\beta^h + \delta^h$, computed from Driscoll and Kraay (1998)'s robust standard error.

Annex Table 3. Effects of credit inclusion and credit booms on financial instability with credit inclusion booms based on the top 15th percentile

Panel A: Model with Interaction

	Dependent variable: Non-Perfoming Loan Rates				Dependent variable: Bank Z-Score			
Variable	t+1	t+2	t+3	t+4	t+1	t+2	t+3	t+4
Boom	0.81* (0.37)	1.15+ (0.66)	1.86+ (1.09)	2.81 (2.08)	0.35 (0.31)	0.49 (0.39)	0.22 (0.52)	0.25 (0.71)
FIBoom	-0.13 (0.25)	-0.78+ (0.46)	-1.03 (0.79)	-1.11 (0.85)	0.09 (0.22)	-0.04 (0.27)	0.27 (0.26)	0.43 (0.28)
Boom*FIBoom	0.31 (0.43)	1.94+ (1.04)	2.05 (1.28)	0.99 (0.96)	-1.26** (0.52)	-0.47 (0.53)	-0.56 (0.72)	0.35 (0.54)
Observations	349	299	250	203	445	390	338	292
Countries	52	50	47	42	59	55	50	49
R2	0.025	0.06	0.08	0.1	0.153	0.23	0.197	0.341

Panel B: Model without Interaction

	Dependent variable: Non-Perfoming Loan Rates				Dependent variable: Bank Z-Score			
Variable	t+1	t+2	t+3	t+4	t+1	t+2	t+3	t+4
Boom	0.86** (0.33)	1.48* (0.65)	2.12+ (1.09)	2.96 (1.99)	0.08 (0.24)	0.39 (0.32)	0.10 (0.46)	0.32 (0.64)
FIBoom	-0.11 (0.24)	-0.62 (0.46)	-0.87 (0.78)	-1.03 (0.86)	-0.07 (0.20)	-0.10 (0.25)	0.19 (0.24)	0.48* (0.24)
Observations	349	299	250	203	445	390	338	292
Countries	52	50	47	42	59	55	50	49
R2	0.024	0.051	0.073	0.098	0.143	0.229	0.196	0.341

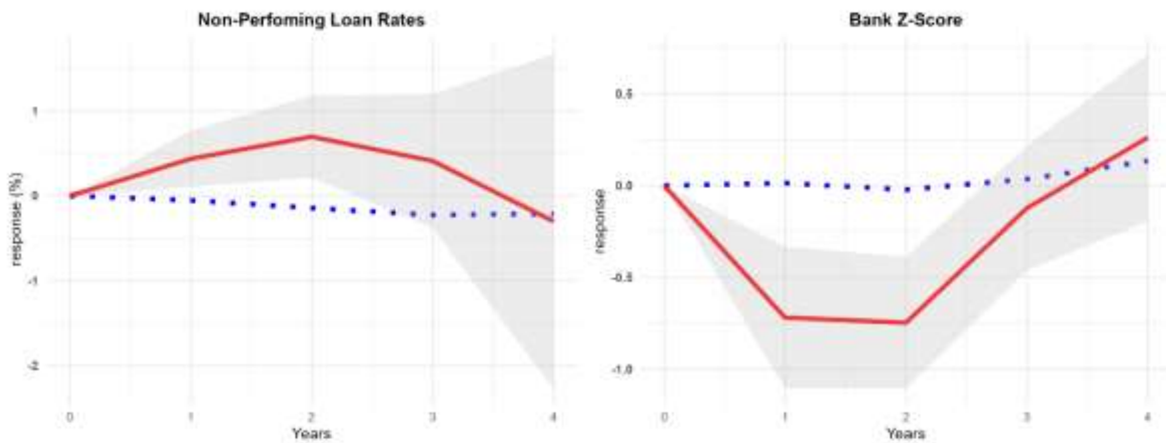
Note: +, *, and ** denote significance at the 10%, 5%, 1% level, respectively. The outcomes are transformed so the presented estimates are read in %. The standard errors are based on Driscoll and Kraay (1998).

3.2 Local Projections regression with continuous Regressor

In Section 3.1, we used $FIBoom_{i,t}$ as one of the main regressor to examine the effects of concurrent financial inclusion and credit booms on financial stability. Similarly, we can replace $FIBoom_{i,t}$ with the standardized $\Delta_3 FI_{i,t}$, which may improve estimation precision due to the increased variation in the regressors.

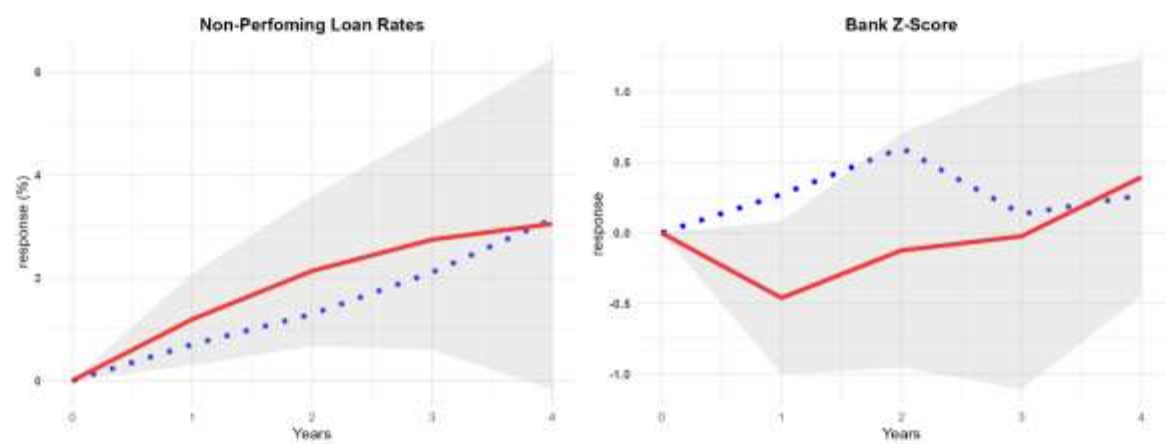
Panel B of Annex Table 4 and the following figures show that similar financial inclusion boom effects and credit boom effects are observed, consistent with the results in the main text. Thus, our findings are robust to the choice of regressor.

