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Peter Karlström*

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Abstract

Recent financial crises have highlighted once again the importance of credit booms as a key determinant of financial instability in both advanced and developing countries. In this study, I examine whether macroprudential policies are effective to address booms in different types of credit. The robust and economically sizeable results show that macroprudential instruments are effective to curb aggregate bank credit booms, and more importantly booms in household credit that pose a larger concern for financial stability. This paper also contributes to the understanding of the mechanisms linking macroprudential policies with credit booms followed by systemic banking crises. I find that a possible mechanism for why macroprudential policies are effective to curb booms succeeded by banking crises could be that these policies reduce financial institutions' exposure to systemic risk.

Keywords: Credit Booms, Macroprudential Policy, Banking Crises, Systemic Risk
JEL classification: C23, G01, G21, G28

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1 Introduction

Credit booms are one of the most robust predictors of financial crises in both advanced and developing countries. Schularick and Taylor (2012) show that credit booms have been a leading determinant of financial crises between 1870-2008. Moreover, Reinhart and Rogoff (2011) confirm that rapidly rising private indebtedness is a key predictor of banking crises. In addition, Dell'Ariccia et al. (2016) find that around one-third of the credit booms in their sample is followed by a banking crisis and two-thirds of the booms are succeeded by a banking crisis or below-trend economic growth.

The empirical evidence shows that macroprudential policies are effective to attenuate the growth of aggregate bank credit and in particular household credit (Cerutti et al. 2017b; Akinci and Olmstead-Rumsey, 2018; Garcia Revelo et al. 2020). This is an important finding given that household credit is strongly associated with banking crises and subpar economic growth (Büyükkaracabak and Valev, 2010; Mian et al., 2017; Alter et al., 2018; Müller and Verner, 2022; Jordà et al., 2022). Nevertheless, in addition to the type of credit, it is essential to account for the magnitude of the credit expansion (credit booms) when assessing the role of macroprudential instruments in maintaining financial stability. A credit boom is an episode where credit growth is faster than for a typical cyclical expansion.

Household credit booms can worsen financial stability for different reasons. First, rapid credit growth is associated with a deterioration in loan quality which may increase the number of non-performing loans (Dell'Arricia et al., 2012). Moreover, credit to households (which is primarily mortgage loans) raises the likelihood of booms and busts in housing prices that often precipitate financial crises (Greenwald and Guren, 2021). Dell'Ariccia et al. (2016) find that macroprudential policies are negatively linked with booms in aggregate bank credit. The authors conclude that further analysis is needed to assess the effectiveness of macroprudential policies to address booms for different types of credit.

This paper contributes to the empirical literature by examining the role of macroprudential policy in curbing booms that differ in the type of credit. I first assess whether macroprudential policies are associated with the likelihood of aggregate bank credit booms and booms followed by systemic banking crises (bad booms) for 41 countries between 2000-2014. The findings show that the macroprudential policy stance is negatively linked with the likelihood of both types of credit booms, and that these results are robust and economically sizeable.

Subsequently, I show that the level of household credit increases during the period before the beginning of bad booms but that this is not the case for good booms (credit booms not followed by systemic banking crises). Once the importance of household credit for financial stability has been established empirically, I examine if the macroprudential policy stance is linked to the likelihood of booms in household credit. The results indicate that macroprudential policies are also effective in curtailing household credit booms. Interestingly, borrower- and financial institution-targeted instruments are found to be economically more important for addressing booms in household credit compared to aggregate bank credit. This suggests that certain macroprudential instruments could be particularly effective for mitigating rapid increases in the type of credit most problematic for financial stability.

This paper also contributes to the understanding of the mechanisms linking macroprudential policies and the reduced likelihood of bad credit booms. A possible mechanism for why macroprudential policies are effective to deal with booms followed by banking crises could be that these policies reduce the exposure of financial institutions to systemic risk. The measure of systemic risk employed in this paper is SRISK which is defined as the capital shortfall of a bank conditional on a severe market decline (Acharya et al., 2012). Consequently, I investigate the link between the macroprudential policy stance and SRISK scaled by GDP for a sample comprising 460 banks in 54 countries. The results show that macroprudential policies are negatively associated with the level of systemic risk for banks and this finding is more pronounced for riskier institutions.

Moreover, an important advantage of using a dummy variable for credit booms (instead of a continuous variable for credit growth) is that it helps to mitigate endogeneity concerns. If macroprudential policies are implemented or tightened at the peak of the credit cycle (or after the peak) then a negative association between the macroprudential policy stance and credit growth is the result of reverse causation (Cerutti et al., 2017a). The problem of reverse causality can be significantly reduced by identifying the specific time for the credit boom and using a lagged coefficient for the macroprudential policy stance (to ensure that the coefficient reflects the situation before the peak).

The paper is organized as follows. Chapter 2 reviews the empirical literature on macroprudential policies, credit booms and systemic risk. Moreover, chapter 3 describes the data, the empirical approach and the method used to identify credit booms. Summary statistics for aggregate macroprudential indexes and individual instruments are provided in chapter 4. The main results are presented in chapter 5 and robustness tests are reported in chapter 6. Chapter 7 discusses whether macroprudential policies also could address banks' systemic risk. Finally, chapter 8 summarizes the main findings in the paper.

2 Related literature

This study complements and expands several strands of the extant literature. First, this paper is related to research aiming to assess the effectiveness of macroprudential regulation in addressing credit booms. However, most empirical papers assess the association between macroprudential policies and the growth rate of credit. Aggregate indexes for macroprudential instruments are generally associated with a reduction in the growth rate of aggregate bank credit and specifically household credit (Cerutti et al. 2017b; Akinci and Olmstead-Rumsey, 2018; Garcia Revelo et al. 2020). Preliminary findings by Cerutti et al. (2017a) also suggest that macroprudential instruments have a stronger negative association with credit growth during the upturn of the credit cycle.

Second, this study is also related to the literature on the effect from different types of credit on economic growth and financial stability. Jappelli and Pagano (1994) provide a theoretical framework showing that an increase in household credit decreases savings and consequently private investment which reduces economic growth. The authors also provide empirical evidence for that liquidity constraints on households enhances economic growth. Furthermore, Büyükkarabacak and Valev (2010) find that rapidly increasing credit to the entire private sector is associated with banking crises. Nevertheless, decomposing the aggregate credit measure shows that household credit has been the driving factor of increased vulnerabilities to systemic banking crises. Credit expansions to the non-tradable sector and the household sector predict financial crises and growth slowdowns according to Müller and Verner (2022). In addition, Mian et al. (2017) show that an increase in the ratio of household credit to GDP is associated with lower GDP growth in the medium run.

There are a few papers that specifically investigates whether macroprudential policies can deal with credit booms. Dell'Ariccia et al. (2016) conduct an empirical exercise finding that an index with macroprudential instruments is negatively associated with the likelihood of booms. The authors further provide preliminary evidence in favor of macroprudential policies being able to address those credit booms that are followed by systemic banking crises. Moreover, macroprudential policies have also been shown to reduce the impact on credit booms from portfolio inflows (Fendoglu, 2017). In addition, Gertler et al. (2020) develop a quantitative model of optimism driven credit booms that can lead to banking panics. Their findings suggest that a tightening of capital requirements reduces the likelihood of bad credit booms with the cost of lower output growth.

I complement the abovementioned studies on credit booms in several aspects. First of all, I differentiate between household credit and aggregate bank credit which is an essential distinction for financial stability. Second, I employ an index for macroprudential policies that measures the sum of tightenings and easings, while the index employed by Dell'Ariccia et al. (2016) measures if a policy was implemented or not in a certain year. The drawback of using dummy variables for macroprudential policies is that the indicator does not take into account the intensity of macroprudential regulation (Galati and Moessner, 2016). In addition, I include several tests that further corroborates the robustness of the key findings.

Finally, Cerutti et al. (2017a) emphasize the importance of moving beyond credit growth as the target variable, and to investigate if macroprudential policies can be employed to address systemic risk. Announcements of macroprudential policy actions have a downward impact on systemic risk for European banks according to Meuleman and Vander Vennet (2020). Moreover, Gehrig and Iannino (2021) find that systemic risk (SRISK) has been contained for the majority of European banks during the Basel process but not for the riskiest institutions. I complement the empirical literature by examining if there is an association between macroprudential policies and banks' systemic risk for both advanced and developing countries.

3 Empirical setting

3.1 Data

The dataset encompasses quarterly data for 41 advanced and developing countries during the period 1970Q1-2014Q4. The countries included in the analysis are listed in Table A18, and variable definitions and sources can be found in Tables A3 and A4 in the appendix. Data to generate the binary dependent variable for credit booms has been collected from the BIS Total Credit Statistics database. Two different types of credit are used in this study: aggregate bank credit and household credit (to the non-financial private sector). Aggregate bank credit comprises both credit to households and firms from the domestic banking sector. The measure on household credit (mortgage and consumer loans) includes domestic bank credit, cross-border credit, and credit from non-bank institutions.

Quarterly data on macroprudential policies for the period 2000Q1-2014Q4 has been collected from the IBRN Prudential Instruments Database (Cerutti et al., 2017b). Following the selection of prudential policies in Cerutti et al. (2017a) the five macroprudential policy instruments in this study are are Loan-to-Value (LTV) caps, concentration limits, interbank exposure limits, reserve requirements on local or foreign currency-denominated accounts. A discrete index (indicator variable) is employed to capture changes in the macroprudential policy instruments that takes value 1 for a tightening and -1 for an easing of the instrument. In addition, the reserve requirement instruments can take values higher or lower than 1 or -1 which better captures the intensity of the changes in contrast to the other macroprudential policy tools (Cerutti et al., 2017b).

Akinci and Olmstead-Rumsey (2018) argue that the ideal index would measure the intensity of macroprudential policies such as using the actual percentage requirement on loan-to-value (LTV) caps. However, borrowers in different countries can face different LTV caps depending on where the property is located or the price of the property which makes it difficult to compare across countries. This problem is not isolated to LTV caps but also applies for other macroprudential instruments.

The main source of the Prudential Instruments Database is the Global Macroprudential Policy Instruments (GMPI) survey and primary information from the IMF or IBRN. This data has been complemented with secondary sources from IMF datasets compiled by Lim et al. (2011) and other databases from Akinci and Olmstead-Rumsey (2018), Kuttner and Shim (2016), and Reinhardt and Sowerbutts (2015). In addition, the database has been reviewed by staff from central banks participating in IBRN to ensure that the dataset is accurate and complete (Cerutti et al., 2017b).

Loan-to-Value Ratio Limits (LTV_CAP) is the maximum amount households or firms can borrow given the collateral. The index for LTV caps measures changes in limits that affect real estate transactions but not changes in banks risk weights linked with LTV ratios. This instrument affects the demand for credit independently of the type of lender. Concentration limits (CONCRAT) constrain the fraction of assets held by a limited number of borrowers. In addition, interbank exposure limits (IBEX) put a ceiling on the fraction of liabilities held by the banking sector or individual banks (Cerutti et al. 2017a).

Reserve requirements (RR) are typically used to conduct monetary policy. However, Cordella et al. (2014) show that these instruments have also been applied as countercyclical macroprudential tools. The GMPI survey asks respondents whether this tool has been used as a monetary policy instrument or a macroprudential policy tool which makes it possible to distinguish when the tool is used as a macroprudential instrument. Information on reserve requirements also indicates whether deposit accounts are denominated in domestic or foreign currency.

Aggregate macroprudential indexes are included in the empirical investigation since they measure to some extent the overall "macroprudential policy stance" in a country. The index MaPP is the sum of the cumulative indexes for all five macroprudential policy instruments. Moreover, since reserve requirements are almost exclusively used in developing countries an aggregate index MaPP_RR is constructed including both reserve requirements instruments. The borrower- and financial institution-targeted instruments LTV caps, concentration limits and interbank exposure limits are included in the aggregate index MaPP_B_FI. In addition, the measures for reserves requirements have been restricted to only take values 1 or -1 for tightenings and easings of the policies in each quarter in the aggregate indexes MaPP and MaPP_RR.

Several local and global control variables are included to control for potential determinants of credit booms. An important global factor is the VIX index (in logs) which is a proxy for the leverage of global banks (Bruno et al. 2017). Moreover, local factors included are the real exchange rate (in logs), CPI inflation, the change in the monetary policy rate and real GDP growth. In addition, to control for country characteristics the level of development is proxied by GDP per capita and the deepness of the financial market is measured by the ratio of credit to GDP.

3.2 Empirical specification

Logit regressions with credit booms as the dependent variable are estimated with White-Huber robust standard errors clustered by country. Country and/or year fixed effects are also included to examine the robustness of the results. However, credit booms did not occur in some countries or for some of the years which substantially reduces the number of observations in Logit estimations with country or year fixed effects. Consequently, Linear Probability Model (LPM) estimations with country and/or year fixed effects are also conducted similarly to in the study by Schularick and Taylor (2012). Moreover, following the empirical approach in Alter et al. (2018) Firth logit estimations are conducted as a robustness check. Finally, all independent variables are lagged one period to mitigate issues of endogeneity following the approach in the study by Cerutti et al. (2017a).

Cumulative indexes (the sum of tightenings net of easings since 2000) are used which gives an idea of a country's "macroprudential policy stance". The reason cumulative indexes are used instead of quarterly changes is that it is difficult to know when macroprudential policy instruments become binding constraints which depend on financial conditions (Akinci and Olmstead-Rumsey, 2018). In addition, cumulative macroprudential indexes have been employed also by Kang et al. (2021) and Chari et al. (2022).

One of the most important concerns is that macroprudential policies are implemented just before or in the middle of a credit boom which leads to endogeneity bias. Consequently, a positive relationship between credit booms and macroprudential policies should be expected. Moreover, Cerutti et al. (2017a) emphasize the risk that macroprudential policies are tightened exactly when the credit boom is peaking or when credit growth slows down after the peak. If this was the case then any negative coefficient between macroprudential policies and credit growth would be due to reverse causation (Cerutti et al., 2017a).

Furthermore, Akinci and Olmstead-Rumsey (2018) stress the fact that the macroprudential policy indexes are imperfect measures of the magnitude of the policy change and it is also not possible to know whether the policy is binding. Both these issues create attenuation bias that influences the significance of the coefficients. To sum up, due to the presence of both endogeneity bias and attenuation bias in the estimations a negative and significant coefficient for the macroprudential policy indexes should be considered a conservative result and is a particularly encouraging finding.

Most of the empirical literature assessing the effectiveness of macroprudential instruments use credit growth as the dependent variable. However, there are three reasons why a credit boom is the appropriate choice of dependent variable in this study. First, the literature shows that episodes of high or excessive credit growth increase the likelihood of financial crises. Consequently, it is important to examine whether macroprudential policies are negatively linked with episodes characterized by excessive credit growth[1].

Second, if countries implement macroprudential policies when the credit cycle is peaking (or when credit growth is slowing down after a crisis), then any negative relationship found between macroprudential policy and credit growth is a consequence of reverse causality (Cerutti et al., 2017a). By identifying the specific time for credit booms measured as a binary variable and using one or several lags for the macroprudential policy index the problem of reverse causality can be significantly reduced.

Finally, a binary dependent variable that captures episodes with particularly high credit growth makes it possible to investigate specifically those booms that precede systemic banking crises (bad booms). This differentiation is important since it has been found by Richter et al. (2021), as well as Gorton and Ordoñez (2019), that bad booms are fundamentally different from credit booms that are not associated with systemic banking crises (good booms).

3.3 Identification of credit booms

The dependent variable (credit boom) is a dummy variable identified using the method by Mendoza and Terrones (2008). The variable takes value one when a boom occurs which is when credit grows faster than during a typical cyclical expansion otherwise zero (Calderón and Kubota, 2012). Moreover, credit booms are estimated for a country only if 10 years of credit data without gaps are available.

