Macroprudential Policy, Credit Booms, and Banks' Systemic Risk

Peter Karlström*

September 15, 2022

Abstract

The purpose of this study is to investigate whether macroprudential policies have been effective to deal with booms in bank and household credit. Most of the previous empirical literature with cross-country data assess the effectiveness of macroprudential policies in curbing credit growth. However, in this study estimations are conducted with a binary dependent variable capturing credit booms. The reason for why credit boom is the appropriate choice of dependent variable in this study is threefold: (i) macroprudential policies are likely to be more effective during the more intense boom phase of the financial cycle, (ii) the problem of reverse causation that can occur if macroprudential policies are tightened during the peak of the credit boom (or during the bust phase) can to a large extent be avoided and (iii) it is possible to investigate specifically those episodes with high credit growth that are followed by banking crises. The results show that an aggregate index including five different macroprudential policy instruments is negatively and significantly associated with domestic bank credit booms. Moreover, macroprudential policies are also found to be effective to reduce the likelihood of booms in household credit. In addition, this study shows that macroprudential policies are effective to address specifically those credit booms that are followed by systemic banking crises. Finally, the results also suggest that a tighter macroprudential policy stance is negatively and significantly associated with the level of systemic risk for banks.

Keywords: Credit Booms, Macroprudential Policy, Banking Crises, Systemic Risk

*Center for Latin American Monetary Studies (CEMLA). E-mail address: pkarlstrom@cemla.org. The author's views do not necessarily reflect those of CEMLA. Draft version, please do not cite without the author's permission. I'm grateful for the comments and suggestions of Guglielmo Barone, Allen N. Berger, Valentina Bruno, Julián Caballero, Eugenio Cerutti, Gabriella Chiesa, Nicola Gennaioli, Roberto Golinelli, James Hamilton, Marcus Ingholt, Paolo Manasse, Alistair Milne, Salvatore Morelli, Sergio Pastorello, Sven Schreiber, Moritz Schularick, Andrea Teglio, and Carolina Ulloa Suarez.

1 Introduction

Credit booms have been found to be one of the most robust predictors of financial crises in both advanced and developing countries. Schularick and Taylor (2012) show in a study covering 14 countries between 1870-2008 that credit booms have been a leading determinant of financial crises. Furthermore, Gourinchas and Obstfeld (2012) find that domestic credit expansion and real currency appreciation have been the most significant and robust precursors of financial crises in both advanced and emerging countries between 1973 and 2010. In addition, Reinhart and Rogoff (2011) confirm that rapidly rising private indebtedness is a key predictor of banking crises. Jordà, Schularick, and Taylor (2016) show that financial stability risk originates in the private sector and not in the public sector in advanced countries. Finally, 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.

There are several theoretical arguments for how the combination of rapid credit growth and financial frictions can lead to excessive risk-taking. First, managerial reputational concerns could contribute to lower lending standards and higher credit cyclicality as emphasized by Rajan (1994). Dell'Ariccia, Igan, and Laeven (2012b) provide empirical evidence for that lending standards in the United States declined more in areas with larger credit booms and house price increases before the subprime crisis. Moreover, Rancière, Tornell and Westermann (2008) argue that excessive risk-taking by financial institutions is more likely with expectations of public bailouts. In addition, banks are likely to take more risks or correlated risk during the upturn of the financial cycle due to externalities from strategic complementarities such as cycles in collateral values (De Nicolò et al., 2012). To conclude, the presence of financial frictions during credit booms leads to excessive risk-taking which emphasizes the relevance of the banking maxim "the worst loans are made in the best of times (Dell'Ariccia et al. 2012a)".

Furthermore, Dell'Ariccia et al. (2016) examine the characteristics of credit booms followed by banking crises or a prolonged period of subpar growth. The authors find that credit booms that are larger in size, last for a longer period, and start from a higher level of credit-to-GDP ratio are more likely to end badly. Gorton and Ordoñez (2016) show that credit booms begin with an increase in productivity which falls much faster during booms followed by crisis. Moreover, several studies such as Mian and Sufi (2014) and Büyükkarabacak and Valev (2010) find that household credit (and not corporate credit) has been the driving factor of increased vulnerabilities to systemic banking crises. In addition, normal recessions and those associated with banking crises are much more severe and prolonged when preceded by a boom in mortgage credit (Jordà et al., 2016). Finally, Richter et al. (2017) find that credit booms associated with house price booms and increasing loan-to-deposit ratios are considerably more likely to be followed by a systemic banking crisis.

The main options to deal with credit booms are monetary policy, fiscal policy, and macroprudential instruments. Monetary policy can influence credit growth through several different channels. A tightening of monetary policy increases the cost of borrowing in all sectors of the economy which lowers the demand for credit. Moreover, a higher interest rate also influences asset prices and collateral values which reduces the ability to borrow (Bernanke and Gertler, 1995). In addition, the growth of leverage and bank risk-taking are reduced by higher interest rates (Dell'Ariccia et al., 2016). However, the effectiveness of monetary policy to mitigate rapid credit growth is limited by several factors. First, the most important limitation is the conflict of objectives between addressing credit booms and to maintain the inflation target. The conflict of objectives is problematic since credit booms often occur during tranquil macroeconomic conditions as for example in the United States before the subprime crisis. Second, if interest rates are raised to reduce credit growth at a time when banks, firms and households already have weak balance sheets, then the present debt burden would increase even further which may cause financial instability. Third, the "impossible trinity" implies that countries with fixed exchange rate regimes and open capital accounts do not have independent monetary policy. A higher interest rate in countries with flexible exchange rate regimes can potentially lead to large capital inflows that increase credit growth unless the intervention is completely sterilized (Dell'Ariccia et al., 2016). Finally, a tighter monetary policy stance may increase financial risks by contributing to a substitution away from loans denominated in domestic currency to foreign currency loans (Rancière et al., 2008).

The empirical evidence for that monetary policy is effective to address credit booms is in general weak. Dell'Ariccia et al. (2016) find that the coefficient of monetary policy tightening is unstable and rarely significant. This suggests that monetary policy is not effective to reduce the occurrence of credit booms in general or those booms that are followed by financial crises or subpar growth. However, endogeneity is a concern in the estimations since policy makers may tighten monetary policy to reduce the likelihood of credit booms which would underestimate the effectiveness of monetary policy. In addition, Merrouche and Nier (2010) provide comprehensive evidence that higher monetary policy rates did not mitigate the build-up of financial imbalances prior to the global financial crisis in the 2000s.

Fiscal policy has both structural and cyclical elements that potentially could reduce the likelihood of credit booms (Dell'Ariccia et al., 2016). Structural policies such as removing mortgage interest tax deductibility could potentially reduce leverage in the long-run. Moreover, conducting counter-cyclical fiscal policy is to some extent likely to influence credit growth via its effect on economic growth. However, traditional fiscal policy instruments are associated with substantial time lags which are problematic when addressing credit booms that require a timely response. Dell'Ariccia et al. (2016) find no empirical support for that the fiscal policy stance is effective to curb credit booms. To sum up, the empirical evidence suggests that monetary and fiscal policies are not effective to address credit booms. The reason for this is likely due to the fact that these policies are relatively blunt instruments with potentially large negative effects on economic performance.