Annex Figure 3. Impulse response functions from credit inclusion boom shocks with the continuous regressor



Note: The red real line depicts the estimated $\gamma^h + \delta^h$, and the blue dashed line depicts the estimated γ^h. The shaded area represents 95% confidence interval for $\gamma^h + \delta^h$, computed from Driscoll and Kraay (1998)'s robust standard error.

Annex Figure 4. Impulse response functions from credit boom shocks with the continuous regressor



Note: The red real line depicts the estimated $\beta^h + \delta^h$, and the blue dashed line depicts the estimated β^h. The shaded area represents 95% confidence interval for $\beta^h + \delta^h$, computed from Driscoll and Kraay (1998)'s robust standard error.

Annex Table 4. Effects of rapid growth in credit inclusion and credit booms on financial instability

Panel A: Model with Interaction

	Dependent variable: Non-Perfoming Loan Rates				Dependent variable: Bank Z-Score			
Variable	t+1	t+2	t+3	t+4	t+1	t+2	t+3	t+4
Boom	0.70* (0.35)	1.29+ (0.72)	2.11 (1.30)	3.14 (2.44)	0.27 (0.28)	0.60 (0.41)	0.13 (0.47)	0.27 (0.67)
FI	-0.05 (0.12)	-0.14 (0.25)	-0.23 (0.39)	-0.21 (0.36)	0.01 (0.10)	-0.02 (0.13)	0.04 (0.14)	0.13 (0.20)
Boom*FI	0.49+ (0.25)	0.84** (0.33)	0.64* (0.30)	-0.09 (0.58)	-0.73** (0.27)	-0.73* (0.31)	-0.16 (0.24)	0.13 (0.37)
Observations	349	299	250	203	445	390	338	292
Countries	52	50	47	42	59	55	50	49
R2	0.029	0.049	0.062	0.081	0.159	0.241	0.195	0.337

Panel B: Model without Interaction

	Dependent variable: Non-Perfoming Loan Rates				Dependent variable: Bank Z-Score			
Variable	t+1	t+2	t+3	t+4	t+1	t+2	t+3	t+4
Boom	0.87** (0.35)	1.52* (0.70)	2.26+ (1.25)	3.11 (2.21)	0.10 (0.24)	0.44 (0.33)	0.10 (0.46)	0.28 (0.65)
FI	-0.01 (0.12)	-0.06 (0.26)	-0.15 (0.39)	-0.22 (0.39)	-0.06 (0.10)	-0.10 (0.14)	0.02 (0.13)	0.15 (0.17)
Observations	349	299	250	203	445	390	338	292
Countries	52	50	47	42	59	55	50	49
R2	0.024	0.039	0.057	0.08	0.144	0.23	0.194	0.336

Note: +, *, and ** denote significance at the 10%, 5%, 1% level, respectively. The outcomes are transformed so the presented estimates are read in %. The standard errors are based on Driscoll and Kraay (1998).

3.3 Alternative variables for FI measure

In the main text, we constructed $FI_{i,t}$ using the number of borrowers (**borrower**) and the number of loan accounts (**loan**) through principal component analysis (PCA):

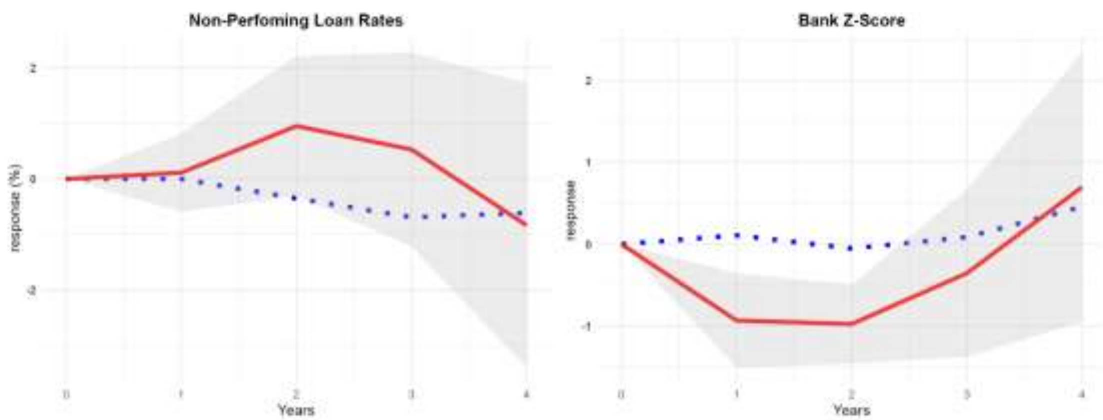
$$FI_{i,t} = w_{i,b}borrower_{i,t} + w_{i,l}loan_{i,t}$$

Although **borrower** and **loan** are similar, it is possible that our findings are driven primarily by one of these variables and sensitive to the weights $(w_{i,b}, w_{i,l})$.

To address this concern, we re-estimated the local projections regression, replacing $FI_{i,t}$ with either $borrower_{i,t}$ or $loan_{i,t}$. To retain consistency, we restricted the analysis to subsamples where both **borrower** and **loan** are not missing. While we focus on the local projections regression here for brevity, no significant differences were observed in the predictive regression.