Let f_{it} be the deviation from the long-run trend in (the log of) real credit per capita in country (i) in quarter (t) and let $\sigma(f_{it})$ be the country-specific standard deviation of this cyclical component. A credit boom is identified when $f_{it} \geq \varphi\sigma(f_{it})$ for one or several

[1]Cerutti et al. (2017a) find some support for that macroprudential policies are more effective during the more intense phase of the financial cycle. GMM estimations are conducted following the approach in Cerutti et al. (2017a) as a preliminary check of whether macroprudential policies are more effective when credit growth is higher. Table A1 in the appendix shows the results with the real growth rate of aggregate bank credit as the dependent variable. The coefficient for the interaction term between the macroprudential index MaPP (including all macroprudential instruments) and the dummy variable for the top 25 percent of credit growth observations is found to be negative and highly significant shown in columns 1 and 5 in Table A1. Moreover, the interaction term with the dummy variable for the top 50% of credit growth observations is also found to be negative but only significant at the 10% level (column 2). However, the coefficients for interaction terms with the bottom 50% or 25% of credit growth observations are insignificant in all estimations shown in columns 3, 4 and 5. In short,the findings confirm the results by Cerutti et al. (2017a).

quarters, where φ is the threshold factor (multiple of the standard deviation). Credit booms are identified with thresholds 1.5, 1.75 and 2 standard deviations using a Hodrick-Prescott (HP) filter with a smoothing parameter of 1600 which is standard for quarterly data (Calderón and Kubota, 2012).

Caballero (2016) emphasizes that a per capita normalization is preferred to a normalization by GDP. If credit is normalized by GDP, then it is not possible to allow for different trends in credit and GDP. This is problematic since Drehmann et al. (2012) find that the financial cycle has a much lower frequency compared to the traditional business cycle. In addition, if both credit and GDP are falling simultaneously but GDP is decreasing faster than credit, then the credit to GDP ratio could incorrectly signal a credit boom.

It is essential to investigate whether the method by Mendoza and Terrones (2008) identifies credit booms that are supported by the data. Figure A1 in the appendix illustrates the average behavior of the real growth rate of aggregate bank credit ten years before and after a boom episode for the period 2000Q1-2014Q4. The illustration shows that the real growth rate of credit increases continuously up to the beginning of the credit boom (vertical line) and then drops to a growth rate of around zero. To conclude, the descriptive evidence suggests that the method by Mendoza and Terrones (2008) is suitable to identify credit boom episodes.

4 Summary statistics

The evolution of aggregate macroprudential indexes (averages) and the frequency of credit booms during the period 2000Q1-2014Q4 is illustrated in Figure 1. Tightenings and easings of macroprudential policies are recorded starting from 2000Q1. Consequently, the macroprudential indexes (cumulative sum of tightenings net of easings) are expected to be close to zero at the beginning of the period which is consistent with Figures 1 and A2. The aggregate index MaPP that includes all five macroprudential instruments (i.e. LTV caps, concentration limits, interbank exposure limits and reserves requirements on accounts denominated in local or foreign currency) show a clear upward trend during the period. Figure 1 shows that the index MaPP starts to increase more rapidly around 2007 which coincides with an increasing frequency of credit booms. The rise in MaPP at the beginning of the global financial crisis is almost completely determined by an increase in the aggregate index for reserve requirements (MaPP_RR).

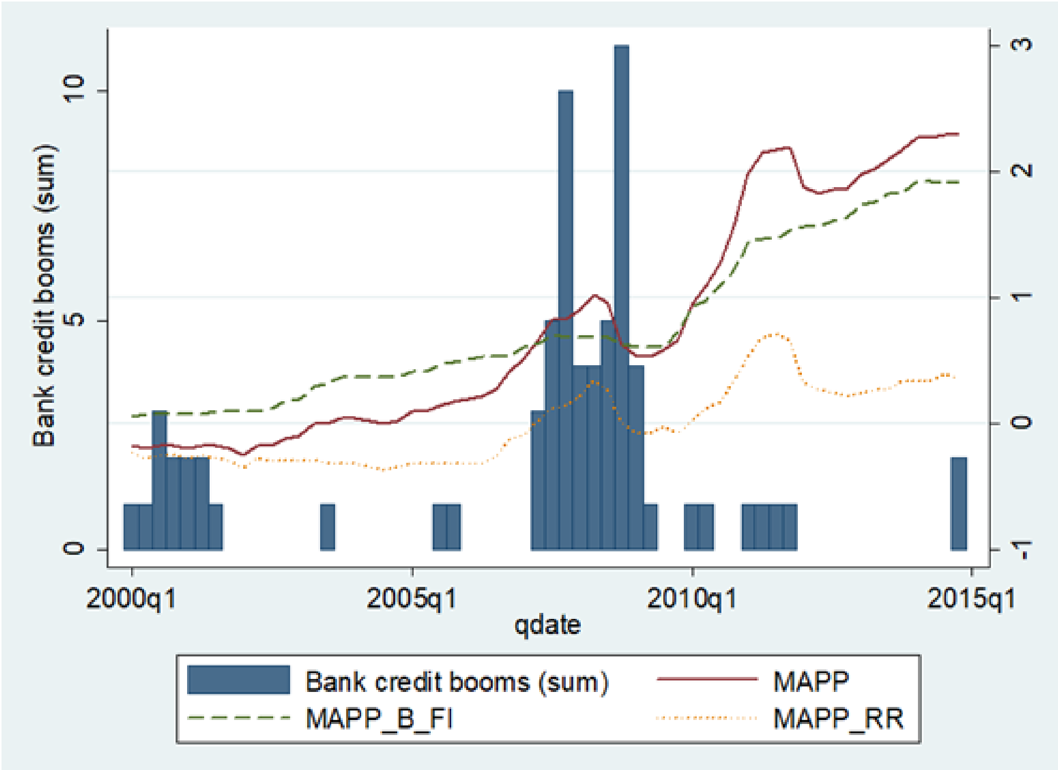
Moreover, Figure A2 shows that the rise in MaPP is mainly caused by tightenings of reserve requirements on deposits denominated in local currency. The aggregate index with borrower- and financial institutions-targeted instruments (MaPP_B_FI) displays a more stable upward trend until 2009. From around 2010 there is a significant rise in the index MaPP driven by an increase in both indexes MaPP_RR and MaPP_B_FI. However, the frequency of the number of credit booms is much lower from 2010 which suggests that many macroprudential policies were tightened during a period when credit growth was relatively low.

Table A5 shows that the aggregate index for borrower- and financial institution-targeted policies (MaPP_B_FI) is positively correlated with the index for reserve requirement policies (MaPP_RR). However, the index MaPP_B_FI is negatively correlated with the central bank policy rate and this is probably because policy rates have been kept low in advanced countries while macroprudential policies have been tightened.

Figure A2 illustrates the development of the five individual macroprudential policy instruments between 2000Q1 and 2014Q4. First, the borrower-targeted instrument Loan-to-Value caps shows a relatively stable upward trend until the end of 2009. However, starting in 2009 until 2014 the average cumulative index for LTV caps triples from around 0.5 to 1.5. In contrast, both financial institution-targeted instruments (i.e. concentration limits and interbank exposure limits) display a smoother upward trend for the entire period.

Furthermore, the index for reserve requirements related to foreign currency shows a relatively flat trend fluctuating around zero until 2010. Finally, the index for reserve requirements on accounts denominated in local currency is negative for almost the entire period which implies that easings were more common than tightenings. However, the

Figure 1: Macroprudential indexes and bank credit booms 2000Q1-2014Q4



Note: The figure shows the frequency of bank credit booms with threshold 1.75 s.d. (left axis) and the average for the aggregate macroprudential policy indexes (right axis).

frequency (or size) of the tightenings of the index was more pronounced during the periods 2006-2008 and 2010-2011.

Table A6 shows pairwise correlations between individual macroprudential policy instruments. Loan-to-Value caps (LTV_CAP) is positively correlated with all other individual policies. However, interbank exposure limits (IBEX) and concentration limits (CONCRAT) are weakly negatively correlated. In addition, the reserve requirement policies (RR_D and RR_FX) are positively correlated.

5 Results

5.1 Macroprudential policies and bank credit booms

Results for estimations with aggregate bank credit booms and the MaPP index are shown in Table 1. The MaPP index has a negative coefficient that is significant at least at the

5% level for all Logit estimations displayed in columns 1-4. Moreover, the coefficient for MaPP is also negative and significant in the LPM estimation with country and year fixed effects (column 5) and the Firth logit estimation (column 6).

The aggregate index MaPP_B_FI including LTV caps, concentration limits and interbank exposure limits has a negative and significant coefficient in all Logit, and Firth logit estimations (columns 1-3) shown in Table 2. Moreover, the index MaPP_RR including reserve requirements on accounts denominated in foreign or domestic currency is negative and significant at the 1% or 10% level for the Logit estimations (columns 4 and 5). However, the index MaPP_RR is not significant in the Firth logit estimation (column 6). The results for the macroprudential sub-indexes show that both borrower- and financial institution-targeted instruments (MaPP_B_FI), as well as reserve requirement policies (MaPP_RR), are negatively associated with credit booms.

The number of bank credit boom observations is 61 in all estimations for the aggregate macroprudential indexes. However, the number of countries is 41 without country fixed effects but only 24 with fixed effects. The reason for the difference in the number of countries is that almost half of the countries either did not experience a credit boom or lack data for at least one control variable during the credit boom episode.

Furthermore, the coefficient for the MaPP index typically remains negative and significant for lags up to 6 quarters which provides additional support for the robustness of the results. Consequently, the aforementioned issue of reverse causality that negative coefficients are due to a tightening of the macroprudential policy instruments at the peak or after the peak of the credit boom is not likely to be the case.

The coefficient for the VIX index is found to be positive and highly significant in all estimations. This is the opposite results to the findings by Bruno et al. (2017) and Akinci and Olmstead-Rumsey (2018) who find a negative coefficient when using credit growth as the dependent variable. However, the dependent variable in this study is credit booms which are relatively frequently succeeded by financial crises. During the 2000s many of the financial crises in advanced countries began almost at the same time as the crisis in the United States which implies that a positive coefficient for the VIX index lagged one quarter is not surprising. In addition, it is only the first lag of the VIX index that is positive and significant while lags 2-5 are negative but not significant. Finally, the level of bank credit to GDP is also positive and significant with country fixed effects.

Results for borrower- and financial institution-targeted instruments are shown in Table A7. The coefficients for Loan-to-Value caps (LTV_CAP) and interbank exposure limits (IBEX) are negative but not significant in any of the estimations. The coefficient for concentration limits (CONCRAT) is not significant in the Logit estimation, however the coefficient is negative and significant at the 10% level in the Firth logit estimation.

Finally, results for reserve requirement policies are shown in Table A8. Reserve requirements on local currency denominated accounts (RR_D) are found to be negative and significant at the 1% level for the Logit estimation with country fixed effects. However, the coefficient is not significant for Logit estimation without country fixed effects and the Firth logit estimation. Moreover, the coefficient for reserve requirements on foreign currency accounts (RR_FX) is negative in all estimations but only significant for the Logit estimation with country fixed effects at the 5% level .

5.2 Credit booms and banking crises

Credit booms have so far been treated as identical and no difference has been made between booms that are benign compared to those followed by systemic banking crises. However, if the purpose of macroprudential policies is to mitigate financial instability, then it is essential to examine whether these policies can be effective to deal with credit booms followed by systemic banking crises.

Data on systemic banking crises has been collected from Laeven and Valencia (2013). The authors define a banking crisis as an event that meets two conditions: "(1) Significant signs of financial distress in the banking system (as indicated by significant bank runs, losses in the banking system, and/or bank liquidations). (2) Significant banking policy intervention measures in response to significant losses in the banking system (Laeven and Valencia, 2013, p. 228)".

A credit boom is defined as "bad" if a systemic banking crisis occurs during the

Table 1: Aggregate macroprudential index and bank credit booms

Variables	Logit (1)	Logit (2)	Logit (3)	Logit (4)	LPM (5)	Firth logit (6)
Log(VIX)	1.464***	1.526***	2.873***	2.850***	0.091***	1.469***
	(0.404)	(0.407)	(0.669)	(0.798)	(0.021)	(0.384)
Real GDP growth	0.093*	0.254***	-0.050	0.020	0.001	0.090**
	(0.050)	(0.068)	(0.067)	(0.081)	(0.002)	(0.043)
Change CB policy rate	0.004	-0.001	0.008	0.004	0.000	0.005
	(0.004)	(0.016)	(0.005)	(0.018)	(0.001)	(0.012)
Inflation	0.145**	0.094	0.048	-0.062	-0.003	0.172**
	(0.060)	(0.158)	(0.064)	(0.150)	(0.003)	(0.072)
Log(real exchange rate)	-1.04	7.592**	-0.140	6.287**	0.137***	-0.088
	(0.131)	(3.083)	(0.135)	(3.136)	(0.052)	(0.093)
Bank credit (% of GDP)	-0.003	0.056***	-0.006	0.074***	0.002***	-0.003
	(0.004)	(0.017)	(0.005)	(0.024)	(0.000)	(0.004)
Log(GDP per capita)	0.670	7.789***	0.345	3.016	0.124***	0.660***
	(0.443)	(2.239)	(0.465)	(2.064)	(0.037)	(0.234)
MaPP	-0.229***	-0.489***	-0.182**	-0.270**	-0.005**	-0.220**
	(0.078)	(0.129)	(0.087)	(0.130)	(0.002)	(0.089)
Country fixed effects	NO	YES	NO	YES	YES	NO
Year fixed effects	NO	NO	YES	YES	YES	NO
Observations	2171	1370	1284	1370	2171	2171
Credit booms	61	61	61	61	61	61
Countries	41	24	41	24	41	41
Prob > chi-sq (LPM: F-test)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Robust standard errors in parenthesis. ***p<0.01, **p<0.05, *p<0.1

Notes: Table showing Logit, Linear Probability Model (LPM) and Firth logit estimations with a binary dependent variable for bank credit booms. The Hodrick-Prescott (HP) filter is used to identify credit booms and the threshold is 1.75 standard deviations. The MaPP index includes all five macroprudential instruments (LTV_CAP, IBEX, CONCRAT, RR_D, and RR_FX) and the time period is 2000Q1-2014Q4. Robust standard errors clustered by country are reported for Logit and LPM estimations without country fixed effects. All independent variables are lagged one quarter.

Table 2: Aggregate macroprudential sub-indexes and bank credit booms

Variables	Logit (1)	Logit (2)	Firth logit (3)	Logit (4)	Logit (5)	Firth logit (6)
Log(VIX)	1.357***	1.363***	1.368***	1.480***	1.658***	1.483***
	(0.402)	(0.403)	(0.383)	(0.413)	(0.408)	(0.383)
Real GDP growth	0.074*	0.213***	0.072*	0.083*	0.241***	0.080*
	(0.044)	(0.061)	(0.042)	(0.050)	(0.066)	(0.043)
Change CB policy rate	0.005	-0.001	0.006	0.004	-0.001	0.005
	(0.004)	(0.015)	(0.012)	(0.004)	(0.015)	(0.012)
Inflation	0.127**	0.081	0.155**	0.142**	0.106	0.168**
	(0.061)	(0.154)	(0.073)	(0.056)	(0.157)	(0.073)
Log(real exchange rate)	-0.097	5.393**	-0.081	-0.118	5.720**	-0.101
	(0.134)	(2.688)	(0.095)	(0.130)	(2.861)	(0.091)
Bank credit (% of GDP)	-0.004	0.057***	-0.003	-0.004	0.0049***	-0.004
	(0.004)	(0.017)	(0.004)	(0.005)	(0.015)	(0.004)
Log(GDP per capita)	0.714*	4.876***	0.706***	0.637	5.199**	0.622***
	(0.406)	(1.891)	(0.230)	(0.446)	(2.038)	(0.237)
MaPP_B_FI	-0.306**	-0.582***	-0.290**			
	(0.128)	(0.208)	(0.127)			
MaPP_RR				-0.220*	-0.537***	-0.205
				(0.131)	(0.192)	(0.135)
Country fixed effects	NO	YES	NO	NO	YES	NO
Year fixed effects	NO	NO	NO	NO	NO	NO
Observations	2171	1370	2171	2171	1370	2171
Credit booms	61	61	61	61	61	61
Countries	41	24	41	41	24	41
Prob > chi-sq	0.0000	0.0000	0.0000	0.0002	0.0000	0.0002

Robust standard errors in parenthesis. ***p<0.01, **p<0.05, *p<0.1
Notes: Table showing Logit and Firth logit estimations with a binary dependent variable for bank credit booms. The Hodrick-Prescott (HP) filter is used to identify credit booms and the threshold is 1.75 standard deviations. The index MaPP_B_FI includes borrower- and financial institutions-targeted macroprudential instruments (LTV_CAP, IBEX, and CONCRAT) and the index MaPP_RR includes reserve requirement instruments (RR_D and RR_FX). The time period is 2000Q1-2014Q4. Robust standard errors clustered by country are reported for Logit estimations without country fixed effects. All independent variables are lagged one quarter.

credit boom or within three years after the end of the boom similar to the approach by Dell'Ariccia et al. (2016) and Richter et al. (2021). If a credit boom episode coincides with a banking crisis but begins after the first year of the crisis then these observations are excluded from the estimations. All credit booms that are not "bad" according to this criterion are defined as "good". The total number of observations for good booms is 188 while the number of bad booms is 80 for the period 1970Q1-2014Q4.