Macroprudential policy instruments offer a more targeted approach to effectively address credit booms compared to monetary and fiscal policy. The main objective of macroprudential policies according to Borio (2003) is "to limit the risk of episodes of financial distress with significant losses in terms of the real output for the economy as a whole (Borio, 2003, p. 2)". The purpose of microprudential instruments, on the contrary, is to limit financial distress at individual institutions irrespective of the effect on the overall economy. Dell'Ariccia et al. (2016) conduct an empirical exercise and find promising results that macroprudential policies can reduce the occurrence of credit booms in general and those followed by financial crises. However, one of the side effects of macroprudential policies is circumvention that could potentially increase systemic risk by shifting credit supply away from the banking sector to non-bank financial institutions. Moreover, Buch and Goldberg (2017) argue that the effects of macroprudential policies can spill over borders via international bank lending. The authors find empirical evidence suggesting that the effects of prudential policies on credit growth spill over to other countries but that these effects on average have not been large.

Furthermore, Dell'Ariccia et al. (2016) mention that their study only includes aggregate bank credit due to data limitations. However, the suitable choice of macroprudential policies to curb credit booms is most likely dependent on the type of credit. Finally, the authors emphasize that further research is needed to investigate the effectiveness of macroprudential policies to deal with booms that differ in the type of credit.

The main purpose of this study is to systematically investigate whether macroprudential policies are effective to address booms in bank and household credit. To directly examine whether macroprudential policies are associated with a lower likelihood of financial crises is not feasible due to the low frequency of crises. In addition, it is important to examine whether the macroprudential instruments are effective to reduce the probability of credit booms associated with systemic banking crises.

De Nicólo et al. (2012) state that "the purpose of macroprudential regulation is to focus on the financial system as a whole, with the ultimate objective of limiting systemic risk (De Nicólo et al., 2012, p. 4)". Consequently, it is essential to not only investigate whether macroprudential regulation is effective to deal with excessive credit growth which is an intermediate goal, but to focus on the ultimate target systemic risk. An ancillary aim of this study is to investigate the impact of macroprudential policies on banks' systemic risk.

The paper is organized as follows. Chapter 2 review the empirical literature on macroprudential policies. Moreover, chapter 3 describes the data, the empirical approach and the method used to identify credit booms. Descriptive 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 Literature review

Bianchi (2011) provide a theoretical framework showing that households fail to internalize the systemic feed-back effects between borrowing decisions, the real exchange rate, and financial constraints. By reducing the amount of debt ex-ante a downward spiral in borrowing capacity can be avoided. The author concludes that correcting the externality reduces the long-run probability of financial crises more than ten times and that there is much to gain from macroprudential regulation.

Cerutti, Claessens and Laeven (2017a) compile a dataset on the implementation of 12 macroprudential policy instruments for 119 countries over the years 2000-2013. A binary variable is used to capture whether a macroprudential instrument is implemented in a certain year. By means of GMM regressions, they find that aggregate and individual indexes for macroprudential instruments are generally associated with a reduction in the growth rate of credit. Moreover, macroprudential instruments seem to be less effective in developed or open countries. In addition, the results suggest that the effectiveness of macroprudential policies is higher during the boom phase of the credit cycle. Finally, the authors emphasize the importance of investigating the effectiveness of macroprudential policies to reduce the probability of financial crises and systemic risk (Cerutti et al., 2017a).

Furthermore, Bruno, Shim and Shin (2017) examine the effectiveness of macroprudential policies and capital flow management tools in 12 Asia-Pacific countries during the period 2004-2013. Contrary to the study by Cerutti et al. (2017a) the authors use a quarterly dataset with cumulative indexes measuring the sum of tightening and loosening actions. The results suggest that macroprudential policies are introduced when monetary policy is tightened and that macroprudential instruments are more effective when they complement monetary policy. One venue for future research suggested by the authors is to examine the direct and spillover effects of macroprudential policies on different types of credit.

Akinci and Olmstead-Rumsey (2018) construct a database with macroprudential instruments in 57 advanced and emerging countries between 2000 and 2013. A cumulative index with the sum of tightenings net of easings is employed to assess the effectiveness of macroprudential instruments similar to the study by Bruno et al. (2017). The study shows that macroprudential instruments have been employed more frequently in both advanced and developing countries after the global financial crisis. Moreover, the authors find that a tightening of macroprudential policies is associated with a lower growth rate in both domestic bank credit as well as household credit. In addition, they find that targeted policies such as loan-to-value caps seem to be more effective particularly in countries with bank-based financial systems.

Fendoğlu (2017) examine the effectiveness of macroprudential instruments for mitigating excessive cycles in credit for 18 major emerging market economies between 2000-2013. The dependent variable is the credit-to-GDP gap where the credit measure includes domestic bank credit as well as credit from non-bank institutions and cross-border credit. In addition, a credit boom constructed with the method by Dell'Ariccia et al. (2016) is also used as the dependent variable. The results suggest that borrower-targeted and domestic reserve requirements are effective to smooth the credit cycle. However, weak results were found for macroprudential policies related to financial institutions and FX-related measures. Finally, none of the macroprudential policy instruments in this study is significantly associated with the probability of credit booms.

In addition, Dell'Ariccia et al. (2016) conduct an empirical exercise to examine whether macroprudential policies are effective to reduce the probability of credit booms. They define a credit boom if either of the following two conditions is fulfilled: (i) the deviation from trend is greater than 1.5 times its standard deviation and the annual growth rate of the credit-to-GDP ratio exceed 10 percent, or (ii) the annual growth rate of the credit-to-GDP ratio exceeds 20 percent. The aggregate macroprudential policy index is computed as the sum of the number of implemented policies similar to the approach by Cerutti et al. (2017a). Finally, the study shows that the aggregate index is negatively and significantly associated with booms in domestic bank credit.

This study contrasts from the paper by Dell'Ariccia et al. (2016) in several different ways. First of all, the authors only investigate if macroprudential policies are effective to deal with booms in domestic bank credit. However, the authors explicitly state that further analysis is needed to assess the effectiveness of macroprudential policies to address booms in different types of credit. Consequently, the aim of this study is to examine if macroprudential policies can address booms in domestic bank credit as well as household credit. Importantly, several studies show that household credit is much more problematic for financial stability compared to firm credit (see discussion in chapter 5.3). In addition, the measure for household credit employed in this study captures total credit to households provided by both banks and other financial institutions. To conclude, it is essential to investigate whether macroprudential policies are effective to address booms in household credit.