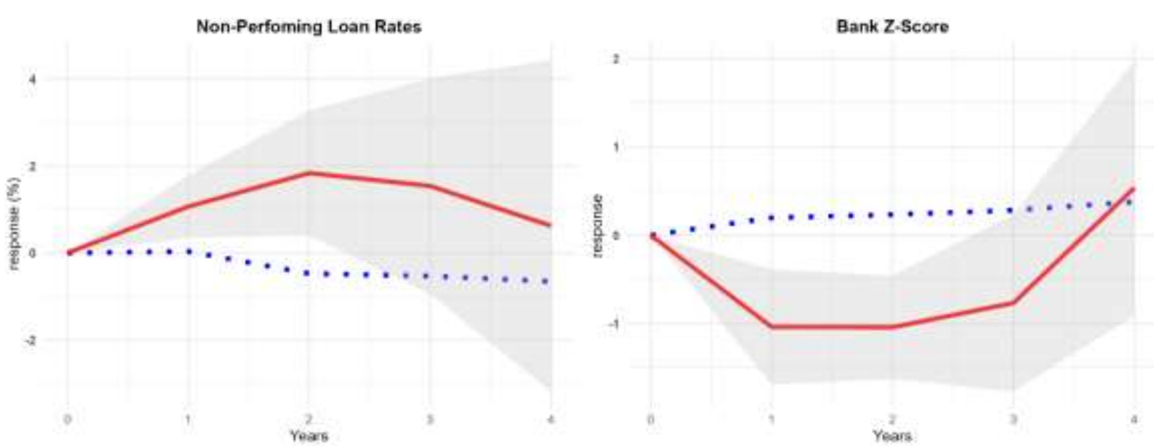
From Annex Tables 5-6 and Annex Figures 5-8, we observe that both **borrower** and **loan** variables yield similar patterns in the estimated effects of financial inclusion and credit booms compared to exercises when the composite FI measure is used. The notable difference is that the estimates with **loan** are more precise than those with **borrower**, likely due to the larger variance of **loan** variable. Overall, there appears to be no significant information loss in using our FI measure.

Annex Figure 5. Impulse response functions from the number of borrowers boom shocks



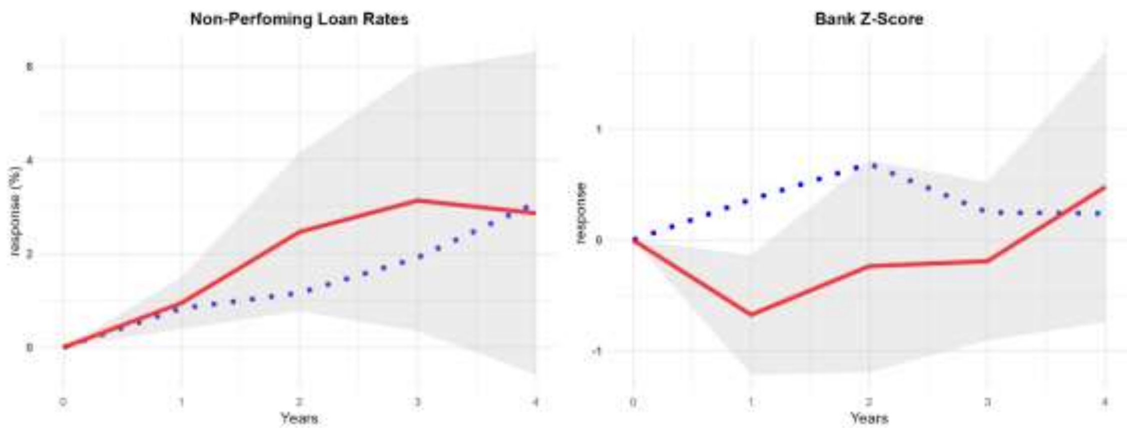
Note: The red real line depicts the estimated $\gamma^h + \delta^h$, and the blue dashed line depicts the estimated γ^h. The shaded area represents 95% confidence interval for $\gamma^h + \delta^h$, computed from Driscoll and Kraay (1998)'s cluster robust standard error.

Annex Figure 6. Impulse response functions from the number of loan accounts boom shocks



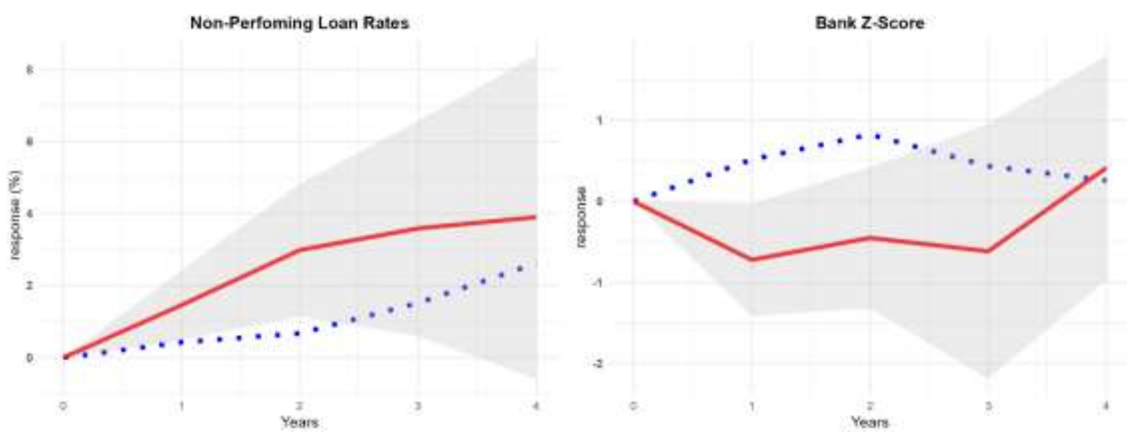
Note: The red real line depicts the estimated $\gamma^h + \delta^h$, and the blue dashed line depicts the estimated γ^h. The shaded area represents 95% confidence interval for $\gamma^h + \delta^h$, computed from Driscoll and Kraay (1998)'s robust standard error.

Annex Figure 7. Impulse response functions from credit boom shocks with the number of borrowers



Note: The red real line depicts the estimated $\beta^h + \delta^h$, and the blue dashed line depicts the estimated β^h. The shaded area represents 95% confidence interval for $\beta^h + \delta^h$, computed from Driscoll and Kraay (1998)'s robust standard error.