Figures A3 and A4 illustrate the behavior of the average ratio of aggregate bank credit to GDP ten years before and after the first quarter of a credit boom episode. Good credit booms are on average characterized by a continuous increase in the ratio of bank credit to GDP up to the first quarter that is above the threshold of 1.75 s.d. illustrated by the vertical line in Figure A3. After the first quarter of the good boom (66 episodes) the ratio of credit to GDP stagnates for five years and then continues to climb.

Figure A4 shows that the ratio of aggregate bank credit to GDP ten years before a bad credit boom (24 episodes) starts at a higher level on average compared to good booms. Moreover, the increase in the level of bank credit (as percent of GDP) is slightly higher on average for bad booms compared to good booms during the decade before the credit boom. When the bad boom has started the level of bank credit to GDP falls back to the level ten years before the credit boom. Importantly, the trend of the average ratio of bank credit to GDP during the decade before both good and bad booms is very similar while the trend diverges once the credit boom has started.

The behavior of the average real GDP growth five years before and after good and bad credit booms is illustrated in Figures A5 and A6. The real growth rate of GDP fluctuates between 4-5 percent during the five years prior to the first quarter of both good and bad credit boom episodes. Just before the credit boom episode begins the growth rate drops for both types of booms. However, the fall in the real growth rate of GDP is much larger for bad booms compared to good booms. Consequently, it is important to examine whether macroprudential policies can be effective to reduce the likelihood of those credit booms that cause substantial economic costs.

Table 3 shows results for Logit, LPM, and Firth logit estimations with good booms and bad booms separately. The coefficient for the aggregate macroprudential policy index MaPP is negative and significant in all Logit estimations with bad credit booms (and weakly significant for the LPM estimation). Moreover, the MaPP index is negative and significant for the Logit and LPM estimations with good credit booms but not for the Firth logit estimation. The results suggest that a tighter macroprudential policy stance reduces the likelihood of both good and bad credit booms.

The fact that macroprudential policies seem to curtail not only bad credit booms but also good booms stresses the importance of the unintended consequences of macroprudential regulation. This finding is consistent with Gertler et al. (2020) and Richter et al. (2020) showing that tightening of macroprudential policies have adverse consequences for output. Nevertheless, Figures A5 and A6 show that GDP growth drops significantly after both good and bad credit booms but more so for booms followed by systemic banking crises. To conclude, the findings suggest that macroprudential policies are effective to address bad credit booms but potentially at the cost of reducing economic growth.

5.3 Macroprudential policies and household credit booms

Mian and Sufi (2010) show using microeconomic data that changes in household leverage were a powerful predictor of the onset and severity of the Great Recession in the United States. Moreover, several studies confirm that credit to the household sector is associated with a higher probability of financial crises (Alter et al., 2018; Büyükkaracabak and Valev, 2010; Müller and Verner, 2022). Mian and Sufi (2014) conclude from the international and U.S. evidence that "*Economic disasters are almost always preceded by a large increase in household debt. In fact, the correlation is so robust that it is as close it gets to an empirical law in macroeconomics* (Mian and Sufi, 2014, p. 9)". Hence, it is essential to examine whether macroprudential policies can be effective to deal with booms in household credit.

Figure A7 illustrates that the average ratio of household credit to GDP does not increase during the ten years preceding a boom in aggregate bank credit (32 episodes) that is not followed by a systemic banking crisis (good boom). In contrast, Figure A8

Table 3: Good and bad bank credit booms

Variables	Good credit boom Logit (1)	Good credit boom LPM (2)	Good credit boom Firth logit (3)	Bad credit boom Logit (4)	Bad credit boom LPM (5)	Bad credit boom Firth logit (6)
Log(VIX)	1.216***	0.022***	1.233**	1.456**	0.022***	1.496***
	(0.413)	(0.008)	(0.514)	(0.614)	(0.007)	(0.628)
Real GDP growth	0.159***	0.004***	0.154***	-0.023	0.001	-0.036
	(0.039)	(0.001)	(0.001)	(0.070)	(0.001)	(0.071)
Change CB policy rate	0.001	0.000	0.004	0.017	0.000	0.019
	(0.002)	(0.001)	(0.013)	(0.014)	(0.001)	(0.014)
Inflation	0.086	0.001	0.147	0.065	-0.001	0.244**
	(0.125)	(0.003)	(0.103)	(0.130)	(0.002)	(0.116)
Log(real exchange rate)	-0.078	0.059	-0.057	-0.063	0.038	-0.020
	(0.212)	(0.040)	(0.108)	(0.250)	(0.031)	(0.165)
Bank credit (% of GDP)	-0.007	0.001**	-0.006	0.005	0.001***	0.005
	(0.006)	(0.000)	(0.005)	(0.008)	(0.000)	(0.006)
Log(GDP per capita)	0.494	0.050*	0.485*	1.448***	0.057***	1.408***
	(0.743)	(0.027)	(0.284)	(0.320)	(0.021)	(0.442)
MaPP	-0.166**	-0.005***	-0.141	-0.515**	-0.002*	-0.502***
	(0.081)	(0.002)	(0.098)	(0.203)	(0.001)	(0.157)
Country fixed effects	NO	YES	NO	NO	YES	NO
Year fixed effects	NO	NO	NO	NO	NO	NO
Observations	2145	2145	2145	2131	2131	2131
Credit booms	35	35	35	21	21	21
Countries	41	41	41	41	41	41
Prob > chi-sq	0.0000	0.0000	0.0091	0.0002	0.0000	0.0001

Robust standard errors in parenthesis. ***p<0.01, **p<0.05, *p<0.1
Notes: Table showing Logit, Linear Probability Model (LPM) and Firth logit estimations with a binary dependent variable for bank credit booms. The Hodrick-Prescott (HP) filter is used to identify credit booms and the threshold is 1.75 standard deviations. The MaPP index includes all five macroprudential instruments (LTV_CAP, IBEX, CONCRAT, RR_D, and RR_FX) and the time period is 2000Q1-2014Q4. A credit boom is defined as "bad" if a systemic banking crisis occurs during the credit boom or within three years after the end of the boom similar to the approach by Dell'Ariccia et al. (2016). If a credit boom episode coincides with a banking crisis but begins after the first year of the crisis then these observations are excluded from the estimations. All credit booms that are not "bad" according to this criterion are defined as "good". Robust standard errors clustered by country are reported for Logit estimations. All independent variables are lagged one quarter.

shows that household credit as percent of GDP increases considerably before a bank credit boom (20 episodes) associated with a banking crisis (bad boom). The different pattern for the ratio of household credit to GDP before good booms and bad booms supports the relevance of household credit for explaining the occurrence of financial crises.

Figures A9 and A10 in the appendix show the behavior of both household and firm credit (% of GDP) around good and bad credit booms. The median ratio of firm credit to GDP increases both before good and bad credit booms. However, while the median ratio of household credit to GDP show a clear upward trend before bad credit booms this is not the case before good credit booms. To sum up, the behavior of household credit contains information that is useful to identify those credit booms that are followed by systemic banking crises.

Table 4 shows the results for the MaPP index and household credit booms with threshold 1.75 standard deviations. The macroprudential index MaPP has a negative coefficient and is significant at the 5% level in all estimations, except for Logit and LPM estimations with country and year fixed effects where the coefficient is significant at the 10% level.

The results for the macroprudential sub-indexes MaPP_B_FI and MaPP_RR are shown in Table A9. The MaPP_B_FI index is negatively and strongly associated with the occurrence of household credit booms in all estimations. However, the coefficient for the MaPP_RR index is negative but only significant at the 10% level in two of the estimations. Finally, the coefficient for the MaPP_B_FI index is larger in the estimations with household credit booms compared to the results for aggregate bank credit booms (Table 2).

5.4 Economic interpretation

The results show that aggregate macroprudential indexes are negatively associated with the probability of booms in both bank and household credit. However, it is important to assess how large the effect is in economic terms of an increase in the macroprudential indexes on the likelihood of credit booms. Consequently, average marginal effects for the

Table 4: Aggregate macroprudential index and household credit booms

Variables	Logit (1)	Logit (2)	Logit (3)	Logit (4)	LPM (5)	Firth logit (6)
Log(VIX)	0.020	0.064	1.594***	1.629*	0.040**	0.039
	(0.624)	(0.527)	(0.609)	(0.989)	(0.020)	(0.474)
Real GDP growth	0.268***	0.482***	0.230**	0.431***	0.006***	0.263***
	(0.072)	(0.095)	(0.114)	(0.123)	(0.002)	(0.051)
Change CB policy rate	-0.002	0.028	-0.002	-0.020	-0.000	0.005
	(0.003)	(0.243)	(0.005)	(0.280)	(0.001)	(0.014)
Inflation	0.170*	0.214	0.128	0.128	0.000	0.219**
	(0.087)	(0.197)	(0.091)	(0.210)	(0.002)	(0.104)
Log(real exchange rate)	0.137	16.541***	0.136	11.378*	0.059	0.139*
	(0.127)	(4.407)	(0.121)	(5.840)	(0.051)	(0.078)
HH credit (% of GDP)	0.016*	0.074***	0.020*	0.238***	0.003***	0.015**
	(0.009)	(0.028)	(0.011)	(0.059)	(0.001)	(0.007)
Log(GDP per capita)	0.180	11.718***	-0.032	7.879*	0.066*	0.190
	(0.461)	(3.410)	(0.500)	(2.765)	(0.039)	(0.274)
MaPP	-0.304***	-0.708***	-0.304**	-0.475*	-0.004*	-0.294***
	(0.099)	(0.170)	(0.146)	(0.250)	(0.003)	(0.089)
Country fixed effects	NO	YES	NO	YES	YES	NO
Year fixed effects	NO	NO	YES	YES	YES	NO
Observations	1990	1031	1276	1031	1990	1990
Credit booms	49	49	49	49	49	49
Countries	37	19	35	19	37	37
Prob > chi-sq (LPM: F-test)	0.0019	0.0000	0.0000	0.0000	0.0000	0.0000

Robust standard errors in parenthesis. ***p<0.01, **p<0.05, *p<0.1
Notes: Table showing Logit, Linear Probability Model (LPM) and Firth logit estimations with a binary dependent variable for household (HH) credit booms. The measure for household credit includes in addition to domestic bank credit also credit from non-bank institutions and cross-border credit. The Hodrick-Prescott (HP) filter is used to identify credit booms and the threshold is 1.75 standard deviations. The MaPP index includes all five macroprudential instruments (LTV_CAP, IBEX, CONCRAT, RR_D, and RR_FX) and the time period is 2000Q1-2014Q4. Robust standard errors clustered by country are reported for Logit and LPM estimations without country fixed effects. All independent variables are lagged one quarter.

macroprudential policy indexes are estimated following the approach by Kirschenmann et al. (2016).

Table 5 shows the average marginal effects for the macroprudential index MaPP from estimations with aggregate bank credit booms. The average standard deviation for the MaPP index is approximately 1.261 for bank credit booms. An increase in the MaPP index by one standard deviation reduces the likelihood of bank credit booms with threshold 1.75 s.d. by approximately 0.77 percentage points. This effect is relatively large in economic terms since the sample frequency of credit booms with this threshold is only 2.81 percent.

Furthermore, the impact of macroprudential policies could be different for credit booms of different sizes. Accordingly, average marginal effects for bank credit booms with thresholds 1.5 and 2 standard deviations are shown in columns 1 and 3 in Table 5. An increase in the MaPP index by one standard deviation reduces the likelihood of smaller credit booms (threshold 1.5 s.d.) by about 1.35 percentage points compared to 0.46 percentage points for larger credit booms (threshold 2 s.d.). However, the sample frequency of smaller credit booms (5.48 percent) is significantly higher compared to larger credit booms (1.47 percent). Hence the effect of an increase in the MaPP index on the likelihood of credit booms relative to the sample frequency is higher for larger credit booms compared to for smaller booms.

It could be of interest to examine whether the effectiveness of macroprudential policies differ between booms in aggregate bank credit and household credit. Since the index for reserve requirements (MaPP_RR) is only significant for smaller household credit booms it is suitable to compare the results for the index with borrower- and financial institution-targeted macroprudential instruments (MaPP_B_FI). An increase in the MaPP_B_FI index by one standard deviation reduces the occurrence of smaller household credit booms (threshold 1.5 s.d.) by 1.09 percentage points compared to 1.06 percentage points for bank credit booms of the same size. Nevertheless, the sample frequency for household credit booms is only 3.92 percent compared to 5.48 percent for booms in bank credit. This implies that the effect of an increase in MaPP_B_FI on the probability of household

Table 5: Average marginal effects for macroprudential indexes

	Bank credit			Household credit		
Variables	1.5 s.d.	1.75 s.d.	2 s.d.	1.5 s.d.	1.75 s.d.	2 s.d.
	(1)	(2)	(3)	(4)	(5)	(6)
MaPP	-0.011***	-0.006***	-0.004**	-0.011***	-0.007**	-0.004
	(0.003)	(0.002)	(0.002)	(0.004)	(0.003)	(0.002)
Observations	2171	2171	2171	1990	1990	1990
Countries	41	41	41	37	37	37
Credit booms	119	61	32	78	49	25
Std. Dev.	1.261	1.261	1.261	1.080	1.080	1.080
MaPP_B_FI	-0.013**	-0.008**	-0.006**	-0.014**	-0.010**	-0.006**
	(0.005)	(0.004)	(0.003)	(0.006)	(0.005)	(0.003)
Observations	2171	2171	2171	1990	1990	1990
Countries	41	41	41	37	37	37
Credit booms	119	61	32	78	49	25
Std. Dev.	0.810	0.810	0.810	0.755	0.755	0.755
MaPP_RR	-0.012***	-0.006*	-0.002	-0.009**	-0.006	-0.003
	(0.005)	(0.003)	(0.002)	(0.006)	(0.005)	(0.003)
Observations	2171	2171	2171	1990	1990	1990
Countries	41	41	41	37	37	37
Credit booms	119	61	32	78	49	25
Std. Dev.	0.629	0.629	0.629	0.497	0.497	0.497

***p<0.01, **p<0.05, *p<0.1

Notes: Table showing average marginal effects for bank credit and household credit booms. The MaPP index includes all five macroprudential instruments (LTV_CAP, IBEX, CONCRAT, RR_D, and RR_FX). The index MaPP_B_FI includes borrower- and financial institutions-targeted macroprudential instruments (LTV_CAP, IBEX, and CONCRAT) and the index MaPP_RR includes reserve requirement instruments (RR_D and RR_FX). The time period is 2000Q1-2014Q4.

credit booms is higher compared to booms in bank credit even though the sample frequency is significantly lower. Moreover, similar results for the MaPP_B_FI index are also found when comparing bank and household credit booms with threshold 1.75 standard deviations.

To conclude, the results suggest that the effect of an increase in the MaPP index on the probability of credit booms is relatively large in economic terms, and this effect seems to be greater for larger credit booms. In addition, borrower- and financial institution-targeted macroprudential policies (MaPP_B_FI) seem to be more effective to deal with booms in household credit compared to bank credit booms.

6 Robustness tests

To examine the robustness of the results it is essential to identify credit booms with different thresholds. Figure A11 illustrates the frequency of credit booms for thresholds with 1.5, 1.75 and 2 standard deviations. The general pattern suggests that credit booms with a lower threshold are significantly more frequent and occur for a longer time than booms with a higher threshold.

The coefficient for the MaPP index is negative and highly significant in all estimations with small credit booms (1.5 s.d.) shown in Table A10. For larger credit booms (2 s.d.) the MaPP index is negative and significant at the 5% level in the Logit estimation but only at the 10% level in the Firth logit estimation. The coefficient is not significant for LPM with both country and year fixed effects. To conclude, the findings suggest that macroprudential policies seem to be effective to deal with both smaller and larger credit booms.