Furthermore, the indicator for macroprudential policies employed by Dell'Ariccia et al. (2016) only measures if a policy was implemented in a certain year. The drawback of using dummy variables for macroprudential policies is that the indicator does not account for the intensity (tightening and loosening) of the policies (Galati Moessner, 2016). In addition, it is particularly problematic to employ binary indicators when assessing the effectiveness of individual macroprudential policies to address credit booms due to the low variability. However, the indicators used in this study measures the cumulative sum of tightenings net of easings since the year 2000. Consequently, the indicators measure the overall "macroprudential policy stance" and have higher variability. Moreover, the indicators in this paper are measured with quarterly frequency compared to yearly frequency in the study by Dell'Ariccia et al. (2016). Moessner and Galati (2016) emphasize the importance of using data with higher frequency since it makes it easier to differentiate the effect of macroprudential policies on credit booms from the impact of other policies. To sum up, the indicators for macroprudential policies employed in this paper are more precise since they measure to some extent the tightness of macroprudential policies at a quarterly frequency.

Finally, the methodology to identify credit booms differ significantly between this study and the paper by Dell'Ariccia et al. (2016). The authors use the ratio of credit divided by GDP whereas in this paper credit is normalized by population. Chapter 3.3 discusses why a per capita normalization is preferred to a normalization by GDP. In addition, this paper also includes several robustness checks such as splitting the data into different country samples and time periods that further strengthens the reliability of the results.

3 Empirical strategy

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 A17 in the appendix. Data to generate the binary dependent variable (credit boom) has been collected from the BIS Total Credit Statistics database. Two different types of credit are used in this study: domestic bank credit and household credit to the non-financial private sector. The measure on credit to households include 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 categorization of prudential policies in Cerutti et al. (2017a) the five macroprudential policy instruments 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 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. Consequently, indicator variables measuring tightenings (+1) and easings (-1) of macroprudential instruments are employed in this study as well as several other studies with cross-country data.

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 (2013), 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 (LTV) Ratio Limits 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. Moreover, concentration limits constrain the fraction of assets held by a limited number of borrowers. In addition, interbank exposure limits put a ceiling on the fraction of liabilities held by the banking sector or individual banks (Cerutti et al. 2017a).

The concentration and interbank exposure limits can be altered by modifying five different characteristics. First, the definition of large exposures "the sum of all exposure values of a bank to a counterparty or to a group of connected counterparties[...] is equal to or above 10 percent of the bank's eligible capital base (Basel Committee on Banking Supervision, 2014)" can be changed. Second, the level of the limit can be modified by changing the definition of the exposures by a bank's capital or in monetary terms. Third, the weight of the exposures to counterparties as well as the duration of the claims can be altered. Fourth, the threshold of aggregate concentration limits defined as the sum of all large exposures for banks can be increased or reduced. Finally, the sectors and assets covered by the policies can be modified by for example only include depository institutions or to also include non-bank financial institutions (Cerutti et al., 2017b).

Reserve requirements (RR) are typically used to conduct monetary policy. However, Cordella et al. (2014) show that these instruments have also been applied as counter-cyclical 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. Moreover, information on reserve requirements indicates whether deposit accounts are denominated in domestic or foreign currency.

Following the approach in Akinci and Olmstead-Rumsey (2018) and Buch and Goldberg (2017) the individual macroprudential policy instruments are included in three aggregate indexes. Aggregate macroprudential indexes are included in the empirical investigation since they measure to some extent the overall "macroprudential policy stance" in a country. However, it is essential to also investigate the effectiveness of individual instruments to deal with credit booms since aggregate indexes capture the change in any regulation included in the index. 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 commonly used in the literature 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. All variable definitions and sources can be found in Tables A2 and A3, and summary statistics are shown in Table A1.

3.2 Empirical specification

Logit regressions with credit booms as the dependent variable are estimated with White-Huber robust standard errors clustered by country. In addition, Logit estimations with country fixed effects and/or year fixed effects are also conducted to examine the robustness of the results. However, credit booms did not occur in some countries or 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). In addition, 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 employed 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 Bergant et al. (2020) 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). Moreover, Figures 1 and 2 show empirical evidence suggesting that many macroprudential policies were tightened after 2009 when credit growth was significantly lower. However, this problem can to some extent be mitigated by using credit booms instead of credit growth as the dependent variable. In short, the issue of reverse causation should be less problematic by identifying the specific time of the credit boom and using macroprudential policy indexes lagged one or more quarters.

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 conclude, due to 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. However, these episodes are typically not captured by using the yearly or quarterly growth rate of credit as the dependent variable. One important argument for using credit booms as the dependent variable is that macroprudential policies are likely to be (more) effective when credit growth is stronger. Consequently, GMM estimations are conducted to assess whether macroprudential policies are more effective when credit growth is higher following the approach in Cerutti et al. (2017a). Four different dummy variables are constructed taking 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%). Table 1 shows the results for dynamic two-step GMM estimations with the real growth rate of domestic bank credit as the dependent variable. All independent variables except the VIX index are treated as endogenous as in the study by Akinci and Olmstead-Rumsey (2018).

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 1. 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 addition, Cerutti et al. (2017a) find some support for that macroprudential policies are more effective during the more intense phase of the financial cycle (top 10% of observations) and particularly so in advanced economies. In short, the preliminary findings that macroprudential policies are (more) effective when credit growth is stronger confirm the relevance of using credit booms as the dependent variable.

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). However, by identifying the specific time for credit booms 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, Schularick and Wachtel (2017) as well as Gorton and Ordoñez (2016) that bad booms are fundamentally different from credit booms that are not associated with systemic banking crises (good booms).

Table 1: GMM estimations with macroprudential policy index

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 domestic 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 study 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 takes 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.

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 year (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 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) emphasize 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 domestic 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 Descriptive statistics

The development 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 2. 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 coincide 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 2 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 considerably larger 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 suggest that many macroprudential policies were tightened during a period when credit growth was relatively low.

Table A4 shows that the aggregate index for borrower- and financial institution-targeted policies (MAPP_B_FI) is correlated with the index for reserve requirement policies (MAPP_RR). Moreover, MAPP_RR is positively correlated with the central bank policy rate. However, the index MAPP_B_FI is negatively correlated with the policy rate and this is probably because policy rates have been kept low in advanced countries while macroprudential policies have been tightened.

Figure 2 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. Conversely, 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. Starting in 2010 the index shows a steady upward trend until 2014. 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 frequency (or size) of the tightenings of the index was more pronounced during the periods 2006-2008 and 2010-2011.

Table A5 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.