Annex Figure 8. Impulse response functions from credit boom shocks with the number of loan accounts



Note: The red real line depicts the estimated $\beta^h + \delta^h$, and the blue dashed line depicts the estimated β^h. The shaded area represents 95% confidence interval for $\beta^h + \delta^h$, computed from Driscoll and Kraay (1998)'s robust standard error.

Annex Table 5. Effects of the number of borrowers and credit booms on financial instability

Panel A: Model with Interaction

	Dependent variable: Non-Perfoming Loan Rates				Dependent variable: Bank Z-Score			
Variable	t+1	t+2	t+3	t+4	t+1	t+2	t+3	t+4
Boom	0.83* (0.41)	1.16 (0.74)	1.92 (1.26)	3.09 (2.43)	0.37 (0.32)	0.69 (0.47)	0.25 (0.63)	0.24 (0.74)
Borrower	-0.00 (0.22)	-0.35 (0.33)	-0.69 (0.54)	-0.61 (0.53)	0.11 (0.22)	-0.05 (0.23)	0.09 (0.29)	0.46 (0.30)
Boom*Borrower	0.11 (0.42)	1.30+ (0.74)	1.22 (0.92)	-0.22 (1.62)	-1.04+ (0.59)	-0.92+ (0.51)	-0.44 (0.63)	0.24 (0.63)
Observations	349	299	250	203	445	390	338	292
Countries	52	50	47	42	59	55	50	49
R2	0.024	0.046	0.067	0.086	0.151	0.234	0.195	0.343

Panel B: Model without Interaction

	Dependent variable: Non-Perfoming Loan Rates				Dependent variable: Bank Z-Score			
Variable	t+1	t+2	t+3	t+4	t+1	t+2	t+3	t+4
Boom	0.86** (0.33)	1.50** (0.64)	2.20+ (1.13)	3.02 (2.02)	0.07 (0.24)	0.40 (0.33)	0.11 (0.48)	0.31 (0.63)
Borrower	0.01 (0.20)	-0.24 (0.34)	-0.58 (0.56)	-0.63 (0.59)	-0.02 (0.20)	-0.17 (0.23)	0.02 (0.29)	0.49+ (0.28)
Observations	349	299	250	203	445	390	338	292
Countries	52	50	47	42	59	55	50	49
R2	0.024	0.041	0.064	0.086	0.143	0.23	0.194	0.343

Note: +, *, and ** denote significance at the 10%, 5%, 1% level, respectively. The outcomes are transformed so the presented estimates are read in %. The standard errors are based on Driscoll and Kraay (1998).

Annex Table 6. Effects of the number of loan accounts and credit booms on financial instability

Panel A: Model with Interaction

	Dependent variable: Non-Perfoming Loan Rates				Dependent variable: Bank Z-Score			
Variable	t+1	t+2	t+3	t+4	t+1	t+2	t+3	t+4
Boom	0.43 (0.35)	0.67 (0.66)	1.52 (1.16)	2.62 (2.25)	0.52 (0.35)	0.83+ (0.44)	0.44 (0.43)	0.26 (0.66)
Loan	0.04 (0.26)	-0.47 (0.42)	-0.53 (0.72)	-0.66 (0.78)	0.20 (0.19)	0.23 (0.26)	0.28 (0.33)	0.38 (0.30)
Boom*Loan	1.03* (0.53)	2.31** (0.73)	2.07** (0.85)	1.28 (0.94)	-1.24** (0.49)	-1.28** (0.53)	-1.05 (0.70)	0.16 (0.38)
Observations	349	299	250	203	445	390	338	292
Countries	52	50	47	42	59	55	50	49
R2	0.031	0.059	0.069	0.086	0.155	0.238	0.201	0.339

Panel B: Model without Interaction

	Dependent variable: Non-Perfoming Loan Rates				Dependent variable: Bank Z-Score			
Variable	t+1	t+2	t+3	t+4	t+1	t+2	t+3	t+4
Boom	0.84** (0.33)	1.53* (0.67)	2.25+ (1.21)	3.11 (2.18)	0.07 (0.24)	0.37 (0.33)	0.09 (0.46)	0.30 (0.65)
Loan	0.14 (0.24)	-0.23 (0.41)	-0.30 (0.66)	-0.50 (0.73)	0.03 (0.18)	0.06 (0.25)	0.14 (0.29)	0.40 (0.27)
Observations	349	299	250	203	445	390	338	292
Countries	52	50	47	42	59	55	50	49
R2	0.025	0.041	0.058	0.082	0.143	0.228	0.195	0.339

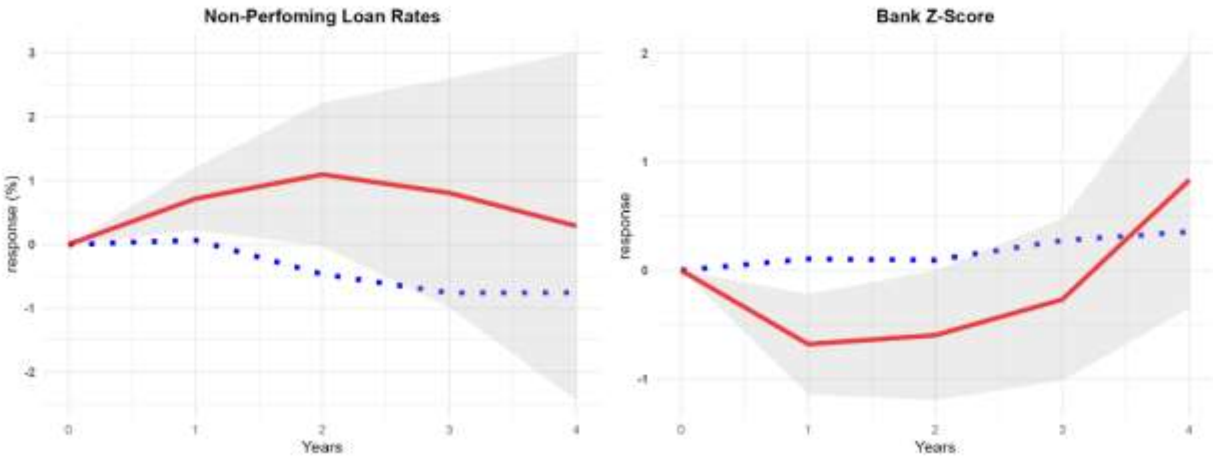
Note: +, *, and ** denote significance at the 10%, 5%, 1% level, respectively. The outcomes are transformed so the presented estimates are read in %. The standard errors are based on Driscoll and Kraay (1998).