The global financial crisis originated in the United States in 2007 and later spread to the rest of the world with large consequences for economic growth and capital flows. A majority of the tightenings of macroprudential policies took place after the beginning of the crisis according to Akinci and Olmstead-Rumsey (2018). Hence, it is important to examine whether macroprudential policies were effective to reduce the likelihood of credit booms both before and after the start of the crisis.

Similar to the approach by Bruno et al. (2017) separate estimations are conducted for the period 2000Q1-2006Q4 and 2007Q1-2014Q4 shown in Table A11. The coefficient for the macroprudential index MaPP is negative and typically significant for both the period before and after the crisis. However, the coefficient for the MaPP index is not significant for LPM estimations with both country and year fixed effects. It should be emphasized that more than two-thirds of the booms occurred during the period 2007Q1-2014Q4.

Furthermore, Akinci and Olmstead-Rumsey (2018) report that a majority of the tightenings of macroprudential policies during the period 2000-2013 were in emerging economies. Figures A12 and A13 illustrate that both country groups employed the borrower- and financial institution-targeted instruments during the period. However, the use of reserve requirements is completely different in advanced economies compared to for developing countries. In advanced countries, reserve requirements related to foreign currency deposits were almost never used during the entire period. Reserve requirements for local currency, on the other hand, show a large drop in the index in 2000 followed by an almost constant trend until 2011 when the index falls to an even lower level. In contrast, in developing countries both types of reserve requirements are being used frequently and show a similar pattern, albeit with higher fluctuations for reserve requirements on deposits denominated in local currency.

Following the approach by Cerutti et al. (2017a) separate estimations are conducted for advanced and developing countries shown in Table A12. One-third of the 41 countries are classified as developing countries and two thirds as advanced economies listed in Table A18. The MaPP index is negative and significant at the 1% or 5% level in all estimations for developing countries shown in Table A12. In addition, the coefficient for the MaPP index is also negative and significant for advanced economies except for the LPM estimation with both country and year fixed effects.

Re-estimating the specifications in Table A12 for the macroprudential sub-indexes shows that index MaPP_B_FI is negative and typically significant for both advanced and developing countries. The sub-index MaPP_RR is found to be negative and significant in all estimations for developing countries but not for advanced economies, which is consistent with the pattern reserve requirement instruments illustrated in Figures A12 and A13.

6.1 Alternative definition of credit booms

Hamilton (2018) argues that detrending the data with a Hodrick-Prescott (HP) filter can lead to spurious dynamic relations in the data that have no basis in the underlying data generating process. Consequently, an alternative method to identify credit booms from Richter et al. (2021) is employed to test the robustness of the results.

The detrending method suggested by Hamilton (2018) assumes that the trend component (t) is the value that could have been predicted with historical data. First, denote

(h) the horizon used to build the prediction. The cyclical component is the difference between the realized value (y_t) and the expectation of the value at (t) formed at time (t-h) based on data available at that time (Richter et al., 2021). Hamilton (2018) suggests that the residual can be obtained by conducting an OLS regression of the following form:

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

The value for horizon (h) is based on the assumption about the cyclical component. Hamilton (2018) suggests a horizon of 2 years for business cycles and 5 years for debt cycles. Since the objective is to identify credit booms the choice of horizon in this study is 20 quarters which correspond to the 5 years for debt cycles.

Once the country-specific residuals have been estimated with the Hamilton filter the method by Mendoza and Terrones (2008) is used to identify credit booms. Consequently, a credit boom is identified if the detrended credit measure is above a threshold which is a multiple of the country-specific standard deviation (Richter et al., 2021).

Table A13 shows the results for the MaPP index and credit booms identified with the Hamilton filter. The coefficient for the aggregate index MaPP is typically negative and significant at the 10% level for aggregate bank credit booms with thresholds 1.75 and 2 standard deviations.

6.2 Additional control variables in the analysis

Bedayo et al. (2020) provide robust findings for Spain suggesting that raising the level of bank capital before loan expansions decreases the growth rate of credit. Consequently, it is important to verify whether the results hold when controlling for other prudential policies such as capital requirements and sector-specific capital buffers. Table A14 reports results for estimations including general capital requirements (CAP_REQ) and an aggregate index for sector-specific capital buffers (SSCB) as additional control variables.

Data on capital requirements and capital buffers has been collected from Cerutti et al. (2017b). The general capital requirements index is constructed from the changes in the regulatory framework in the Basel Accords and revisions I, II, II.5 and III. Moreover, it is assumed that the implementation of the Basel Accords never loosens the existing regulation which implies that the index for capital requirements never takes value -1. The sector-specific capital buffer index measures regulatory changes that aim to reduce the growth in bank claims to specific sectors of the economy.

Table A14 shows that the coefficient for the MaPP index is negative and significant at the 5% level for credit booms identified with the Hamilton filter and boom threshold 1.75 (except for LPM with country fixed effects). In addition, the coefficient for MaPP is negative and significant in all estimations with the HP filter.

7 Macroprudential policy and banks' systemic risk

In the previous sections, I find robust evidence that a tighter macroprudential policy stance reduces the likelihood of credit booms, particularly those that are followed by a systemic banking crisis (i.e., bad booms). But the question is what could explain the strong association between macroprudential policies and such bad booms. A possible explanation could lay in the effect that macroprudential regulation exerts on systemic risk, a type of risk that has been shown to be associated with those financial institutions most likely to be bailed out during times of crisis (Brownlees and Engle, 2017; Grinderslev and Kristiansen, 2016).

If macroprudential policy is effective in curbing large buildups of systemic risk leading to increased fragility in the financial sector the likelihood of bad booms would decrease, in line with my previous findings. Hence, the potential effect of macroprudential policies on systemic risk could provide a mechanism that explains the particular association between the macroprudential policy stance and bad booms. To explore this conjecture, I examine whether macroprudential policies are associated with a lower level of systemic risk for banks.

The dataset for systemic risk encompasses yearly data for 460 banks in 54 advanced and developing countries between 2000-2015. Variable definitions and sources are shown in table A15. In addition, the countries included in this study and the number of banks in each country are listed in table A19.

The measure of systemic risk employed in this study is SRISK developed by Brownlees and Engle (2017). SRISK measures the capital shortfall of a bank conditional on a severe market decline (Acharya et al., 2012). In other words, SRISK tells us how much capital a bank is expected to need, in addition to reserves, during a financial crisis. To sum up, SRISK can be interpreted as a measure of a bank's exposure to systemic risk and is informative when assessing the resiliency of a bank (Gehrig and Iannino, 2021).

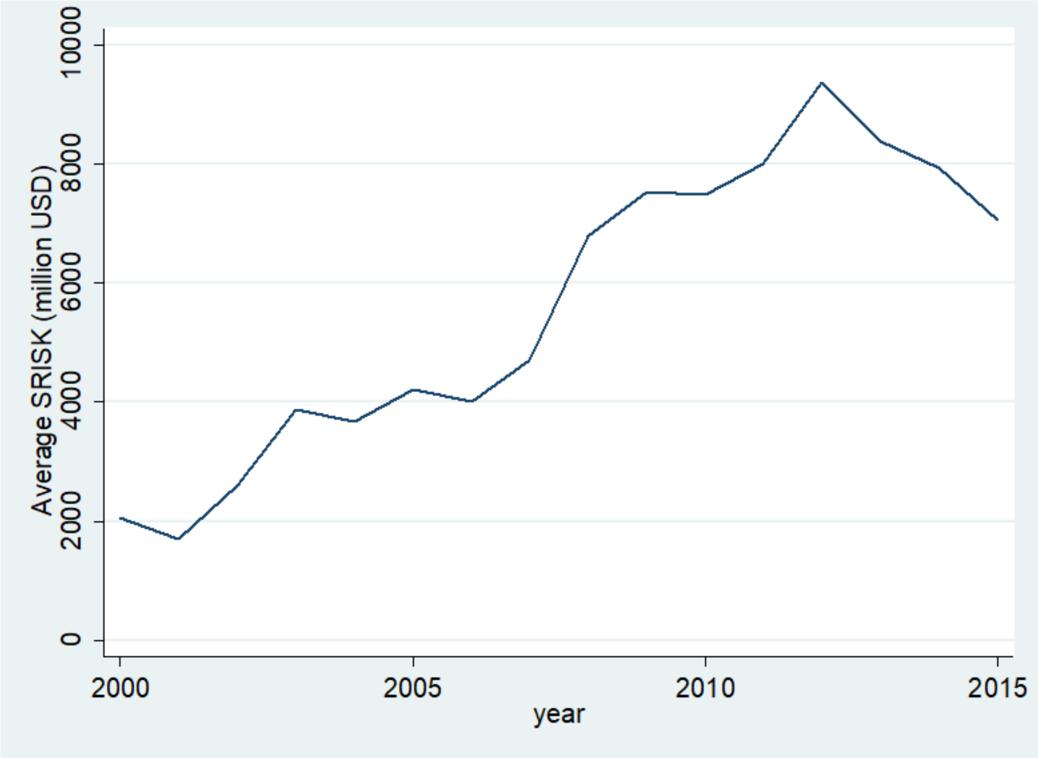
Moreover, Engle (2018) argues that "credit growth is excessive if the financial sector does not have sufficient capital to cover market value losses in a downturn (Engle, 2018, p. 2)". This notion of excessive credit growth is consistent with the finding that increasingly risky credit is issued towards the end of the credit cycle by financial institutions that do not have sufficient capital to cover the losses during a downturn. This is how a credit boom can lead to a financial crisis. To conclude, SRISK is a measure of excessive credit growth for a financial institution that potentially could help explaining the occurrence of credit booms followed by financial crises.

Benoit et al. (2017) find a strong link between a firm's marginal expected shortfall and the systematic risk of the firm measured by beta. SRISK includes both the marginal expected shortfall and market capitalization which is a proxy for the size of the firm. Accordingly, the SRISK measure takes into account both the "too-interconnected-to-fail" and the "too-big-to-fail" paradigms (Benoit et al., 2017).

Table A16 shows that both beta (systematic risk) and market capitalization (size) are positively and significantly correlated with SRISK as expected. The evolution of average positive SRISK between 2000 and 2015 is shown in Figure 2.

Several control variables which have been found to influence systemic risk are included in the estimations. First, the bank-level measures are "size" and "leverage" similar to the papers by Altunbas et al. (2018) and Karolyi et al. (2018). The variable "leverage" is divided by ten thousand to ease interpretation. Second, in addition to the bank-specific measures a number of country-level variables are also included following Karolyi et al. (2018). Real GDP growth controls for economic performance and is likely to affect

Figure 2: Evolution of positive SRISK between 2000-2015



Note: The figure shows average positive SRISK (in million USD) for banks during the period 2000-2015.

systemic risk. Moreover, non-interest income is a proxy for non-core banking activities and concentration measures the share of assets held by the three largest banks. In addition, market return and volatility are included to take into account the development on the stock market. Finally, the variable log (GDP per capita) is included to control for the level of development.

Moreover, the macroprudential policy indexes are constructed in the same way as before, with the only difference that the cumulative sum of tightenings net of easings in the fourth quarter is used when aggregating the data to yearly frequency.

A series of regressions are estimated to examine the link between macroprudential policy conditions and the level of systemic risk for banks. Since this is a cross-country study SRISK has been scaled by GDP in all estimations following the approach in Sedunov (2021). Table A17 shows the results for SRISK scaled by real GDP and the aggregate macroprudential indexes. The coefficient for the aggregate index MaPP has a negative and highly significant coefficient in estimations with year and country fixed effects. However, the coefficient is negative but not significant in the estimation with year and bank fixed effects. Moreover, the index including borrower- and financial institutions-targeted instruments MaPP_B_FI is not significant in any of the estimations. Finally, the coefficient for the index MaPP_RR is negative and significant at the 1% level with country and year fixed effects (but only significant at the 10% level with bank and year fixed effects).

Gehrig and Iannino (2021) show in their study that the evolution of SRISK for European banks has been non-linear during the period 2000-2015. They find that the very large build-up of SRISK since 2000 has been driven mainly by the upper two quintiles of banks. Consequently, quantile regressions for the 0.25, 0.5, and 0.75 quantiles are estimated to address the presence of non-linearities. As an approximation for country "fixed effects" the Mundlak-Chamberlin devise is applied which include time averages of all time-varying regressors (Chamberlin and Ricker-Gilbert, 2016; Wooldridge, 2010).

Table 6 shows the results for 0.25, 0.50 and 0.75 quantile regressions. The coefficient for the MaPP index is negative and highly significant for 0.50 and 0.75 quantiles but not for the 0.25 quantile. Similarly, the coefficients for both sub-indexes MaPP_B_FI and MaPP_RR are negative and highly significant for the upper quantiles. Interestingly, the results for the MaPP index are the opposite of the findings in the paper by Gehrig and Iannino (2021). The authors find significant and negative coefficients only for lower quantiles using dummy variables to account for the Basel process. To conclude, the results in this study suggest that a tighter macroprudential stance is negatively associated with SRISK-to-GDP for banks at upper quantiles.

8 Concluding remarks

Credit booms are one of the most important determinants of financial crises in advanced and developing countries. The objective of macroprudential policy is to avoid macroeconomic costs related to financial instability. Consequently, the main contribution of this study is to investigate whether macroprudential policies have been effective to deal with

Table 6: Quantile regressions with SRISK scaled by GDP

Variables	(1) Q.0.25	(2) Q.0.50	(3) Q.0.75	(4) Q.0.25	(5) Q.0.50	(6) Q.0.75	(7) Q.0.25	(8) Q.0.50	(9) Q.0.75
Size	0.267***	0.843***	1.372***	0.276***	0.789***	1.318***	0.278**	0.840***	1.373***
	(0.057)	(0.148)	(0.341)	(0.058)	(0.151)	(0.312)	(0.055)	(0.156)	(0.368)
Leverage	0.000	0.000	-0.003*	0.000	0.000	-0.002*	0.000	0.000	-0.003**
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Real GDP growth	-0.022*	-0.070***	-0.271***	-0.028**	-0.086***	-0.288**	-0.026**	-0.070***	-0.251**
	(0.013)	(0.024)	(0.104)	(0.012)	(0.027)	(0.115)	(0.013)	(0.022)	(0.123)
Market return	-0.002*	-0.006*	-0.009	-0.002	-0.002	-0.007	-0.001	-0.005	-0.008
	(0.001)	(0.004)	(0.006)	(0.001)	(0.005)	(0.005)	(0.001)	(0.004)	(0.005)
Volatility	0.021***	0.049***	0.081*	0.019***	0.043***	0.062**	0.020***	0.050***	0.077*
	(0.006)	(0.016)	(0.042)	(0.006)	(0.015)	(0.029)	(0.006)	(0.016)	(0.043)
Non-interest income	-0.005	-0.005	0.018	-0.004	-0.005	0.004	-0.005	-0.000	0.018
	(0.004)	(0.011)	(0.027)	(0.004)	(0.010)	(0.032)	(0.004)	(0.011)	(0.031)
Concentration	-0.006**	-0.024***	-0.021	-0.005*	0.018**	0.007	-0.006**	-0.019**	0.004
	(0.003)	(0.008)	(0.033)	(0.003)	(0.009)	(0.043)	(0.003)	(0.009)	(0.037)
MaPP	-0.023	-0.156***	-0.293***						
	(0.016)	(0.037)	(0.096)						
MaPP_B_FI				-0.065	-0.273***	-0.535**			
				(0.047)	(0.101)	(0.257)			
MaPP_RR							-0.016	-0.163***	-0.301***
							(0.017)	(0.043)	(0.111)
Year effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	2958	2958	2958	2958	2958	2958	2958	2958	2958
Countries	54	54	54	54	54	54	54	54	54
Banks	387	387	387	387	387	387	387	387	387
R-squared	0.1843	0.2000	0.1942	0.1812	0.1967	0.1905	0.1813	0.1970	0.1926

Robust standard errors in parenthesis. ***p<0.01, **p<0.05, *p<0.1
Notes: Table showing results for 0.25, 0.50 and 0.75 quantile regressions with SRISK scaled by real GDP as the dependent variable. The MaPP index includes all five macroprudential instruments (LTV_CAP, IBEX, CONCRAT, RR_D and RR_FX). The index MaPP_B_FI includes borrower- and financial institutions-targeted macroprudential instruments (LTV_CAP, IBEX, and CONCRAT) and the index MaPP_RR includes reserve requirement instruments (RR_D and RR_FX). As an approximation to "fixed effects" the Mundlak-Chamberlin device is applied which includes time averages of all time-varying regressors (Wooldridge, 2010). Year effects are captured by year dummies. Macroprudential indexes measure the cumulative sum of tightenings net of easings since 2000 (Akinci Olmstead-Rumsey, 2017). The time period is 2000-2015 and all independent variables are lagged one period. The standard errors are clustered for banks (Parente et al., 2016).

booms in aggregate bank credit and household credit.