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

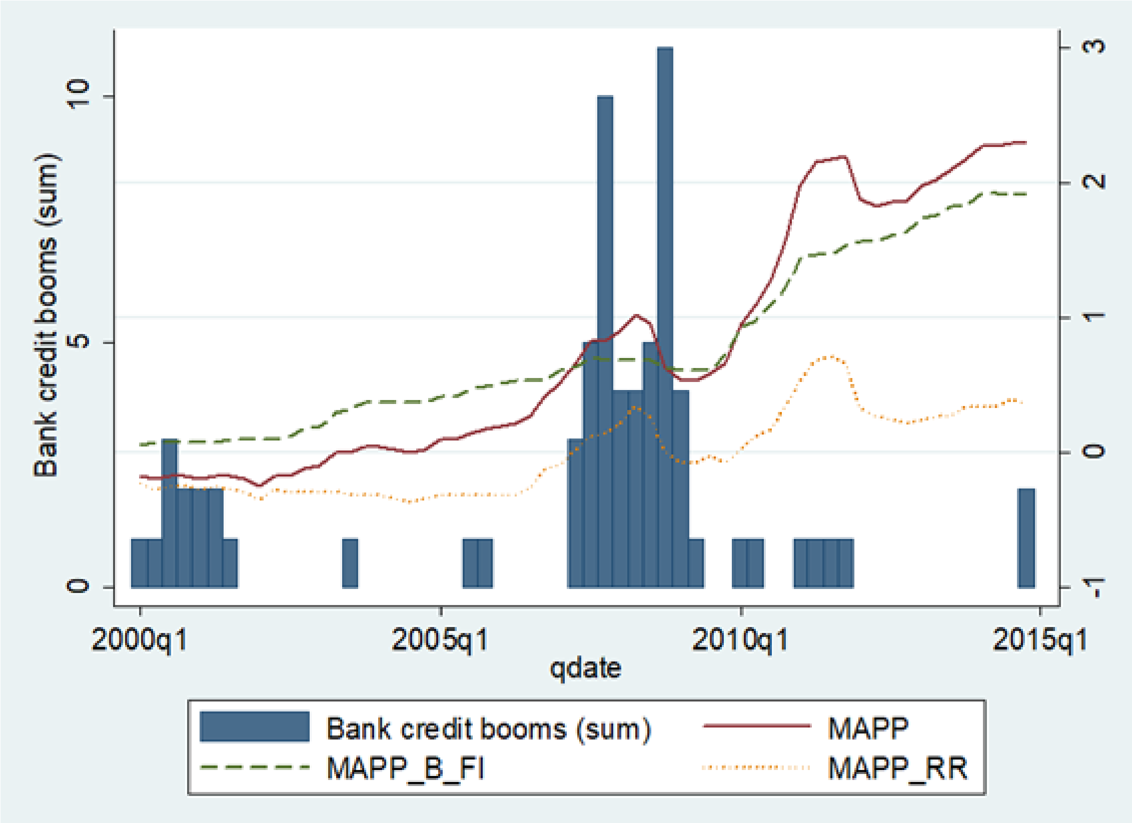
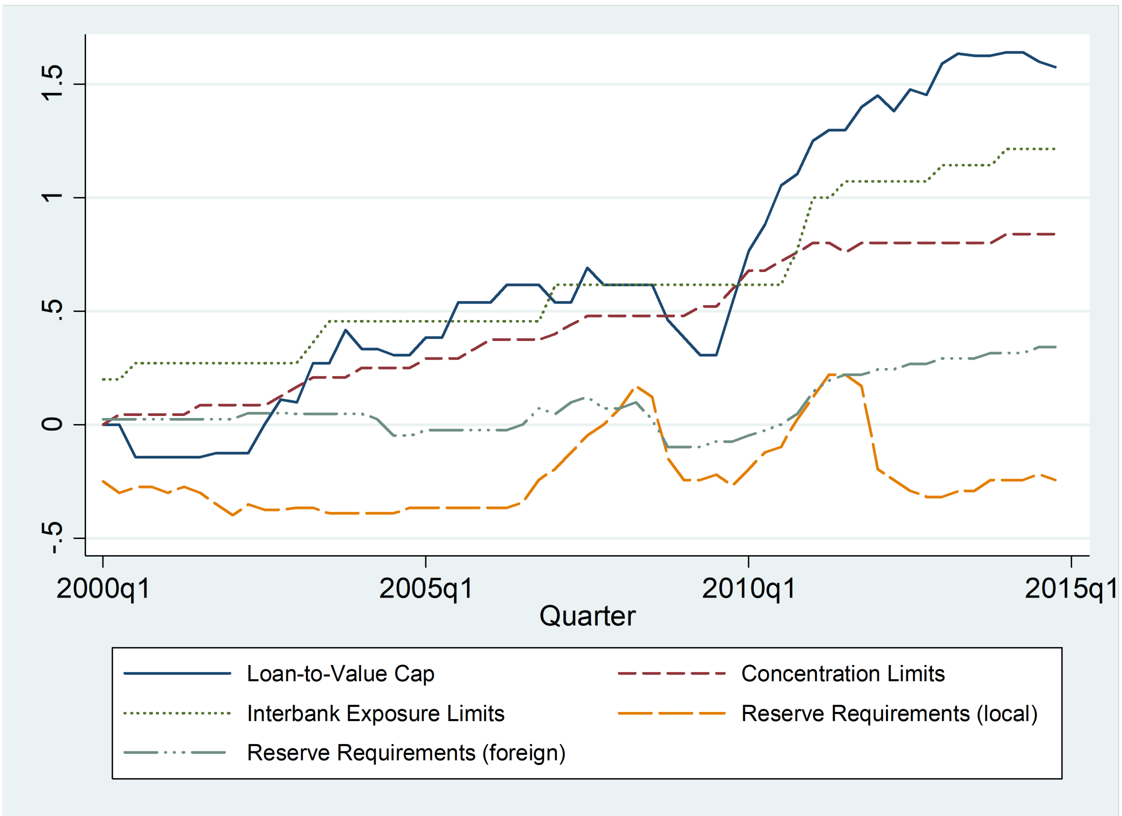


Figure 2: Macroprudential policy instruments (averages) 2000Q1-2014Q4



5 Results

5.1 Macroprudential policies and bank credit booms

Results for estimations with bank credit booms and the aggregate index MAPP including all five macroprudential policies are shown in Table 2. 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). Finally, the MAPP index is also negative and significant in the Firth logit estimation shown in 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 3. 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 4-5). However, the index MAPP_RR is not significant in the Firth logit estimation (column 6). The results for the macroprudential sub-indexes suggests that both borrower- and financial institution-targeted instruments (MAPP_B_FI), as well as reserve requirement policies (MAPP_RR), are effective to deal with credit booms.

The number of bank credit boom observations is 61 in all estimations for the aggregate 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 provide 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 (not credit growth) which are often 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. Moreover, the coefficient for the real exchange rate is positive and significant only in the estimations with country fixed effects. 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 A6. 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 for CONCRAT is negative and significant at the 10% level in the Firth logit estimation (column 6).

Finally, results for reserve requirement policies are shown in Table A7. 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)".

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) and Richter et al. (2017). 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 3 and 4 illustrate the behavior of the average ratio of domestic 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

Table 2: Aggregate macroprudential policy 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 domestic 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 3: Aggregate macroprudential policy 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 domestic bank credit booms. The Hodrick-Prescott (HP) filter is used to identify credit booms and the threshold is 1.75 standard deviations. The indexes 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.

to GDP up to the first quarter that is above the threshold of 1.75 s.d. illustrated by the vertical line in Figure 3. After the first quarter of the good boom (66 episodes) the ratio of credit to GDP stagnate for five years and then continues to climb.

Figure 4 shows that the ratio of bank credit to GDP ten years before a bad credit boom (24 episodes) start 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 completely after the credit boom.