3.4 Credit with a different threshold

In the main text, all results are based on credit booms identified using a threshold set at 1.75 times the standard deviation of the cyclical component of credit growth. Here, we alternatively identify credit booms using a threshold of 1.5 times the standard deviation, focusing on the local projections regressions to assess whether the results are sensitive to the choice of threshold.

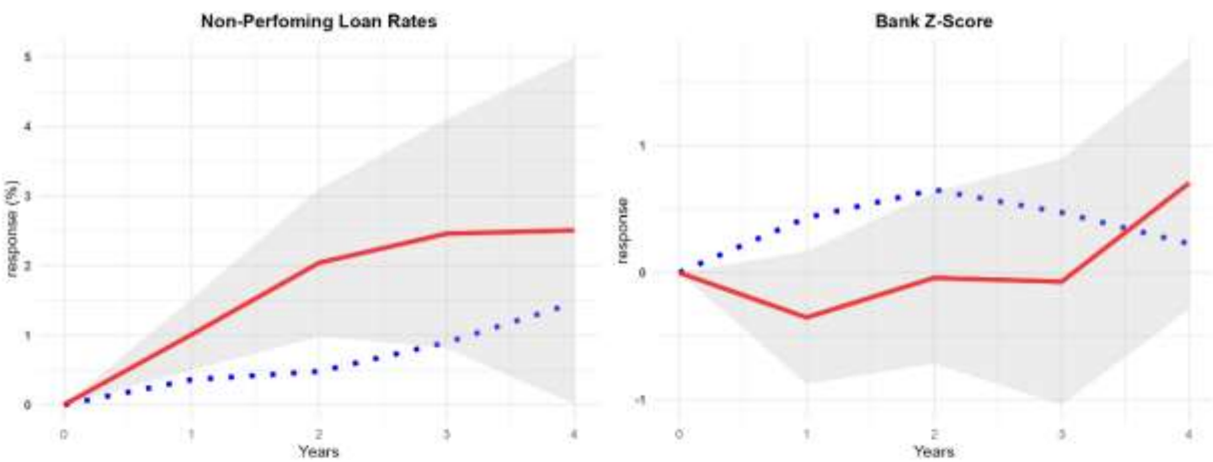
Annex Figures 9 and 10, along with Annex Table 7, present the baseline local projections regression results with the relaxed credit boom threshold. We find that these results are consistent with those reported in the main text, indicating that our analysis is robust to different thresholds used to identify credit booms.

Annex Figure 9. Impulse response functions from credit inclusion boom shocks with a relaxed credit boom threshold



Note: The red real line depicts the estimated $\gamma^h + \delta^h$, and the blue dashed line depicts the estimated γ^h. The shaded area represents 95% confidence interval for $\gamma^h + \delta^h$, computed from Driscoll and Kraay (1998)'s robust standard error.

Annex Figure 10. Impulse response functions from credit boom shocks with a relaxed credit boom threshold



Note: The red real line depicts the estimated $\gamma^h + \delta^h$, and the blue dashed line depicts the estimated γ^h. The shaded area represents 95% confidence interval for $\gamma^h + \delta^h$, computed from Driscoll and Kraay (1998)'s robust standard error.

Annex Table 7. Effects of credit inclusion booms and credit booms on financial instability with a relaxed credit boom threshold

Panel A: Model with Interaction

	Dependent variable: Non-Perfoming Loan Rates				Dependent variable: Bank Z-Score			
Variable	t+1	t+2	t+3	t+4	t+1	t+2	t+3	t+4
Boom	0.36 (0.23)	0.48 (0.43)	0.90 (0.68)	1.46 (1.26)	0.43 (0.36)	0.65 (0.43)	0.47 (0.37)	0.23 (0.55)
FIBoom	0.07 (0.26)	-0.47 (0.40)	-0.76 (0.72)	-0.75 (0.77)	0.10 (0.20)	0.09 (0.27)	0.27 (0.31)	0.36 (0.29)
Boom*FIBoom	0.65 (0.47)	1.56* (0.74)	1.56 (0.99)	1.04 (1.15)	-0.79 (0.51)	-0.69 (0.55)	-0.54 (0.56)	0.48 (0.41)
Observations	349	299	250	203	445	390	338	292
Countries	52	50	47	42	59	55	50	49
R2	0.026	0.045	0.057	0.061	0.149	0.233	0.2	0.345

Panel B: Model without Interaction

	Dependent variable: Non-Perfoming Loan Rates				Dependent variable: Bank Z-Score			
Variable	t+1	t+2	t+3	t+4	t+1	t+2	t+3	t+4
Boom	0.60** (0.22)	1.06** (0.45)	1.46+ (0.80)	1.85 (1.36)	0.15 (0.24)	0.40 (0.32)	0.27 (0.38)	0.39 (0.52)
FIBoom	0.16 (0.23)	-0.23 (0.39)	-0.50 (0.64)	-0.57 (0.66)	-0.02 (0.18)	-0.02 (0.25)	0.18 (0.27)	0.44+ (0.24)
Observations	349	299	250	203	445	390	338	292
Countries	52	50	47	42	59	55	50	49
R2	0.023	0.034	0.048	0.057	0.144	0.229	0.198	0.343

Note: +, *, and ** denote significance at the 10%, 5%, 1% level, respectively. The outcomes are transformed so the presented estimates are read in %. The standard errors are based on Driscoll and Kraay (1998).