The results strongly suggest that aggregate indexes with macroprudential policies are negatively and significantly associated with booms in aggregate bank credit. In addition, the results also show that macroprudential policies are suitable to address those credit booms that are followed by systemic banking crises. These findings suggest that macroprudential policies are not only effective to reduce the likelihood of periods with strong credit growth, but may also be useful to curb credit booms that precede financial crises.

Furthermore, booms in household credit have been identified as particularly important for the occurrence and severity of financial crises. This implies that it is essential to examine the effectiveness of macroprudential policies on household credit and not only on the measure with aggregate bank credit. The results show that macroprudential policies are negatively linked to the likelihood of booms in household credit, which is an important finding since this type of credit poses a higher risk for financial stability.

Finally, a possible mechanism explaining why macroprudential policies are effective in curtailing credit booms followed by systemic banking crises is that these policies reduce the build-up of banks' systemic risk. The findings show that the macroprudential policy stance is negatively associated with the level of systemic risk for banks. This association seems to be more pronounced for riskier financial institutions.

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Appendix

Table A1: GMM estimations with macroprudential indexes and bank credit growth

Variables	(1)	(2)	(3)	(4)	(5)
Real bank credit growth	0.1813*	0.1769*	0.1121	0.1433	0.1970
	(0.0933)	(0.0947)	(0.1058)	(0.0920)	(0.1512)
Real GDP growth	0.0012**	0.0012**	0.0013**	0.0012**	0.0016***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0006)
Change CB policy rate	0.0003*	0.0003	0.0002	0.0003*	-0.0025**
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0012)
Log(VIX)	-0.0006	-0.0006	-0.0004	-0.0003	0.0006
	(0.0021)	(0.0024)	(0.0022)	(0.0023)	(0.0024)
MaPP	0.0010**	0.0016**	0.0012	0.0005	0.0008
	(0.0004)	(0.0008)	(0.0011)	(0.0005)	(0.0007)
MaPP * Top 25%	-0.0014***				-0.0016**
	(0.0003)				(0.0008)
MaPP * Top 50%		-0.0018*			
		(0.0009)			
MaPP * Bottom 50%			-0.0017		
			(0.0027)		
MaPP * Bottom 25%				0.0014	0.0003
				(0.0026)	(0.0031)
Observations	2123	2123	2123	2123	2123
Countries	40	40	40	40	40
Instruments	37	37	37	37	37
AR(1)	0.000	0.000	0.000	0.000	0.045
AR(2)	0.164	0.152	0.375	0.274	0.221
Hansen J-test	0.275	0.232	0.311	0.201	0.184

Robust standard errors in parenthesis. ***p<0.01, **p<0.05, *p<0.1

Notes: Table showing dynamic two-step GMM estimations with the real growth rate of bank credit as the dependent variable. All regressors are treated as endogenous (including the interaction term) except the VIX index which is treated as exogenous similar to in the paper by Akinci and Olmstead-Rumsey (2018). The time period is 2000Q1-2014Q4. The MaPP index includes all five macroprudential instruments (LTV_CAP, IBEX, CONCRAT, RR_D, and RR_FX). The focus of this exercise is to assess the effectiveness of macroprudential policies during the boom phase of the financial cycle. Consequently, the dummy variables top 25%, top 50%, bottom 50% and bottom 25% only take value one for observations with positive credit growth. The four different dummy variables take value one for the following quarterly values: Top 25% (credit growth $>$ 3.4%), Top 50% (credit growth $>$ 1.9%), Bottom 50% (0% $<$ credit growth $<$ 1.9%) and Bottom 25% (0% $<$ credit growth $<$ 1%). All independent variables except the VIX index are lagged one quarter.

Table A2: Summary statistics of variables

Variables	Mean	Median	Min	Max	Std.Dev.	Obs
Dependent variables						
Bank credit boom 1.75 s.d.	0.029	0	0	1	0.167	2448
Household credit boom 1.75 s.d.	0.026	0	0	1	0.160	2197
Real bank credit growth	0.013	0.011	-0.178	0.190	0.028	2192
Prudential policy indexes						
LTV_CAP	0.874	1	-3	8	1.935	873
IBEX	0.665	0	0	4	0.872	738
CONCRAT	0.458	0	-1	4	0.829	1455
RR_D	-0.226	0	-5	13	1.600	2448
RR_FX	0.081	0	-6	11	0.857	2448
CAP_REQ	0.259	0	0	2	0.581	2388
SSCB	0.312	0	-2	6	1.022	2448
MaPP	0.776	0	-5	25	3.191	2448
MaPP_B_FI	0.784	0	-2	9	1.581	2448
MaPP_RR	-0.008	0	-5	16	2.141	2448
Control variables						
Log(VIX)	2.976	2.961	2.401	4.071	0.348	2448
Real GDP growth	2.960	2.938	-14.376	26.509	3.577	2385
Change CB policy rate	-0.086	0	-102.010	135.760	3.697	2286
Inflation	0.798	0.596	-17.799	20.532	1.309	2448
Log(GDP per capita)	6.680	7.009	3.413	8.513	1.045	2432
Log(real exchange rate)	1.680	1.025	-0.675	9.852	2.365	2432
Bank credit (% of GDP)	83.300	84.450	8.500	229.300	41.837	2448
Household credit (% of GDP)	53.908	53.100	0.600	139.500	32.002	2193

Notes: The table shows summary statistics for all observations between 2000Q1-2014Q4.

Table A3: Definitions and sources for macroprudential indexes

Variables	Definition	Source
LTV_CAP	Cumulative change in the Loan-to-Value (LTV) cap.	Cerrutti et al. (2017b)
IBEX	Cumulative change in the interbank exposure limit.	Cerrutti et al. (2017b)
CONCRAT	Cumulative change in concentration limits. Limits banks' exposures to specific borrowers or sectors.	Cerrutti et al. (2017b)
RR_D	Cumulative change in reserve requirements on local currency-denominated accounts.	
	This instrument can take values higher or lower than 1 or -1 in each quarter.	Cerrutti et al. (2017b)
RR_FX	Cumulative change in reserve requirements on foreign currency-denominated accounts.	
	This instrument can take values higher or lower than 1 or -1 in each quarter.	Cerrutti et al. (2017b)
MaPP	Sum of LTV_CAP, IBEX, CONCRAT, RR_D, and RR_FX.	
	All individual instruments are adjusted to have maximum and minimum changes of 1 and -1 in each quarter.	Cerrutti et al. (2017b)
MaPP_B_FI	Sum of LTV_CAP, IBEX, and CONCRAT.	Cerrutti et al. (2017b)
MaPP_RR	Sum of RR_D and RR_FX.	
	All individual instruments are adjusted to have maximum and minimum changes of 1 and -1 in each quarter.	Cerrutti et al. (2017b)
CAP_REQ	Cumulative change in general capital requirements. This index measures regulatory changes in the Basel Accords.	Cerrutti et al. (2017b)
SSCB	Cumulative change in sector-specific capital buffers.	Cerrutti et al. (2017b)

Notes: The macroprudential indexes measure the cumulative sum of tightenings net of easings since 2000.

Table A4: Definitions and sources for variables used in estimations with credit booms

Variables	Definition	Source
Log(VIX)	The log of the VIX index.	VIX Historical Price Data (CBOE).
Real GDP growth	The quarterly growth rate of real GDP.	IMF IFS.
Change CB policy rate	Quarterly change in the central bank policy rate.	IFS Central Bank Policy rate if available otherwise Discount Rate of Repurchase Agreement Rate. ECB deposit facility rate for Eurozone countries.
Inflation	The quarterly growth rate of the consumer price index.	IMF IFS.
Log(GDP per capita)	Log of GDP per capita.	BIS, IMF IFS, and World Bank Databank.
Log(real exchange rate)	Log of the real exchange rate.	IMF IFS.
Bank credit (% of GDP)	The ratio of domestic bank credit to GDP.	Adjusted domestic bank credit to the private non-financial sector divided by GDP (BIS) Otherwise, depository corporations' domestic claims on private sector (IMF IFS) divided by nominal GDP (World Bank WDI). All in LCU.
Real bank credit growth	The growth rate of real domestic bank credit to the private sector.	Adjusted domestic bank credit to the private non-financial sector (BIS), otherwise depository corporations' domestic claims on private sector (IMF IFS); divided by the GDP deflator (World Bank WDI). All in LCU.
Household credit (% of GDP)	The ratio of private sector household credit to GDP. The measure for household credit includes in addition to domestic bank credit also credit from non-bank institutions and cross-border credit.	Adjusted household credit to the private non-financial sector divided by GDP (BIS).

Table A5: Correlation between macroprudential sub-indexes and other policies

	MaPP_B_FI	MaPP_RR	CB policy rate	CAP_REQ	SSCB
MaPP_B_FI	1.0000				
MaPP_RR	0.4574*	1.0000			
CB policy rate	-0.0822*	0.1269	1.0000		
CAP_REQ	0.2726*	-0.0093	-0.1518*	1.0000	
SSCB	0.0781*	0.2422*	0.0374	0.1485*	1.0000

Notes: The table shows the correlation between aggregate macroprudential indexes and other policies in 41 countries between 2000Q1-2014Q4. The aggregate indexes are MaPP_B_FI (including LTV_CAP, IBEX, and CONCRAT) and MaPP_RR (including RR_D and RR_FX). The other policies are the central bank policy rate (CB policy rate), capital requirements (CAP_REQ) and sector-specific capital buffers (SSCB).
*signifies that the correlation is significant at the 5% level.

Table A6: Correlation between individual macroprudential policies

	LTV_CAP	IBEX	CONCRAT	RR_D	RR_FX
LTV_CAP	1.0000				
IBEX	0.4542*	1.0000			
CONCRAT	0.4180*	-0.0973	1.0000		
RR_D	0.5711*	-0.0089	-0.0839*	1.0000	
RR_FX	0.2660*	0.0119	-0.0505	0.3811*	1.0000

Notes: The table shows the correlation between the cumulative indexes for five macroprudential policy instruments in 41 countries between 2000Q1-2014Q4. The policies are Loan-to-Value Caps (LTV_CAP), interbank exposure limits (IBEX), concentration limits (CONCRAT), reserve requirements on accounts denominated in local currency (RR_D) and foreign currency (RR_FX).
*signifies that the correlation is significant at the 5% level.

Table A7: Borrower- and financial institution-targeted macroprudential policies

Variables	Logit (1)	Firth logit (2)	Logit (3)	Firth logit (4)	Logit (5)	Firth logit (6)
Log(VIX)	1.367**	1.405*	1.478***	1.462*	0.773	0.796
	(0.660)	(0.731)	(0.466)	(0.822)	(0.479)	(0.494)
Real GDP growth	-0.061	-0.059	0.163*	0.141	0.170***	0.164***
	(0.075)	(0.081)	(0.091)	(0.143)	(0.053)	(0.055)
Change CB policy rate	0.921***	0.981**	0.864*	0.644	0.001	0.002
	(0.271)	(0.436)	(0.474)	(0.822)	(0.003)	(0.012)
Inflation	-0.024	-0.088	0.169	0.172	0.108	0.156
	(0.061)	(0.096)	(0.329)	(0.433)	(0.069)	(0.096)
Log(real exchange rate)	-0.102	-0.025	0.031	0.068	-0.170	-0.136
	(0.340)	(0.192)	(0.197)	(0.237)	(0.210)	(0.138)
Bank credit (% of GDP)	0.002	0.001	-0.001	0.000	-0.004	-0.004
	(0.009)	(0.007)	(0.006)	(0.010)	(0.006)	(0.005)
Log(GDP per capita)	0.953*	0.847**	0.850*	0.664	1.145**	1.097***
	(0.293)	(0.421)	(0.496)	(0.738)	(0.558)	(0.311)
LTV_CAP	-0.158	-0.141				
	(0.204)	(0.182)				
IBEX			-0.776	-0.637		
			(0.500)	(0.465)		
CONCRAT					-0.647	-0.565*
					(0.454)	(0.306)
Country fixed effects	NO	NO	NO	NO	NO	NO
Year fixed effects	NO	NO	NO	NO	NO	NO
Observations	807	807	645	645	1275	1275
Credit booms	16	16	16	16	38	38
Countries	25	25	14	14	25	25
Prob > chi-sq	0.0001	0.0544	0.0000	0.5924	0.0000	0.0050

Robust standard errors in parenthesis. ***p<0.01, **p<0.05, *p<0.1
Notes: Table showing Logit and Firth logit estimations with a binary dependent variable for bank credit booms. Loan-to-Value Caps (LTV_CAP) is a borrower-targeted instrument while interbank exposure limits (IBEX) and concentration limits (CONCRAT) are financial institution-targeted policies according to the categorization of macroprudential policies by Cerutti et al. (2017a). The Hodrick-Prescott (HP) filter is used to identify credit booms and the threshold is 1.75 standard deviations. The time period is 2000Q1-2014Q4. Robust standard errors are clustered by country. All independent variables are lagged one quarter.

Table A8: Reserve requirement policies

Variables	Logit (1)	Logit (2)	Firth Logit (3)	Logit (4)	Logit (5)	Firth logit (6)
Log(VIX)	1.478***	1.677***	1.486***	1.389***	1.508***	1.389***
	(0.412)	(0.410)	(0.383)	(0.403)	(0.402)	(0.378)
Real GDP growth	0.079*	0.241***	0.076*	0.065	0.217***	0.061
	(0.047)	(0.066)	(0.043)	(0.045)	(0.062)	(0.041)
Change CB policy rate	0.005	-0.001	0.006	0.005	-0.001	0.006
	(0.004)	(0.015)	(0.012)	(0.004)	(0.015)	(0.012)
Inflation	0.140**	0.114	0.167**	0.128**	0.087	0.152**
	(0.056)	(0.155)	(0.074)	(0.059)	(0.155)	(0.072)
Log(real exchange rate)	-0.113	5.700**	-0.096	-0.130	4.565*	-0.110
	(0.127)	(2.733)	(0.091)	(0.135)	(2.738)	(0.094)
Bank credit (% of GDP)	-0.004	0.049**	-0.004	-0.005	0.050***	-0.005
	(0.005)	(0.015)	(0.004)	(0.005)	(0.015)	(0.004)
Log(GDP per capita)	0.663	5.136***	0.648***	0.653	4.232**	0.647***
	(0.440)	(1.930)	(0.236)	(0.411)	(1.925)	(0.236)
RR_D	-0.215	-0.655***	-0.208			
	(0.145)	(0.245)	(0.147)			
RR_FX				-0.363	-1.613**	-0.114
				(0.332)	(0.746)	(0.407)
Country fixed effects	NO	YES	NO	NO	YES	NO
Year fixed effects	NO	NO	NO	NO	NO	NO
Observations	2171	1370	2171	2171	1370	2171
Credit booms	61	61	61	61	61	61
Countries	41	22	41	41	24	41
Prob > chi-sq	0.0000	0.0000	0.0002	0.0000	0.0000	0.0002

Robust standard errors in parenthesis. ***p<0.01, **p<0.05, *p<0.1
Notes: Table showing Logit and Firth logit estimations with a binary dependent variable for bank credit booms. The macroprudential instruments are reserve requirements on accounts denominated in domestic currency (RR_D) and foreign currency (RR_FX). The Hodrick-Prescott (HP) filter is used to identify credit booms and the threshold is 1.75 standard deviations. The time period is 2000Q1-2014Q4. Robust standard errors clustered by country are reported for Logit estimations without country fixed effects. All independent variables are lagged one quarter.