The behavior of the average real GDP growth five years before and after good and bad credit booms is illustrated in Figures A2 and A3. 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 4 shows results for Logit, LPM, and Firth logit estimations with good booms and bad booms separately. The coefficient for the aggregate macroprudential policy instrument MAPP is negative and significant in all estimations with bad credit booms except for the LPM estimation with both country and year fixed effects. Moreover, the aggregate index MAPP is negative and significant for the Logit and LPM estimations with good credit booms but not for the Firth logit estimation. To conclude, the results suggest that macroprudential policies are not only effective to deal with credit booms but also specifically those booms that are followed by systemic banking crises.

Figure 3: Average ratio of domestic bank credit to GDP around good boom episodes

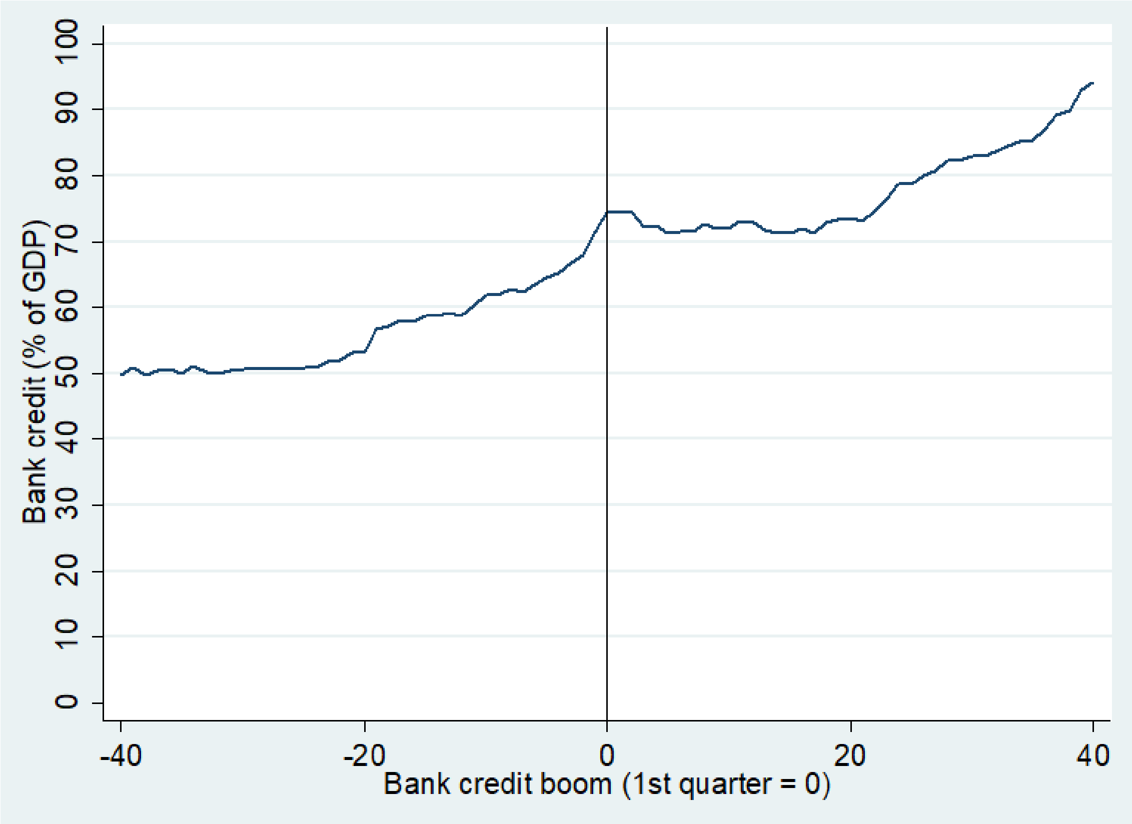


Figure 4: Average ratio of domestic bank credit to GDP around bad boom episodes

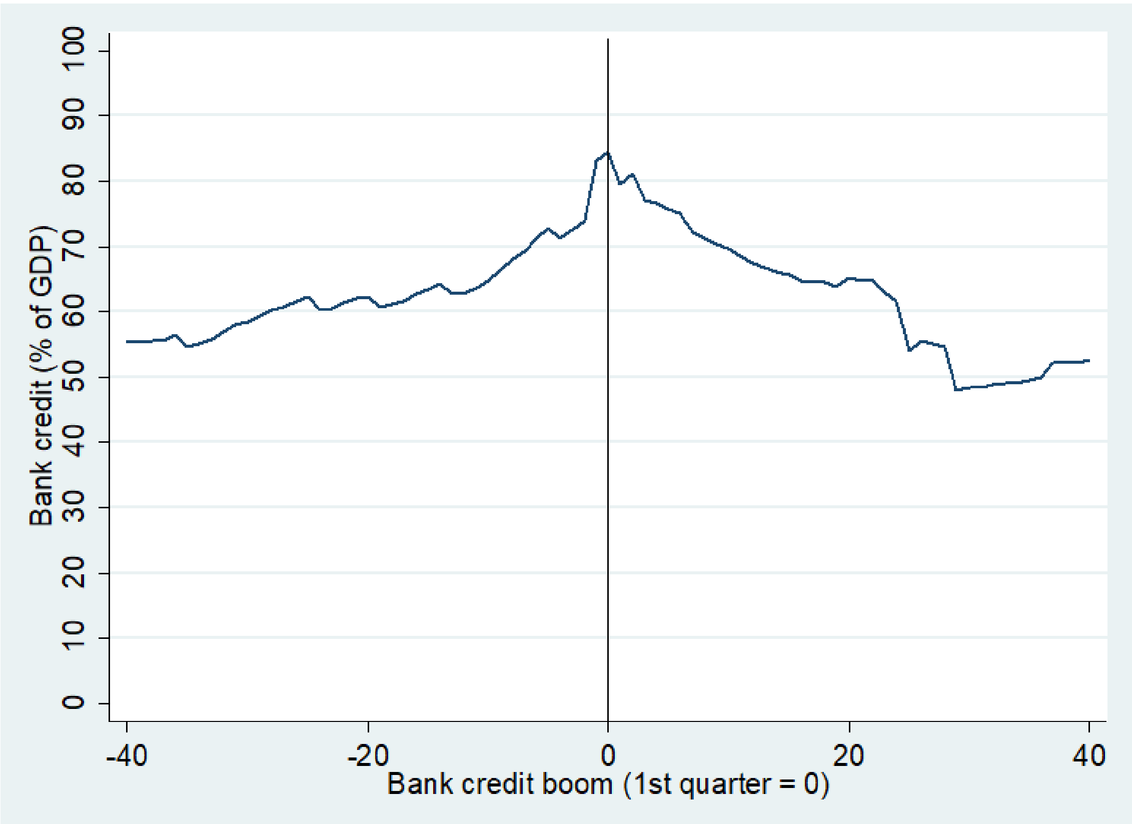


Table 4: Good and bad credit booms

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***	0.039**	1.233**	1.456**	0.059***	1.496***
	(0.413)	(0.016)	(0.514)	(0.614)	(0.013)	(0.628)
Real GDP growth	0.159***	0.002*	0.154***	-0.023	-0.001	-0.036
	(0.039)	(0.001)	(0.056)	(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	-0.002	0.244**
	(0.125)	(0.003)	(0.103)	(0.130)	(0.002)	(0.116)
Log(real exchange rate)	-0.078	0.055	-0.057	-0.063	0.021	-0.020
	(0.212)	(0.042)	(0.108)	(0.250)	(0.032)	(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	0.040	0.485*	1.448***	0.047**	1.408***
	(0.743)	(0.003)	(0.284)	(0.320)	(0.023)	(0.442)
MAPP	-0.166**	-0.004**	-0.141	-0.515**	-0.000	-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	YES	NO	NO	YES	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 domestic 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.