Annex 4. Riskiness of Credit Allocation

As an alternative measure for financial instability, we could use the measure of riskiness of credit allocation, originally proposed by Greenwood and Hanson (2013) and shown by Brandao Marques and others (2022) to be a significant predictor for future financial stress. The measure is constructed for four different firm-level vulnerability indicators—leverage (total debt to total assets), debt overhang (total debt to earnings before interest, taxes, depreciation, and amortization [EBITDA]), interest coverage ratio (ICR; EBITDA to interest expenses) and expected default frequency (EDF). We denote these variables as **rca_lev**, **rca_debt**, **rca_icr**, and **rca_edf**, respectively[14].

For each firm-level vulnerability indicator, the measure is built as follows: First, every year, each firm is assigned the value (from 1 to 10) of its decile in the distribution of the indicator in the country where it is located. A higher decile represents a larger value of the underlying vulnerability. Second, firms are similarly sorted by the changes in net debt to lagged total assets into five equal-sized bins. Firms in the bin with the largest increases in debt are called “top issuers,” and firms in the bin with the largest decreases in debt are the “bottom issuers.” Finally, the measure is computed as the difference between the average vulnerability decile for the top issuers and the corresponding average for the bottom issuers.

Since the **RCA** series are constructed using listed firms sampled mainly from middle-to-high income countries, as Annex Table 8 shows, we have much fewer observations and number of countries than **npl** and **zscore** when matched to our credit inclusion measure. Also, the relationship between our credit inclusion measure and the **RCA** series is subtle, as it is not clear whether a set of listed firms that make up the RCA sample contains new borrowers, which is what we capture with FI.

Annex Table 8. Summary Statistics for the RCA series when matched to the main data

Variable	N	Countries	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75
rca_lev	252	21	-0.11	0.96	-2.7	-0.75	0.43
rca_debt	250	21	-0.18	0.87	-3.1	-0.68	0.33
rca_icr	251	21	-0.06	0.81	-2.2	-0.57	0.47
rca_edf	244	21	0.0021	0.96	-3.2	-0.62	0.63

Source: Authors’ calculations.

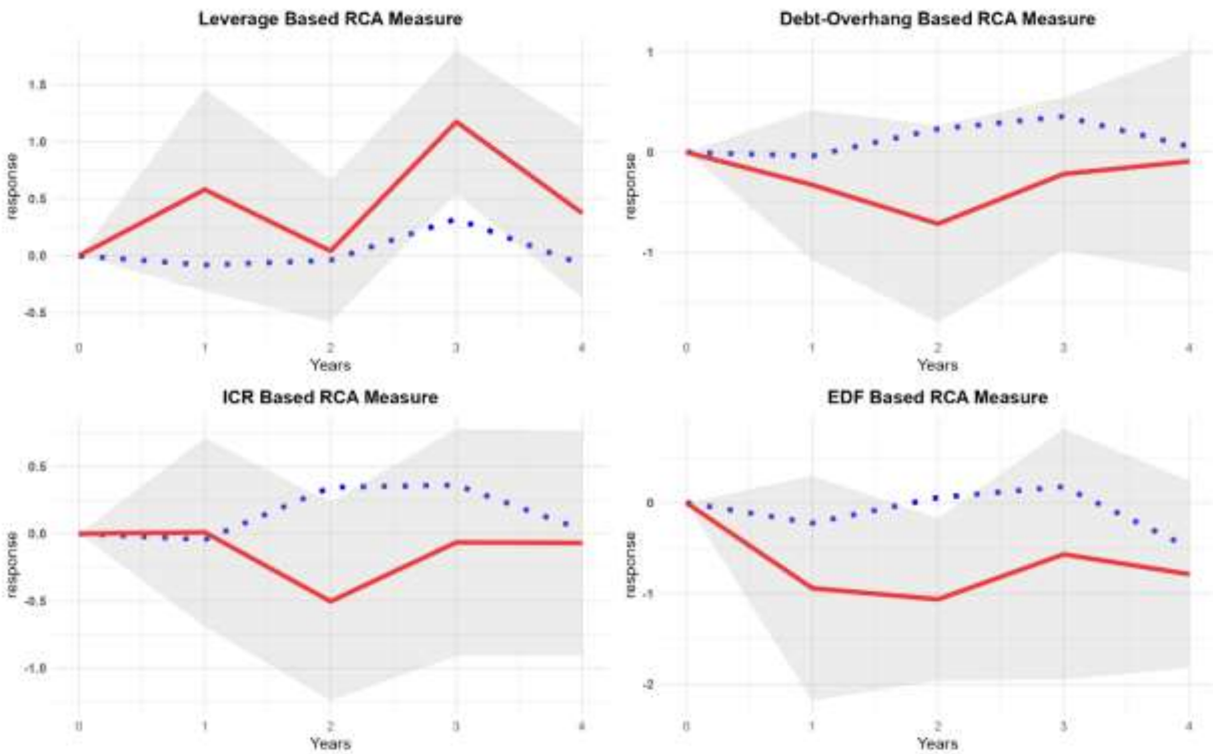
Nevertheless, we perform the same analysis as in Section 3.2 to test whether there is a measurable association between increases in credit inclusion and the riskiness of the pool of borrowers captured by the RCA indicators. We replace the dependent variables---**npl** and **zscore**---with the RCA series. Annex Figure 11 shows the impulse response functions from credit inclusion boom shocks for the four RCA series, using the same settings as in our main analysis. The results tend to be noisy, possibly due to a weak association between the RCA measures and the credit inclusion measure. The strongest results are for the leverage-based RCA measure; we find evidence of negative effects of credit inclusion booms during credit booms on financial stability, as indicated by increases in RCA. That is, following rapid increases in credit inclusion, leverage of the top issuers tends to expand relative to that of bottom issuers, a sign of mounting financial strains. In contrast, for the EDF-based RCA measure, we observe weak and opposite effects, with credit inclusion booms during credit booms leading to decreases in the RCA measure.