Table A9: Aggregate macroprudential sub-indexes and household credit booms

Variables	Logit (1)	Logit (2)	Firth logit (3)	Logit (4)	Logit (5)	Firth logit (6)
Log(VIX)	-0.101	-0.106	0.039	-0.027	0.126	-0.006
	(0.600)	(0.525)	(0.474)	(0.643)	(0.522)	(0.471)
Real GDP growth	0.239***	0.462***	0.263***	0.238***	0.492***	0.233***
	(0.075)	(0.096)	(0.051)	(0.072)	(0.092)	(0.049)
Change CB policy rate	-0.001	-0.084	0.005	-0.001	-0.028	0.006
	(0.003)	(0.230)	(0.014)	(0.004)	(0.242)	(0.014)
Inflation	0.143	0.167	0.219**	0.139	0.162	0.193*
	(0.094)	(0.202)	(0.104)	(0.085)	(0.196)	(0.110)
Log(real exchange rate)	0.159	21.461***	0.139*	0.088	10.523***	0.090
	(0.120)	(4.883)	(0.078)	(0.103)	(3.546)	(0.073)
HH credit (% of GDP)	0.014	0.075**	0.015**	0.012	0.062	0.011*
	(0.009)	(0.030)	(0.007)	(0.009)	(0.026)	(0.007)
Log(GDP per capita)	0.244	15.828***	0.190	0.110	6.523**	0.115
	(0.439)	(3.963)	(0.274)	(0.463)	(2.726)	(0.275)
MaPP_B_FI	-0.441***	-1.205***	-0.294***			
	(0.159)	(0.273)	(0.089)			
MaPP_RR				-0.245	-0.444*	-0.240*
				(0.158)	(0.236)	(0.131)
Country fixed effects	NO	YES	NO	NO	YES	NO
Year fixed effects	NO	NO	NO	NO	NO	NO
Observations	1990	1031	1990	1990	1031	1990
Credit booms	49	49	49	49	49	649
Countries	37	19	37	37	19	37
Prob > chi-sq	0.0373	0.0000	0.0000	0.0036	0.0000	0.0003

Robust standard errors in parenthesis. ***p<0.01, **p<0.05, *p<0.1
Notes: Table showing Logit and Firth logit estimations with a binary dependent variable for household credit booms. The measure for household credit includes in addition to domestic bank credit also credit from non-bank institutions and cross-border credit. The Hodrick-Prescott (HP) filter is used to identify credit booms and the threshold is 1.75 standard deviations. The index MaPP_B_FI includes borrower- and financial institutions-targeted macroprudential instruments (LTV_CAP, IBEX, and CONCRAT) and the index MaPP_RR includes reserve requirement instruments (RR_D and RR_FX). The time period is 2000Q1-2014Q4. Robust standard errors clustered by country are reported for Logit estimations without country fixed effects. All independent variables are lagged one quarter.

Table A10: Credit booms with different thresholds

Variables	Boom threshold 1.5 s.d. Logit (1)	LPM (2)	Firth logit (3)	Boom threshold 2 s.d. Logit (4)	LPM (5)	Firth logit (6)
Log(VIX)	1.632***	0.085**	1.622***	1.789***	0.077***	1.781***
	(0.393)	(0.027)	(0.304)	(0.644)	(0.015)	(0.511)
Real GDP growth	0.077*	0.005***	0.076**	0.092	0.001	0.090
	(0.045)	(0.002)	(0.033)	(0.056)	(0.001)	(0.063)
Change CB policy rate	0.712***	0.005***	0.687***	0.005	0.000	0.018
	(0.187)	(0.001)	(0.172)	(0.006)	(0.001)	(0.018)
Inflation	0.250***	-0.003	0.255***	0.025	-0.002	-0.022
	(0.079)	(0.004)	(0.084)	(0.084)	(0.003)	(0.188)
Log(real exchange rate)	-0.184*	0.330***	-0.172**	0.013	0.044	0.034
	(0.109)	(0.069)	(0.075)	(0.151)	(0.039)	(0.117)
Bank credit (% of GDP)	0.003	0.004***	0.003	-0.010*	0.001***	-0.010*
	(0.004)	(0.000)	(0.003)	(0.006)	(0.000)	(0.006)
Log(GDP per capita)	0.536	0.267***	0.524***	1.113**	0.050*	1.072***
	(0.345)	(0.048)	(0.176)	(0.482)	(0.027)	(0.332)
MaPP	-0.221***	-0.009***	-0.214***	-0.259***	-0.002	-0.242*
	(0.067)	(0.003)	(0.063)	(0.095)	(0.002)	(0.125)
Country fixed effects	NO	YES	NO	NO	YES	NO
Year fixed effects	NO	YES	NO	NO	YES	NO
Observations	2171	2171	2171	2171	2171	2171
Credit booms	119	119	119	32	32	32
Countries	41	41	41	41	41	41
Prob > chi-sq (LPM: F-test)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0003

Robust standard errors in parenthesis. ***p<0.01, **p<0.05, *p<0.1

Notes: Table showing Logit, Linear Probability Model (LPM) and Firth logit estimations with a binary dependent variable for bank credit booms. The Hodrick-Prescott (HP) filter is used to identify credit booms with thresholds 1.5 or 2 standard deviations. The MaPP index includes all five macroprudential instruments (LTV_CAP, IBEX, CONCRAT, RR_D, and RR_FX) and the time period is 2000Q1-2014Q4. Robust standard errors are clustered by country for Logit estimations. All independent variables are lagged one quarter.

Table A11: Estimations for different time periods

	2000Q1-2006Q4			2007Q1-2014Q4		
Variables	Logit	LPM	Firth logit	Logit	LPM	Firth logit
	(1)	(2)	(3)	(4)	(5)	(6)
Log(VIX)	1.968***	0.007	1.832**	1.392***	0.109***	1.392***
	(0.711)	(0.043)	(0.742)	(0.380)	(3.161)	(4.006)
Real GDP growth	0.332***	0.009***	0.317***	0.054	0.004	0.053
	(0.089)	(0.003)	(0.088)	(0.050)	(1.436)	(1.398)
Change CB policy rate	0.896*	0.005***	0.744***	0.875***	0.027*	0.863***
	(0.450)	(0.001)	(0.268)	(0.339)	(1.869)	(3.234)
Inflation	0.141	-0.004	0.181	0.344**	-0.003	0.343***
	(0.194)	(0.005)	(0.246)	(0.160)	(-0.400)	(2.495)
Log(real exchange rate)	-1.756***	0.489***	-1.455***	-0.068	0.556***	-0.059
	(0.580)	(0.087)	(0.553)	(0.124)	(3.049)	(-0.767)
Bank credit (% of GDP)	0.005	0.002***	0.005	0.001	0.007***	0.001
	(0.009)	(0.001)	(0.008)	(0.004)	(7.902)	(0.222)
Log(GDP per capita)	-1.051**	0.330***	-0.909**	0.658*	0.524***	0.635***
	(0.490)	(0.069)	(0.457)	(0.398)	(4.415)	(3.217)
MaPP	-0.966*	-0.010	-0.923***	-0.207***	-0.008	-0.198***
	(0.493)	(0.008)	(0.331)	(0.067)	(-1.316)	(-3.532)
Country fixed effects	NO	YES	NO	NO	YES	NO
Year fixed effects	NO	YES	NO	NO	YES	NO
Observations	938	938	938	1233	1233	1233
Credit booms	31	31	31	88	88	88
Countries	37	37	37	41	41	41
Prob > chi-sq (LPM: F-test)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Robust standard errors in parenthesis. ***p<0.01, **p<0.05, *p<0.1
Notes: Table showing Logit, Linear Probability Model (LPM) and Firth logit estimations with a binary dependent variable for bank credit booms. Separate estimations for time periods 2000Q1-2006Q4 and 2007Q1-2014Q4. The Hodrick-Prescott (HP) filter is used to identify credit booms with threshold 1.5 standard deviations. The MaPP index includes all five macroprudential instruments (LTV_CAP, IBEX, CONCRAT, RR_D, and RR_FX). Robust standard errors are clustered by country for Logit estimations. All independent variables are lagged one quarter.

Table A12: Estimations for different country samples

Variables	Advanced countries Logit (1)	LPM (2)	Firth logit (3)	Developing countries Logit (4)	LPM (5)	Firth logit (6)
Log(VIX)	1.779***	0.100***	1.769***	1.535	0.076*	1.591**
	(0.355)	(0.035)	(0.345)	(1.377)	(0.040)	(0.648)
Real GDP growth	0.052	-0.000	0.051	0.153***	0.008***	0.171**
	(0.053)	(0.003)	(0.040)	(0.030)	(0.003)	(0.067)
Change CB policy rate	0.931***	0.037**	0.901***	0.560***	0.005***	0.017
	(0.326)	(0.016)	(0.273)	(0.191)	(0.001)	(0.017)
Inflation	0.294**	-0.004	0.294*	0.235*	0.001	0.192**
	(0.128)	(0.007)	(0.157)	(0.138)	(0.005)	(0.082)
Log(real exchange rate)	-0.347*	0.603***	-0.323**	-0.091	0.378***	-0.053
	(0.189)	(0.134)	(0.126)	(0.160)	(0.096)	(0.120)
Bank credit (% of GDP)	0.005	0.003***	0.005	0.008	0.008***	0.008
	(0.005)	(0.001)	(0.003)	(0.012)	(0.001)	(0.008)
Log(GDP per capita)	1.094**	0.502***	1.081***	0.771*	0.296***	0.760*
	(0.491)	(0.116)	(0.258)	(0.432)	(0.047)	(0.442)
MaPP	-0.214**	-0.003	-0.211***	-0.237**	-0.015***	-0.196**
	(0.103)	(0.006)	(0.081)	(0.097)	(0.003)	(0.094)
Country fixed effects	NO	YES	NO	NO	YES	NO
Year fixed effects	NO	YES	NO	NO	YES	NO
Observations	1563	1563	1563	608	608	608
Credit booms	96	96	96	23	23	23
Countries	27	27	27	14	14	14
Prob > chi-sq (LPM: F-test)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0036

Robust standard errors in parenthesis. ***p<0.01, **p<0.05, *p<0.1
Notes: Table showing Logit, Linear Probability Model (LPM) and Firth logit estimations with a binary dependent variable for bank credit booms. Separate estimations for advanced and developing countries. The Hodrick-Prescott (HP) filter is used to identify credit booms with threshold 1.5 standard deviations. The MaPP index includes all five macroprudential instruments (LTV_CAP, IBEX, CONCRAT, RR_D, and RR_FX). Robust standard errors are clustered by country for Logit estimations. All independent variables are lagged one quarter.

Table A13: Credit booms identified with the Hamilton filter

Variables	Boom threshold 1.75 s.d. Logit (1)	LPM (2)	Firth logit (3)	Boom threshold 2 s.d. Logit (4)	LPM (5)	Firth logit (6)
Log(VIX)	-0.080	0.055***	-0.058	0.123	0.016	0.165
	(0.570)	(0.016)	(0.362)	(0.686)	(0.012)	(0.556)
Real GDP growth	0.090**	0.002	0.088**	0.099**	0.001	0.096*
	(0.045)	(0.002)	(0.038)	(0.040)	(0.001)	(0.057)
Change CB policy rate	0.002	0.000	0.006	0.003	0.000	0.008
	(0.003)	(0.000)	(0.012)	(0.002)	(0.000)	(0.013)
Inflation	0.194**	0.007	0.210***	0.224**	0.006	0.240***
	(0.082)	(0.005)	(0.063)	(0.092)	(0.003)	(0.071)
Log(real exchange rate)	-0.303***	-0.007***	-0.287***	-0.453*	-0.004**	-0.400**
	(0.104)	(0.002)	(0.097)	(0.253)	(0.002)	(0.163)
Bank credit (% of GDP)	0.010**	0.000*	0.010***	0.008	0.000	0.008*
	(0.004)	(0.000)	(0.003)	(0.008)	(0.000)	(0.005)
Log(GDP per capita)	-0.214	-0.011	-0.212	-0.761*	-0.012	-0.724***
	(0.311)	(0.012)	(0.174)	(0.364)	(0.009)	(0.252)
MaPP	-0.111	-0.003*	-0.101*	-0.228*	-0.002*	-0.199*
	(0.075)	(0.002)	(0.052)	(0.130)	(0.001)	(0.108)
Country fixed effects	NO	NO	NO	NO	NO	NO
Year fixed effects	NO	YES	NO	NO	YES	NO
Observations	2149	2149	2149	2149	2149	2149
Credit booms	79	79	79	33	33	33
Countries	41	41	41	41	41	41
Prob > chi-sq (LPM: F-test)	0.0021	0.0004	0.0003	0.0101	0.0000	0.0005

Robust standard errors in parenthesis. ***p<0.01, **p<0.05, *p<0.1
Notes: Table showing Logit, Linear Probability Model (LPM) and Firth logit estimations with a binary dependent variable for bank credit booms. The Hamilton filter is used to identify credit booms with thresholds 1.75 or 2 standard deviations. The MaPP index includes all five macroprudential instruments (LTV_CAP, IBEX, CONCRAT, RR_D, and RR_FX) and the time period is 2000Q1-2014Q4. Robust standard errors are clustered by country for Logit estimations. All independent variables are lagged one quarter.

Table A14: Estimations with bank-capital-based prudential policies

Variables	Hodrick-Prescott filter Logit	LPM	Firth logit	Hamilton filter Logit	LPM	Firth logit
	(1)	(2)	(3)	(4)	(5)	(6)
Log(VIX)	1.178***	0.037***	1.198***	0.208	0.010	0.230
	(0.447)	(0.012)	(0.408)	(0.578)	(0.014)	(0.398)
Real GDP growth	0.080	0.005***	0.077*	0.113**	0.008***	0.112***
	(0.053)	(0.001)	(0.045)	(0.045)	(0.002)	(0.039)
Change CB policy rate	0.004	0.000	0.005	0.002	-0.000	0.005
	(0.004)	(0.001)	(0.012)	(0.003)	(0.001)	(0.012)
Inflation	0.129**	-0.000	0.157**	0.202**	0.000	0.217***
	(0.058)	(0.003)	(0.073)	(0.083)	(0.004)	(0.063)
Log(real exchange rate)	-0.126	0.146***	-0.108	-0.308***	0.172***	-0.291***
	(0.116)	(0.051)	(0.094)	(0.101)	(0.058)	(0.098)
Bank credit (% of GDP)	-0.003	0.001***	-0.002	0.009**	0.002***	0.009***
	(0.005)	(0.000)	(0.004)	(0.004)	(0.000)	(0.003)
Log(GDP per capita)	0.568	0.143***	0.556**	-0.229	-0.109***	-0.228
	(0.384)	(0.035)	(0.245)	(0.321)	(0.040)	(0.178)
CAP_REQ	-0.748	-0.016**	-0.591	0.414	0.001	0.432**
	(0.576)	(0.007)	(0.439)	(0.451)	(0.008)	(0.206)
SSCB	-0.461	-0.006	-0.430	-0.033	-0.002	-0.025
	(0.470)	(0.006)	(0.282)	(0.186)	(0.006)	(0.132)
MaPP	-0.238**	-0.007***	-0.219**	-0.129**	-0.003	-0.119**
	(0.097)	(0.002)	(0.101)	(0.065)	(0.002)	(0.052)
Country fixed effects	NO	YES	NO	NO	YES	NO
Year fixed effects	NO	NO	NO	NO	NO	NO
Observations	2156	2156	2156	2134	2134	2134
Credit booms	61	61	61	79	79	79
Countries	40	40	40	40	40	40
Prob > chi-sq (LPM: F-test)	0.0000	0.0000	0.0003	0.0013	0.0000	0.0003

Robust standard errors in parenthesis. ***p<0.01, **p<0.05, *p<0.1
Notes: Table showing Logit, Linear Probability Model (LPM) and Firth logit estimations with a binary dependent variable for bank credit booms. The boom threshold is 1.75 standard deviations in all estimations. The Hodrick-Prescott (HP) filter or the Hamilton filter is used to identify credit booms. The MaPP index includes all five macroprudential instruments (LTV_CAP, IBEX, CONCRAT, RR_D, and RR_FX) and the time period is 2000Q1-2014Q4. Robust standard errors clustered by country for Logit estimations without country fixed effects. All independent variables are lagged one quarter. The bank-capital-based prudential policies are capital requirements (CAP_REQ) and sector-specific capital buffers (SSCB).