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. Furthermore, Büyükkarabacak and Valev (2010) investigate the role of household and corporate credit expansions in banking crises for 37 developing and advanced countries. Rapidly increasing credit to the entire private sector is associated with banking crises. However, decomposing the aggregate credit measure shows that household credit has been the driving factor of increased vulnerabilities to systemic banking crises. Corporate credit has a statistically significant effect on the probability of a subsequent banking crisis although it is weaker and less robust (Büyükkarabacak and Valev, 2010).

Jordà, Schularick, and Taylor (2016) provide a new disaggregated dataset including both mortgage and non-mortgage credit for 17 advanced economies since 1870. The authors show that mortgage lending on banks' balance sheets has doubled during the 20th century driven by lending to households. Moreover, both normal recessions and those associated with financial crises since World War II tend to be considerably more severe and have a slower recovery when preceded by a large expansion in mortgage credit. Conversely, non-mortgage credit booms have basically no effect on the likelihood of recessions today (Jordà et al., 2016).

Figure 5 illustrates that the average ratio of household credit to GDP does not increase during the ten years preceding a boom in domestic bank credit (32 episodes) that is not followed by a systemic banking crisis (good boom). However, Figure 6 shows that household credit as percent of GDP increase considerably before a bank credit boom (20 episodes) associated with a banking crisis (bad boom). The different pattern of the ratio of household credit to GDP before good booms and bad booms confirm the relevance of household credit for explaining the occurrence of financial crises.

Figures A4 and A5 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. Household credit (% of GDP) does not seem to increase before good credit booms in contrast to for firm credit. In short, the behavior of household credit contains information that is useful to identify those credit booms that are followed by financial crises.

Knyazeva et al. (2009) argue that external financing is essential for private investment and economic growth. However, this refers almost exclusively to corporate credit and not household credit. 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 a liquidity constraint on households enhances economic growth.

Furthermore, Beck et al. (2012) show that corporate credit is positively correlated with growth while the relationship between household credit and growth is insignificant. In addition, Bezemer et al. (2015) find that credit to non-financial firms raises economic growth. However, financial development was mostly credit to real estate and other assets since 1990 which does not contribute to growth. In short, new bank lending is not

Figure 5: Average household credit (% of GDP) around good credit booms

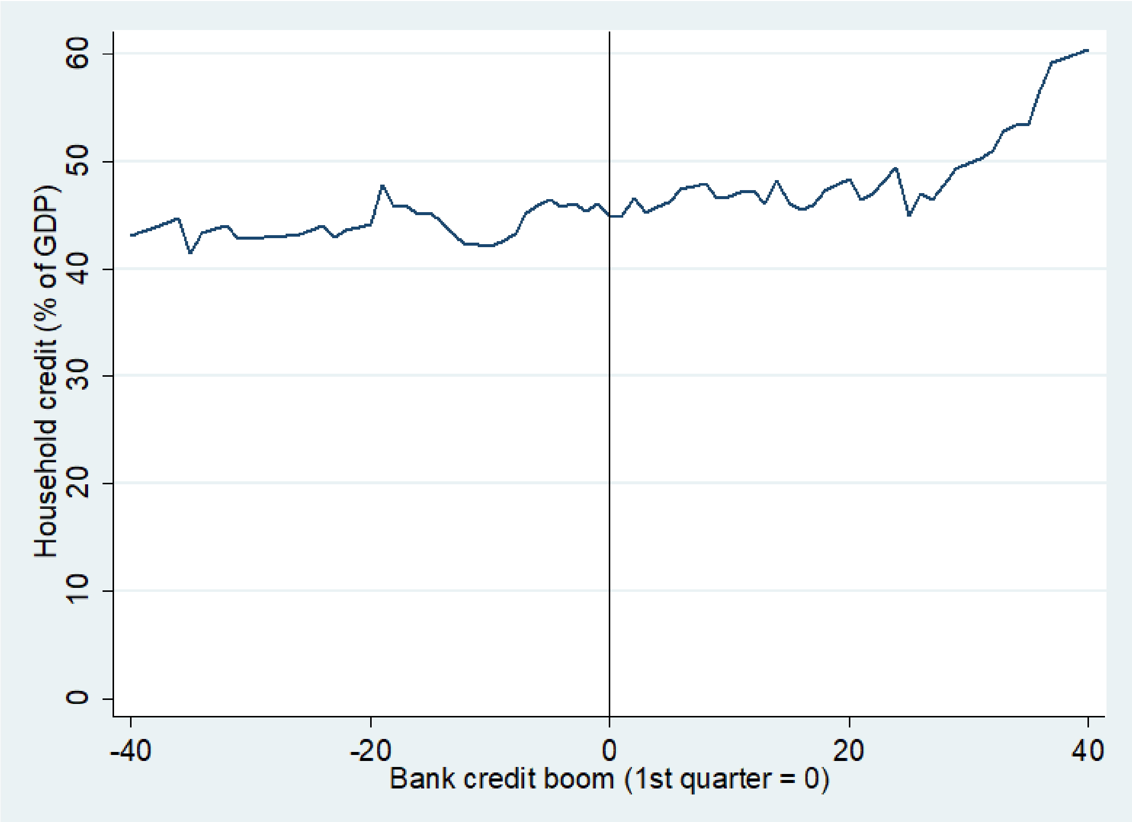
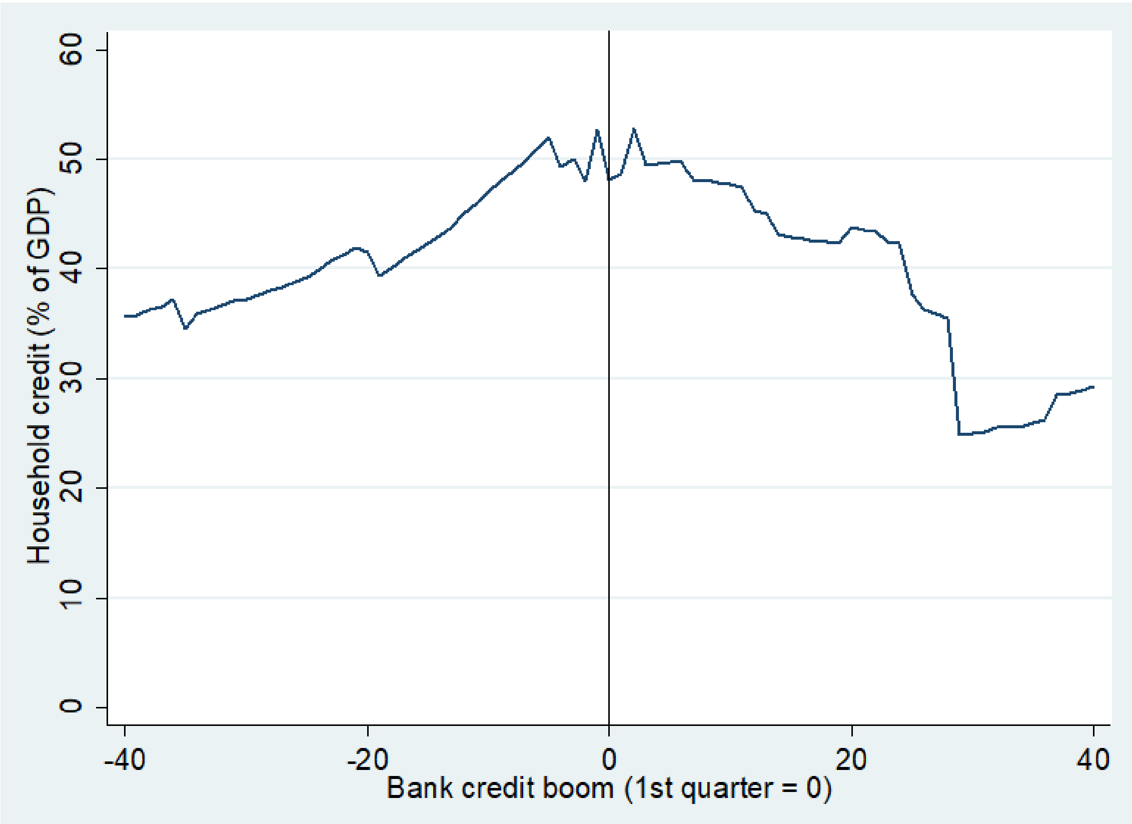