Given that rapid decreases in the RCA measures are often accompanied by sharp economic downturns (Brandão-Marques et al., 2022), the result using the EDF-based RCA measure can also be interpreted as

[14] We thank Jerome Vandenbussche for sharing the **RCA** series.

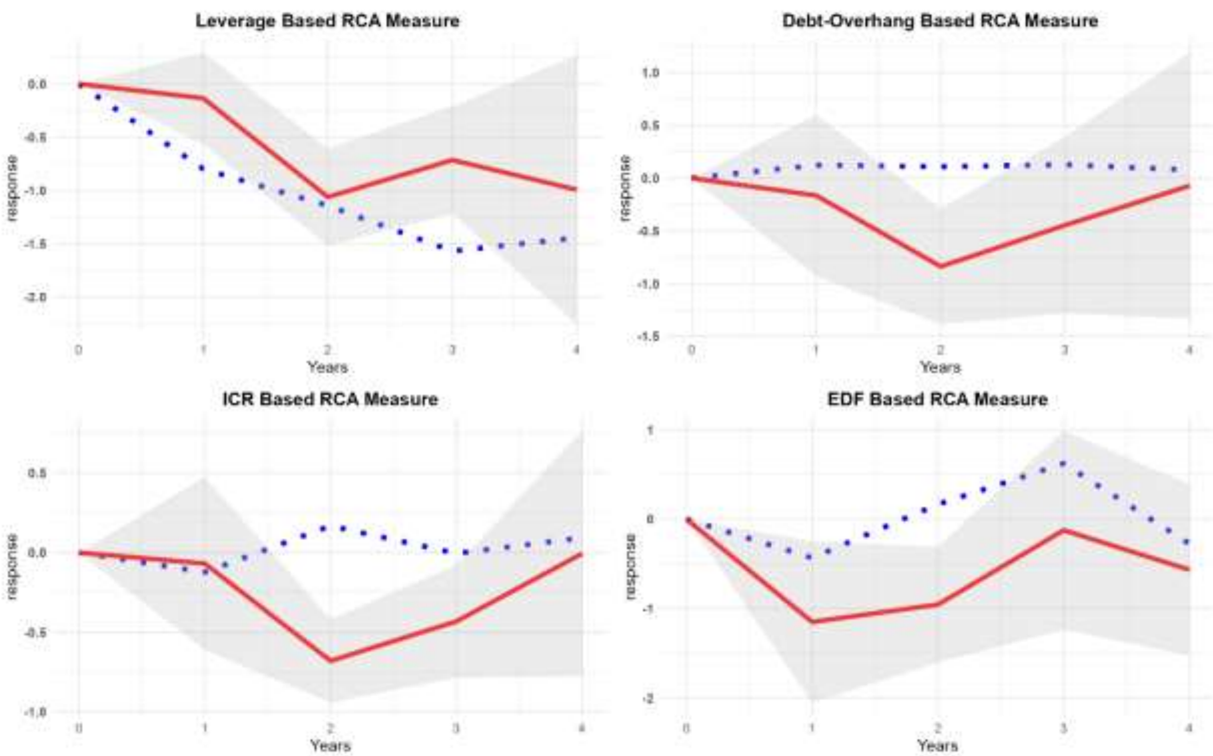
evidence of negative effects on financial stability. When focusing on the effects of credit booms, Annex Table 9 and Annex Figure 12 show that credit booms during credit inclusion booms lead to significant reductions across all RCA measures, possibly indicating immediate financial instability and economic downturns. This finding is consistent with the results in Section 3.1, where we observe the negative effects of credit booms on subsequent GDP growth rates.

Annex Figure 11. The impulse response functions from credit inclusion boom shocks for the RCA measures



Note: The red real line depicts the estimated $\gamma^h + \delta^h$, and the blue dashed line depicts the estimated γ^h. The shaded area represents 95% confidence interval for $\gamma^h + \delta^h$, computed from Driscoll and Kraay (1998)'s robust standard error.

Annex Figure 12. The impulse response functions from credit boom shocks for the RCA measures



Note: The red real line depicts the estimated $\beta^h + \delta^h$, and the blue dashed line depicts the estimated β^h. The shaded area represents 95% confidence interval for $\beta^h + \delta^h$, computed from Driscoll and Kraay (1998)'s robust standard error.

Annex Table 9. Effects of credit inclusion and credit booms on financial instability measured by the RCA measures

Panel A: Leverage and Debt-Overhang Based RCA

	Dependent variable: Leverage Based RCA Measure				Dependent variable: Debt-Overhang Based RCA Measure			
Variable	t+1	t+2	t+3	t+4	t+1	t+2	t+3	t+4
Boom	-0.80** (0.20)	-1.14* (0.50)	-1.57** (0.46)	-1.44** (0.42)	0.12 (0.39)	0.11 (0.47)	0.13 (0.76)	0.08 (0.98)
FIBoom	-0.08 (0.21)	-0.04 (0.21)	0.32 (0.22)	-0.08 (0.28)	-0.04 (0.18)	0.23 (0.21)	0.36 (0.30)	0.06 (0.31)
Boom*FIBoom	0.66* (0.29)	0.08 (0.64)	0.85 (0.65)	0.45 (0.36)	-0.29 (0.42)	-0.95 (0.63)	-0.57 (0.64)	-0.15 (0.55)
Observations	152	135	118	101	150	133	116	99
Countries	17	17	17	16	17	17	17	16
R2	0.432	0.5	0.455	0.496	0.32	0.391	0.408	0.253