Table A15: Definitions and sources for variables used in estimations with SRISK

Variables	Definition	Source
SRISK-to-GDP	Positive SRISK scaled by real GDP.	NYU's V-Lab, World Bank Databank
Size	Log of market capitalization (bank-level data).	NYU's V-Lab
Leverage	Leverage ratio (bank-level data). The leverage ratio is defined as the sum of book value of total liabilities and market capitalization as percent of market capitalization.	NYU's V-Lab
Real GDP Growth	Year-over-year change in GDP.	World Development Indicator
Volatility	The annual stock market volatility.	Global Financial Development Database
Market return	The annual stock market return.	Global Financial Development Database
Non-interest income	The annual value for aggregate non-interest income relative to the banking system's total income.	Global Financial Development Database
Concentration	The assets of the three largest commercial banks as percent of total assets for the banking sector.	Global Financial Development Database
GDP per capita	Log of GDP per capita.	World Development Indicators

Table A16: Correlation between banks' SRISK, beta, and market capitalization

	SRISK	Beta	Market Cap.
SRISK	1.0000		
Beta	0.315*	1.0000	
Market Cap.	0.545*	0.187*	1.0000

*signifies that the correlation is significant at the 5% level.

Table A17: Estimations with macroprudential indexes and SRISK-to-GDP

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Size	2.207***	-2.072***	2.140***	-2.213***	2.209***	-2.036***
	(0.297)	(0.563)	(0.291)	(0.543)	(0.300)	(0.543)
Leverage	0.001	0.002**	0.001	0.002**	0.001	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Real GDP growth	-0.302***	-0.172***	-0.329***	-0.176***	-0.302***	-0.171***
	(0.068)	(0.062)	(0.071)	(0.062)	(0.069)	(0.063)
Market return	-0.012**	-0.000	-0.006	0.003	-0.010*	0.000
	(0.006)	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)
Volatility	0.106***	-0.020	0.116***	-0.018	0.111***	-0.18
	(0.025)	(0.032)	(0.025)	(0.031)	(0.026)	(0.032)
Non-interest income	0.005	-0.027	0.006	-0.028	0.004	-0.027
	(0.044)	(0.060)	(0.044)	(0.060)	(0.043)	(0.060)
Concentration	0.010	-0.021	0.022	0.017	0.010	-0.021
	(0.022)	(0.027)	(0.022)	(0.027)	(0.022)	(0.026)
MaPP	-0.368***	-0.102				
	(0.080)	(0.085)				
MaPP_B_FI			-0.296	0.073		
			(0.183)	(0.258)		
MaPP_RR					-0.465***	-0.164*
					(0.101)	(0.090)
Year fixed effects	YES	YES	YES	YES	YES	YES
Country fixed effects	YES	NO	YES	NO	YES	NO
Bank fixed effects	NO	YES	NO	YES	NO	YES
Observations	2958	2958	2958	2958	2958	2958
Countries	54	54	54	54	54	54
Banks	387	387	387	387	387	387
R-squared	0.5425	0.8148	0.5393	0.8146	0.5428	0.8150

Robust standard errors in parenthesis. ***p<0.01, **p<0.05, *p<0.1
Notes: Table showing OLS regressions with SRISK scaled by real GDP as the dependent variable. The MaPP index includes all five macroprudential instruments (LTV_CAP, IBEX, CONCRAT, RR_D, and RR_FX). Moreover, the sub-index MaPP_B_FI is the sum of LTV_CAP, IBEX, CONCRAT. In addition, MaPP_RR includes both reserve requirement instruments (RR_D, and RR_FX). Macroprudential indexes measure the cumulative sum of tightenings net of easings since 2000 (Akinci Olmstead-Rumsey, 2017). The time period is 2000-2015 and all independent variables are lagged one period. The standard errors are clustered for banks.

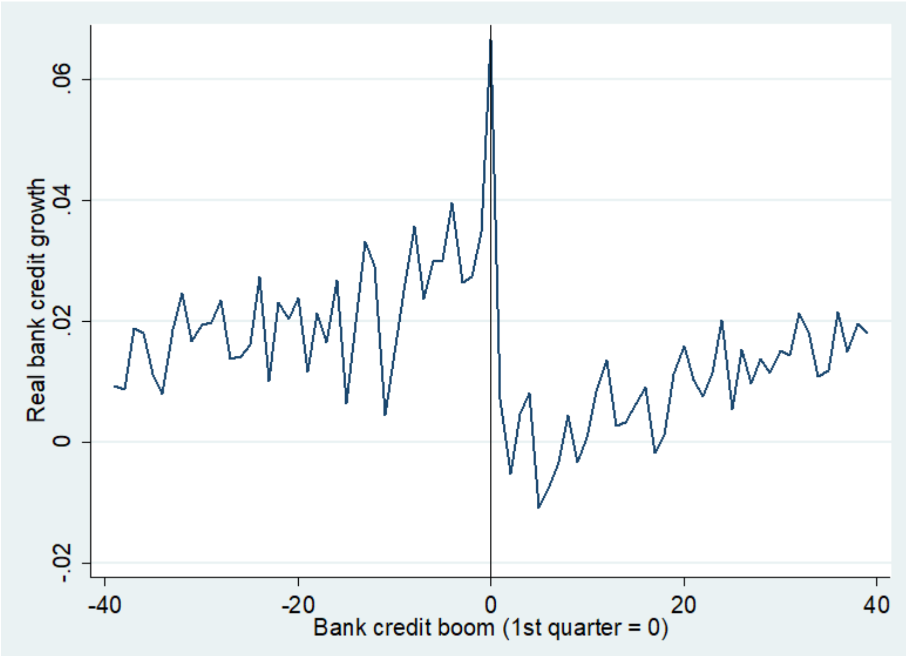
Table A18: List of countries for bank credit booms

Advanced countries	Developing countries
Australia	Brazil
Austria	China
Belgium	Colombia
Canada	Hungary
Czech Republic	India
Denmark	Indonesia
Finland	Malaysia
France	Mexico
Germany	Poland
Greece	Russia
Hong Kong	Saudi Arabia
Ireland	South Africa
Israel	Thailand
Italy	Turkey
Japan	
Luxembourg	
Netherlands	
New Zealand	
Norway	
Portugal	
Singapore	
South Korea	
Spain	
Sweden	
Switzerland	
United Kingdom	
United States	

Table A19: List of countries for systemic risk

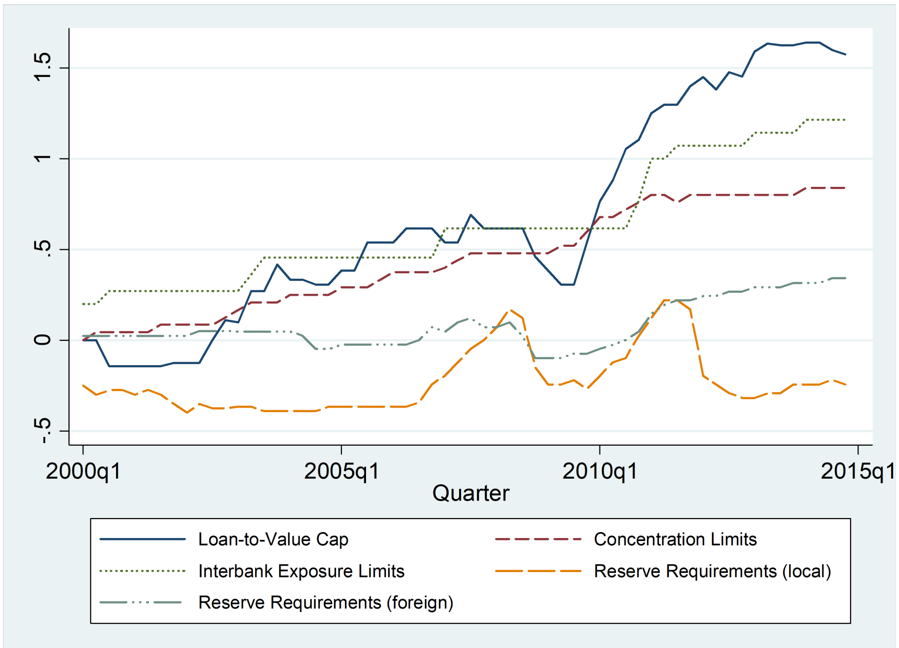
Advanced countries	#Banks	Developing countries	#Banks
Australia	6	Argentina	4
Austria	6	Brazil	5
Belgium	4	Chile	6
Canada	8	China	25
Czech Republic	2	Colombia	4
Denmark	5	Croatia	2
Finland	2	Hungary	2
France	14	India	40
Germany	10	Indonesia	11
Greece	8	Kuwait	5
Hong Kong	7	Lebanon	2
Ireland	5	Malaysia	9
Israel	4	Mexico	4
Italy	18	Nigeria	3
Japan	31	Peru	5
Luxembourg	1	Philippines	5
Malta	2	Romania	2
Netherlands	4	Russia	7
Norway	3	Saudi Arabia	10
Portugal	4	South Africa	6
Singapore	3	Thailand	7
Slovak Republic	1	Turkey	13
Slovenia	1	Ukraine	2
South Korea	9	Vietnam	3
Spain	11		
Sweden	5		
Switzerland	11		
Taiwan	18		
United Kingdom	8		
United States	67		

Figure A1: Average growth rate of real domestic bank credit around booms



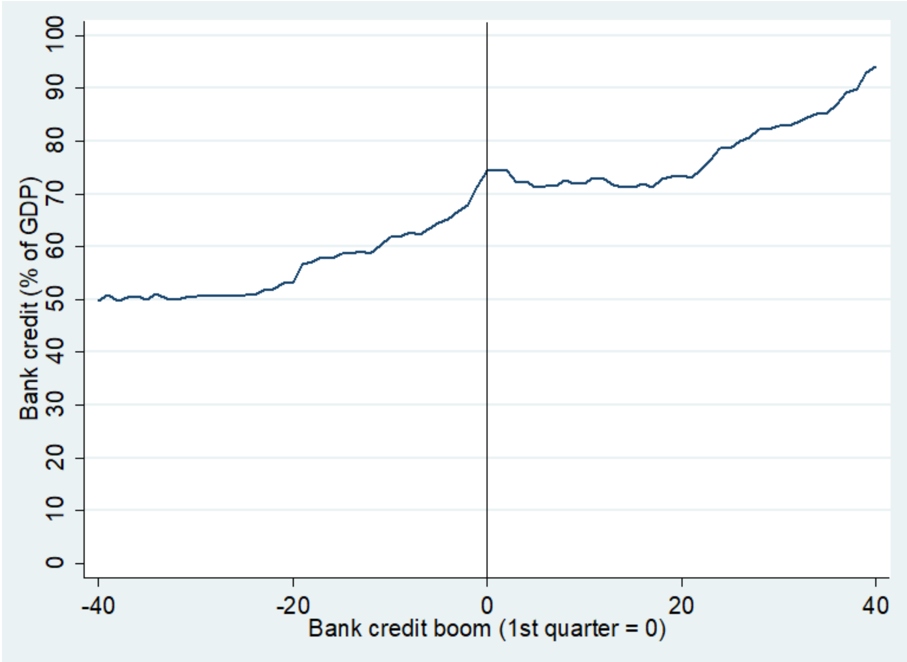
Note: The figure shows average real bank credit growth 40 quarters before and after the first quarter of a boom in bank credit with threshold 1.75 s.d.

Figure A2: Macroprudential policy instruments 2000Q1-2014Q4



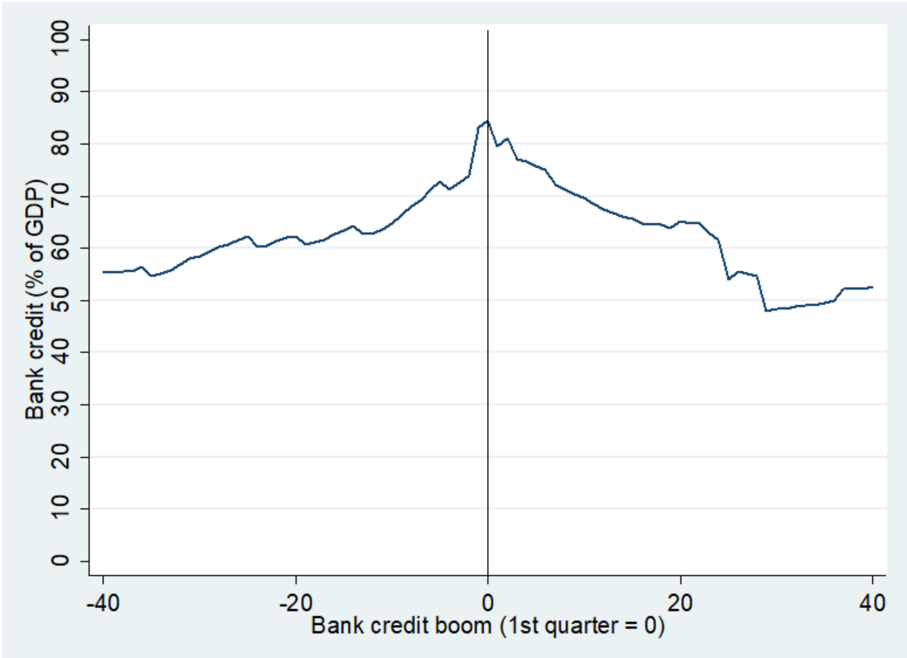
Note: The figure shows the average for the 5 macroprudential instruments for all countries between 2000Q1-2014Q4.

Figure A3: Average ratio of bank credit to GDP around good booms



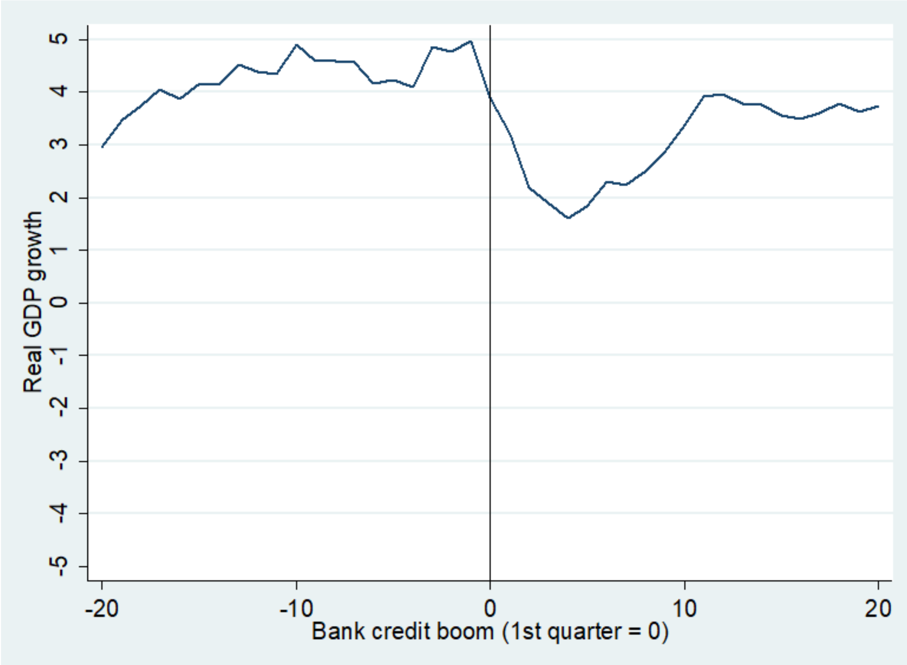
Note: The figure shows the average ratio of bank credit (% of GDP) 40 quarters before and after the first quarter of boom in bank credit not followed by a systemic banking crisis (good boom).

Figure A4: Average ratio of bank credit to GDP around bad booms



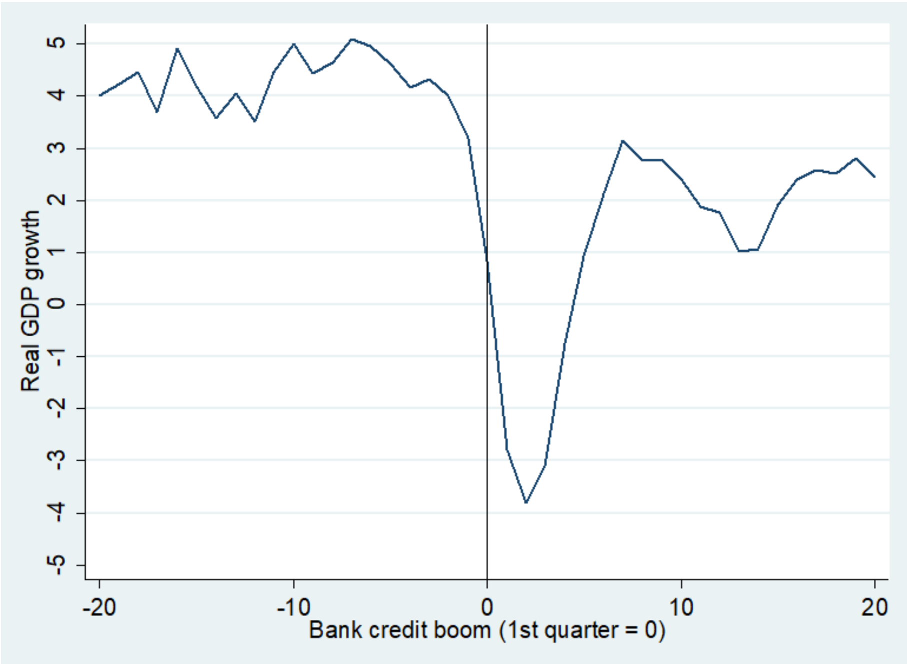
Note: The figure shows the average ratio of bank credit (% of GDP) 40 quarters before and after the first quarter of boom in bank credit followed by a systemic banking crisis (bad boom).