Figure 6: Average household credit (% of GDP) around bad credit booms s



primarily credit to firms which implies that financial development may no longer be good for growth.

Finally, Mian and Sufi 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 Sufi, 2014, p. 9)". To sum up, it is essential to examine whether macroprudential policies can be effective to deal with booms in household credit.

Table 5 shows the results for the MAPP index and household credit booms with threshold 1.75 standard deviations. The measure of household credit includes not only domestic bank credit but also credit from non-bank financial institutions and cross-border credit. Consequently, this credit measure is suitable to assess the effectiveness of macroprudential policies since it addresses the issue of circumvention discussed in the introductory chapter. 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 A8. 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. In addition, the MAPP_B_FI index has a higher statistical significance in estimations with household credit booms compared to the results for bank credit booms (Table 3) while the opposite is true for the MAPP_RR index. Finally, it should be emphasized that only 10 developing countries are included in the estimations with household credit booms compared to 14 countries for bank credit booms.

5.4 Economic interpretation

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

Table 6 shows the average marginal effects for the macroprudential index MAPP (column 1 in Table 2, and columns 1 and 4 in Table A9) from estimations with 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 standard deviations by approximately 0.77 percentage points. This effect is relatively large in economic terms since the sample

Table 5: Aggregate macroprudential policy 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.

frequency of credit booms with this threshold is only 2.81 percent. Moreover, the results in Table 6 also show that sub-index MAPP_B_FI reduce the probability of bank credit booms (threshold 1.75 s.d.) by about 0.66 percentage points compared to 0.37 percentage points for sub-index MAPP_RR. This finding is not entirely surprising, since reserve requirements on accounts denominated in local or foreign currency are mainly used in developing countries.

Furthermore, the effectiveness of macroprudential policies could be different between credit booms of different size. 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 6. An increase in the MAPP index by one standard deviation reduce 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). Consequently, the effect of an increase in the MAPP index on the occurrence of credit booms relative to the sample frequency is higher for larger credit booms compared to smaller booms. In addition, similar results are also found for the aggregate index MAPP and household credit booms with thresholds 1.5 and 1.75 standard deviations.

It could be of interest to examine whether the effectiveness of macroprudential policies differ between booms in bank and household credit. Since MAPP_RR is only significant for smaller household credit booms it is suitable to compare the results for the sub-index 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. However, 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 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. In addition, these findings are robust to only including advanced countries in the estimations which implies that the country sample is the same for household and bank credit booms.

To sum up, 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 moreover 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.

Table 6: 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 domestic bank and household credit booms. The MAPP index includes all five macroprudential instruments (LTV_CAP, IBEX, CONCRAT, RR_D, and RR_FX). The indexes 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.

6 Robustness tests

To examine the robustness of the results it is essential to identify credit booms with different thresholds. Figure A6 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. Table A9 shows that the number of credit boom episodes double from 61 to 119 when the boom threshold is 1.5 instead of 1.75 standard deviations. Similarly, the number of credit booms is 32 with a threshold of 2 standard deviations which is only half of the number of episodes compared to for a boom threshold of 1.75 standard deviations. In short, the number of credit booms and the magnitude of these booms differs considerably depending on whether the boom threshold is 1.5, 1.75 or 2 standard deviations.

The coefficient for the MAPP index is negative and significant at the 1% level in all estimations with small credit booms (1.5 s.d.) shown in Table A9. 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 were after the beginning of the crisis according to Akinci and Olmstead-Rumsey (2018). Consequently, it is essential 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 A10. The coefficient for the macroprudential index MAPP is negative and typically significant for both the period before the crisis (2000Q1-2006Q4) and after (2007Q1-2014Q4). 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 A7 and A8 illustrate the development of individual macroprudential policies for advanced and developing countries separately. The index for Loan-to-Value caps displays a similar pattern for both advanced and developing countries although the index is generally at a higher average level in developing countries. Moreover, the index for concentration limits increases gradually over the entire period in advanced countries while in developing countries the index rises until around 2007 and then remain stable until 2014. In addition, interbank exposure limits show a similar pattern to concentration limits for the two country groups. However, the index for interbank exposure limits was in 2014 twice as high on average in advanced countries compared to developing countries, while the index for concentration limits was at a similar level for both country groups in this year.

The use of reserve requirements is completely different in advanced economies compared to for developing countries as shown in Figures A7 and A8. In advanced countries, reserve requirements related to foreign currency deposits were almost never used during the entire period. Reserve requirements related to 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. However, 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 A11. One-third of the 41 countries are classified as developing countries and two thirds as advanced economies shown in Table A17. The MAPP index is negative and significant at the 1% or 5% level in all estimations for developing countries shown in Table 17. In addition, the coefficient for the MAPP index is also negative and significant for advanced economies except for LPM estimation with both country and year fixed effects.

In addition, re-estimating the specifications in Table A11 for the macroprudential sub-indexes shows that index MAPP_B_FI is negative and typically significant for both advanced and developing countries. In addition, the sub-index MAPP_RR is found to be negative and significant in all estimations for developing countries. However, the MAPP_RR index is not significant in Logit and LPM estimations for advanced economies, which is consistent with the pattern for individual reserve requirement policies illustrated in Figures A7 and A8.