Panel B: ICR and EDF Based RCA

	Dependent variable: ICR Based RCA Measure				Dependent variable: EDF Based RCA Measure			
Variable	t+1	t+2	t+3	t+4	t+1	t+2	t+3	t+4
Boom	-0.12 (0.11)	0.17 (0.23)	-0.01 (0.46)	0.09 (0.64)	-0.43 (0.27)	0.17 (0.44)	0.62 (0.80)	-0.28 (0.65)
FIBoom	-0.04 (0.16)	0.34 (0.25)	0.36+ (0.21)	0.03 (0.25)	-0.22 (0.19)	0.06 (0.26)	0.18 (0.33)	-0.50 (0.30)
Boom*FIBoom	0.05 (0.25)	-0.85+ (0.48)	-0.43 (0.52)	-0.10 (0.59)	-0.72 (0.82)	-1.12** (0.37)	-0.74 (0.63)	-0.29 (1.01)
Observations	152	135	118	101	142	127	112	97
Countries	17	17	17	16	16	16	16	16
R2	0.373	0.444	0.456	0.409	0.488	0.475	0.473	0.643

Note: +, *, and ** denote significance at the 10%, 5%, 1% level, respectively. The outcomes are transformed so the presented estimates are read in %. The standard errors are based on Driscoll and Kraay (1998).

References

Ahamed, M., & Mallick, S. (2019). Is financial inclusion good for bank stability? International evidence. *Journal of Economic Behavior & Organization*, 403-427.

Andrieş, A., Ongena, S., & Sprincean, N. (2024). Sectoral Credit Allocation and Systemic Risk. *Journal of Financial Stability*, 101363.

Barajas, A., Choi, W., Gan, K., Guérin, P., Mann, S., Wang, M., & Xu, Y. (2021). Loose Financial Conditions, Rising Leverage, and Risks to Macro-Financial Stability. *IMF Working Papers*.

Ben Naceur, S., Candelon, B., & Mugrabi, F. (2024). Systemic Implications of Financial Inclusion. *IMF Working Papers*.

Brandão-Marques, L., Chen, Q., Raddatz, C., Vandenbussche, J., & Xie, P. (2022). The riskiness of credit allocation and financial stability. *Journal of Financial Intermediation*.

Brandão-Marques, L., Gelos, G., Narita, M., & Nier, E. (2020). Leaning Against the Wind: A Cost-Benefit Analysis for an Integrated Policy Framework. *IMF Working Papers*.

Canay, I. (2011). A Simple Approach to Quantile Regression for Panel Data. *The Econometrics Journal*, 368-386.

Cihak, M., Mare, D., & Melecky, M. (2016). he Nexus of Financial Inclusion and Financial Stability: A Study of Tradeoffs and Synergies. *World Bank Policy Research Working Paper 7722 (Washington, DC: World Bank Group)*.

Dabla-Norris, E., Ji, Y., Townsend, R., & Unsal, F. (2015). Identifying Constraints to Financial Inclusion and Their Impact on GDP and Inequality: A Structural Framework for Policy. *IMF Working Papers 15/22*.

Demyanyk, Y., & Van Hemert, O. (2011). Understanding the Subprime Mortgage Crisis. *The Review of Financial Studies*, 1848–1880.

Driscoll, J., & Kraay, A. (1998). Consistent Covariance Matrix Estimation with Spatially Dependent Panel Data. *The Review of Economics and Statistics*, 549-560.

Greenwood, R., Hanson, S., Shleifer, A., & Sørensen, J. (2022). Predictable Financial Crises. *The Journal of Finance*, 77: 863-921.

Hamilton, J. (2018). Why You Should Never Use the Hodrick-Prescott Filter. *The Review of Economics and Statistics*, 831–843.

Han, R., & Melecky, M. (2013). Financial Inclusion for Financial Stability: Access to Bank Deposits and Growth of Deposits in the Global Financial Crisis. *World Bank Policy Research Working Paper 6577 (Washington, DC: World Bank Group)*.

Jorda, Ò. (2005). Estimation and Inference of Impulse Responses by Local Projections. *American Economic Review*, 161-182.

Jorda, Ò., & Taylor, A. (2016). The Time for Austerity: Estimating the Average Treatment Effect of Fiscal Policy. *The Economic Journal*, 219-255.

Kirti, D. (2018). Lending Standards and Output Growth. *IMF Working Papers*.

Laeven, L., & Valencia, F. (2020). Systemic Banking Crises Database II. *IMF Econ Rev*, 307-361.

Mehrotra, A., & Yetman, J. (2015, March). Financial Inclusion-Issues for Central Banks. *BIS Quarterly Review*, 83-96.

Mendoza, E., & Terrones, M. (2008). An Anatomy of Credit Booms: Evidence From Macro Aggregates and Micro Data. *IMF Working Papers*.

Mian, A., & Sufi, A. (2009). The Consequences of Mortgage Credit Expansion: Evidence from the U.S. Mortgage Default Crisis. *The Quarterly Journal of Economics*, 1449–1496.

Mian, A., Sufi, A., & Verner, E. (2017). Household Debt and Business Cycles Worldwide. *The Quarterly Journal of Economics*, 1755–1817.

Müller, K., & Verner, E. (2023). Credit Allocation and Macroeconomic Fluctuations. *The Review of Economic Studies*.

Sahay, R., Cihak, M., N'Diaye, P., Barajas, A., Bi, R., Gao, Y., . . . Yousefi, R. (2015). Rethinking Financial Deepening: Stability and Growth in Emerging Markets. *Staff Discussion Note 15/08 (Washington, DC: International Monetary Fund)*.

Sahay, R., Cihak, M., N'Diaye, P., Barajas, A., Mitra, S., Kyobe, A., . . . Yousefi, R. (2015). Financial Inclusion: Can it Meet Multiple Macroeconomic Goals? *Staff Discussion Note 15/17 (Washington, DC: International Monetary Fund)*.

Schularick, M., & Taylor, A. (2012). Credit Booms Gone Bust: Monetary Policy, Leverage Cycles, and Financial Crises. *American Economic Review*, 1029–61.

World Bank. (2025). *Financial Inclusion*. Retrieved 1 21, 2025, from https://www.worldbank.org/en/topic/financialinclusion

PUBLICATIONS

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Working Paper No. WP/2026/008