Figure A5: Average real growth rate of GDP around good booms



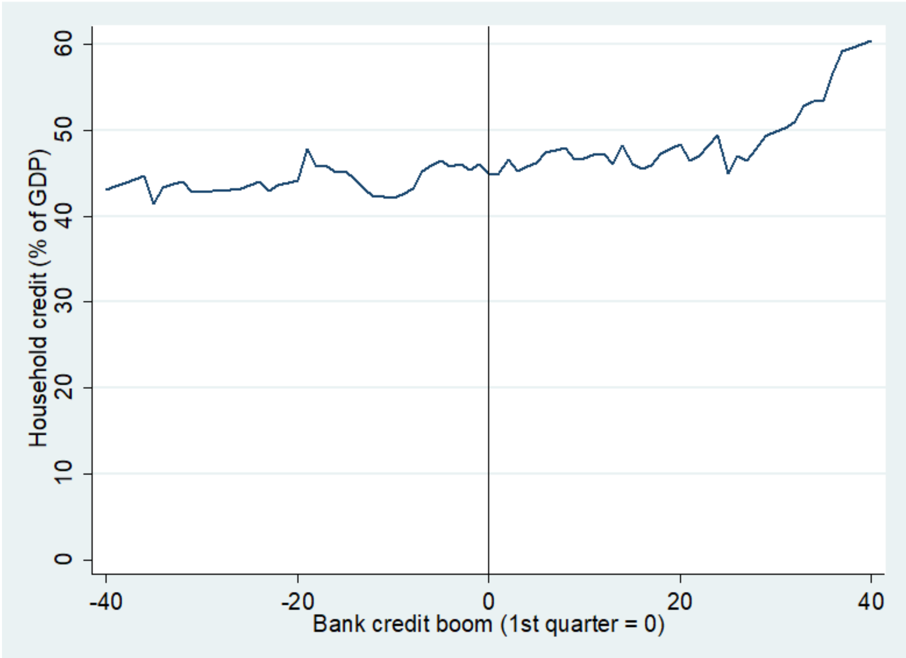
Note: The figure shows the average real GDP growth 20 quarters before and after the first quarter of boom in bank credit not followed by a systemic banking crisis (good boom).

Figure A6: Average real growth rate of GDP around bad booms



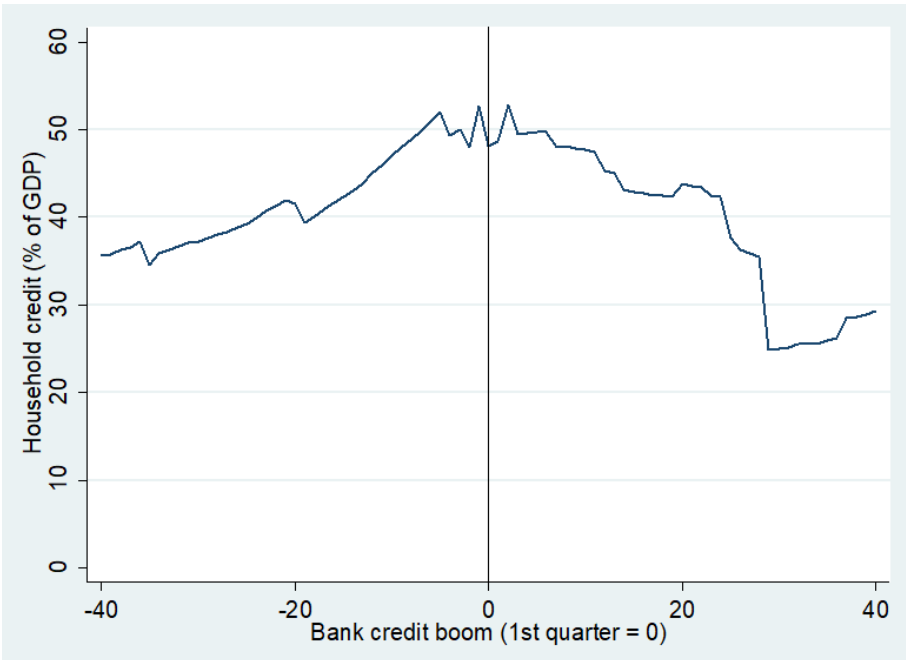
Note: The figure shows the average real GDP growth 20 quarters before and after the first quarter of boom in bank credit followed by a systemic banking crisis (bad boom).

Figure A7: Average household credit (% of GDP) around good booms



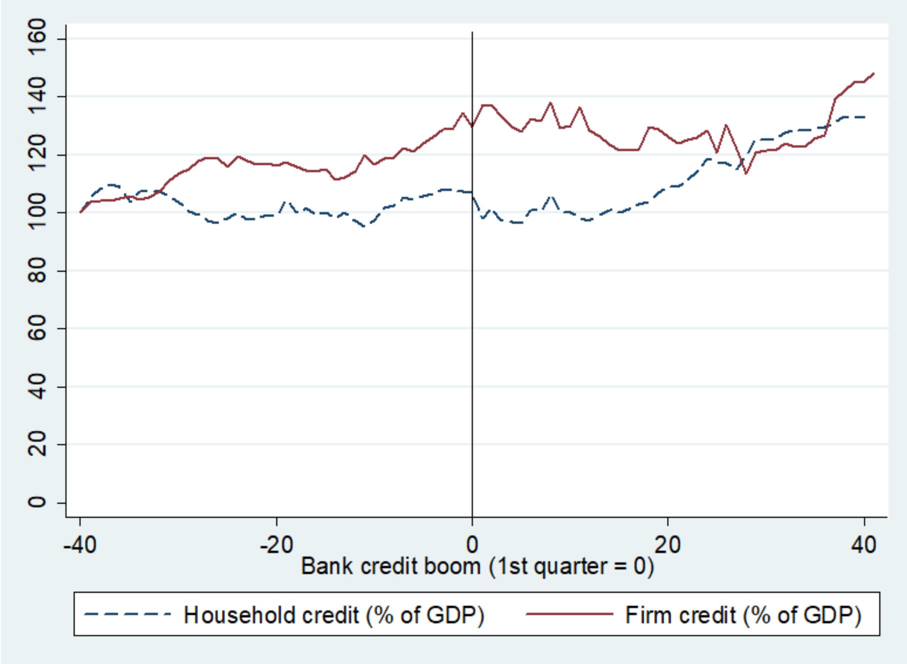
Note: The figure shows the average ratio of household credit (% of GDP) 40 quarters before and after the first quarter of boom in bank credit not followed by a systemic banking crisis (good boom).

Figure A8: Average household credit (% of GDP) around bad booms



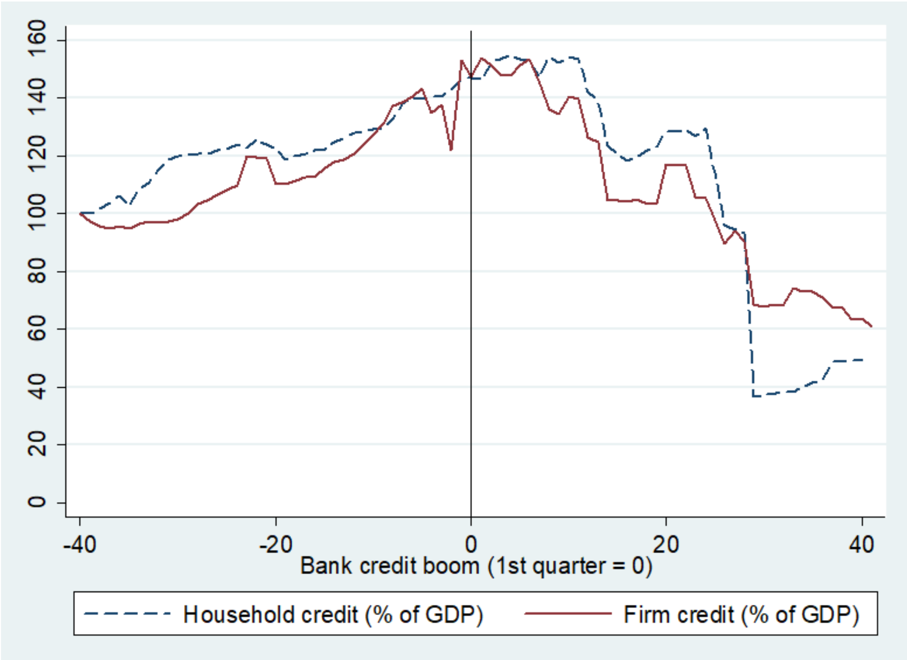
Note: The figure shows the average ratio of household credit (% of GDP) 40 quarters before and after the first quarter of boom in bank credit followed by a systemic banking crisis (bad boom).

Figure A9: Median ratio of household and firm credit (% of GDP) around good booms



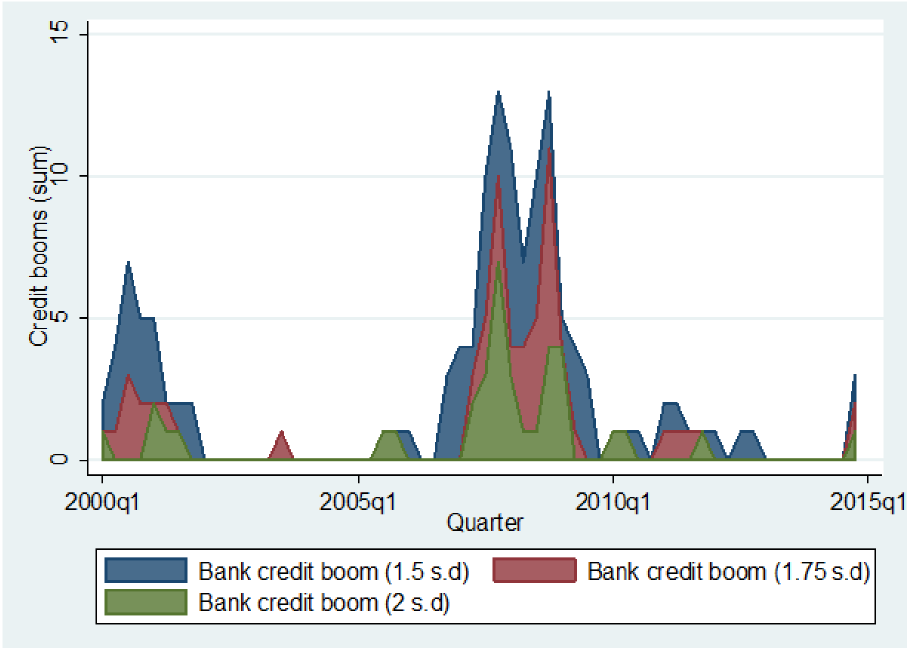
Note: The figure shows the median ratio of household and firm credit (% of GDP) 40 quarters before and after the first quarter of boom in bank credit not followed by a systemic banking crisis (good boom).

Figure A10: Median ratio of household and firm credit (% of GDP) around bad booms



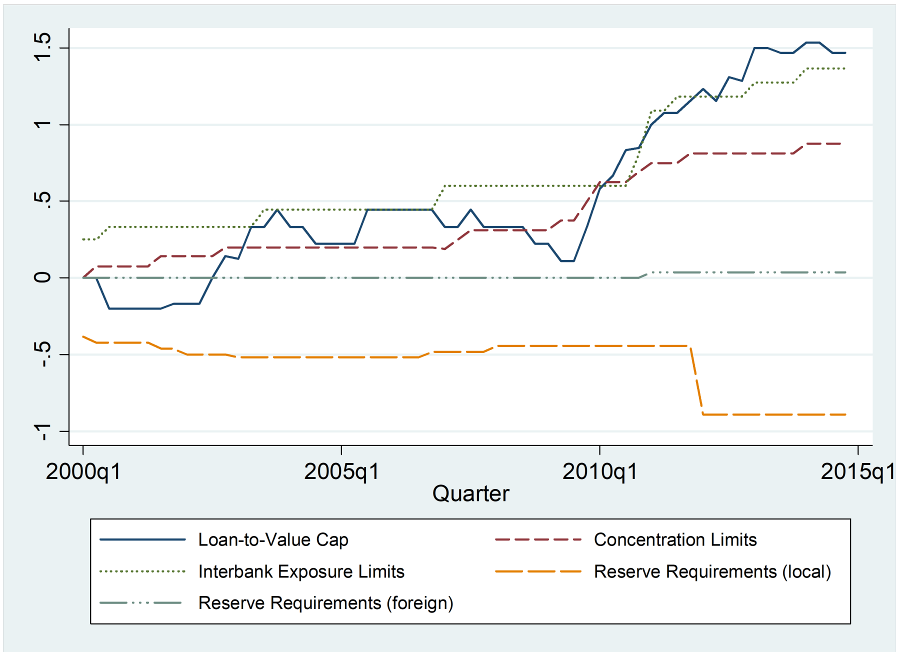
Note: The figure shows the median ratio of household and firm credit (% of GDP) 40 quarters before and after the first quarter of boom in bank credit followed by a systemic banking crisis (bad boom).

Figure A11: Distribution of credit booms with different thresholds



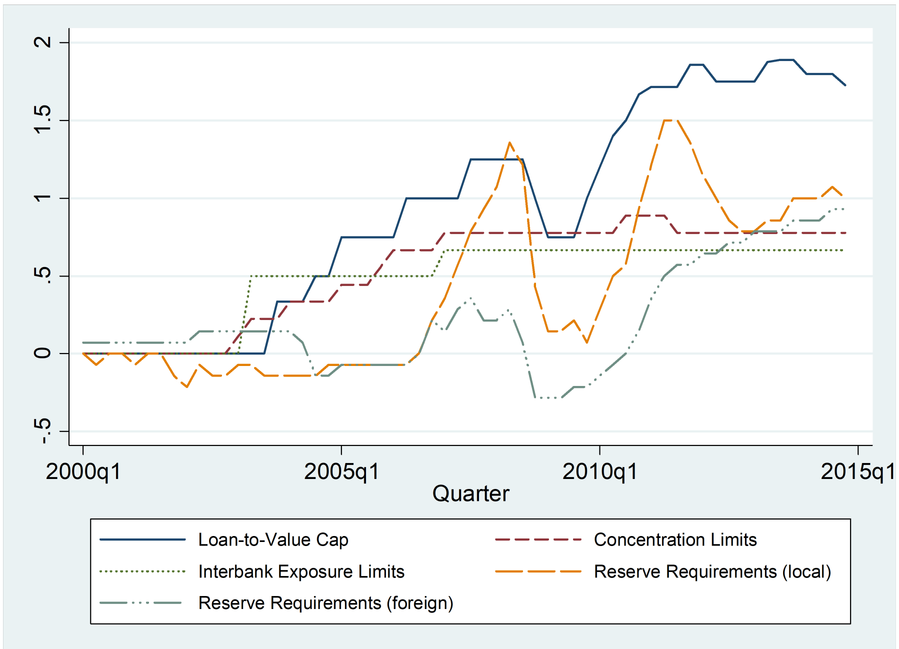
Note: The figure shows the frequency of bank credit booms with threshold 1.5, 1.75, or 2 s.d. between 2000Q1-2014Q4.

Figure A12: Macroprudential policy instruments in advanced countries



Note: The figure shows the average for the 5 macroprudential instruments in advanced countries between 2000Q1-2014Q4.

Figure A13: Macroprudential policy instruments in developing countries



Note: The figure shows the average for the 5 macroprudential instruments in developing countries between 2000Q1-2014Q4.

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