6.1 Alternative definition of credit booms

Hamilton (2017) 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, Schularick, and Wachtel (2017) is employed to test the robustness of the results.

The detrending method suggested by Hamilton (2017) 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., 2017). Hamilton (2017) 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 (2017) suggest 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. Furthermore, Hamilton (2017) argues that using more than 4 lags, including more variables or a non-linear specification are unnecessary to extract the stationary component. In addition, including more parameters to estimate the regression has a considerable drawback. The more parameters included the more the small-sample estimates are expected to differ from the asymptotic predictions.

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., 2017).

Table A12 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 bank credit booms with thresholds 1.75 and 2 standard deviations.

6.2 Additional control variables in the analysis

It is important to verify whether the results hold when controlling for other prudential policies. Table A13 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 A13 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 at the 5% level in all estimations with the HP filter.

7 Macroprudential policy and banks' systemic risk

It has been shown in this study that a tighter macroprudential policy stance is negatively associated with the likelihood of credit booms. This part of the study aims to investigate the impact of macroprudential policy on banks' systemic risk.

7.1 Data and descriptive statistics

The dataset encompasses yearly data for 460 banks in 54 advanced and developing countries between 2000-2015. Variable definitions and sources are shown in table A14. In addition, the countries included in this study and the number of banks in each country are listed in table A18.

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. Moreover, 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).

Benoit et al. (2017) provide empirical results showing 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. Consequently, the SRISK measure takes into account both the "too-interconnected-to-fail" and the "too-big-to-fail" paradigms (Benoit et al., 2017).

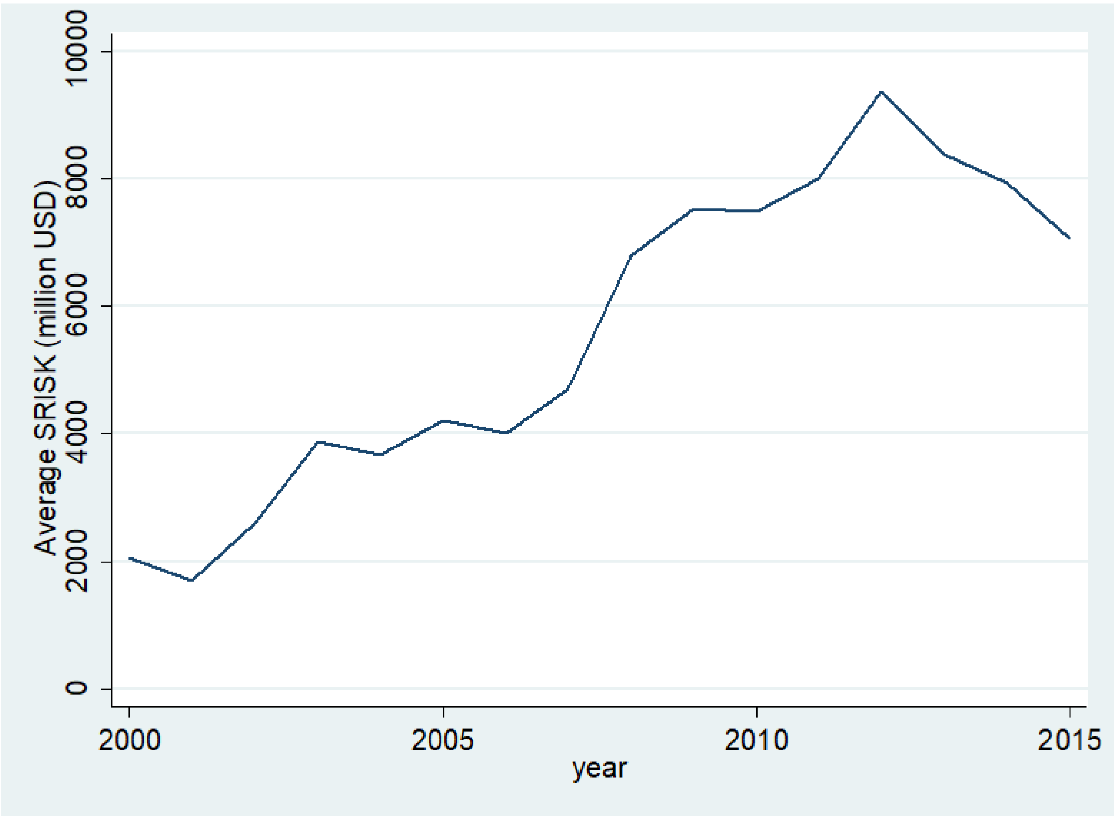
Table A15 shows that both beta (systematic risk) and market capitalization (size) are positively and significantly correlated with SRISK as expected. In addition, the evolution of average positive SRISK between 2000 and 2015 is shown in Figure 7.

Moreover, the SRISK measure has been found to be useful to identify those institutions that may have a large influence on systemic risk. Brownlees and Engel (2015) show in their study that those banks that were most likely to be bailed out by the US government and receive support from the Federal Reserve had the highest levels of SRISK before the crisis.

Several control variables which have been found to influence systemic risk are included in the estimations (see table A14 in the appendix). First, the bank-level measures are "size" and "leverage" similar to the papers by Altunbas et al. (2018) and Karolyi et al. (2017). 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. (2017). Real GDP growth controls for economic performance and is likely to affect 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 development.

Finally, 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.

Figure 7: Evolution of positive SRISK between 2000-2015



7.2 Results

OLS regressions with only year fixed effects or combined year and country (or bank) fixed effects 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 Karolyi et al. (2018) and Sedunov (2021).

Moreover, 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 are estimated to address the presence of non-linearities following the approach in the study by Gehrig and Iannino (2021). The quantile regressions are estimated for the 0.25, 0.50 and 0.75 quantiles including country effects and year dummies with standard errors clustered for banks (Parente et al., 2016). As an approximation for country “fixed effects” the Mundlak-Chamberlin devise is applied which include time averages of all time-varying regressors (Wooldridge, 2010; Chamberlin Ricker-Gilbert, 2016).

Estimations with aggregate macroprudential indexes and SRISK scaled by real GDP are shown in Table A16. 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. In addition, the coefficient for the index MAPP_RR is negative and significant at the 1% level with country and year fixed effects (but only at the 10% level with bank and year fixed effects).

Results for 0.25, 0.50 and 0.75 quantile regressions are shown in Table 7. 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. Interestingly, in contrast to the previous results both indexes MAPP_B_FI and MAPP_RR are negative and highly significant for the 0.50 and 0.75 quantile regressions. The results suggest that a tighter macroprudential stance is negatively associated with SRISK-to-GDP for banks at upper quantiles.

Table 7: Quantile regressions with macroprudential indexes

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 indexes 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).

8 Conclusions

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 booms in bank and household credit.

The results strongly suggest that aggregate indexes with macroprudential policies are negatively and significantly associated with booms in domestic bank credit. In addition, the results also show that aggregate indexes with macroprudential policies are suitable to address specifically those credit booms that are followed by systemic banking crises. This finding suggests that macroprudential policies are not only effective to reduce credit growth but may also be useful to curb credit booms that lead to a financial crisis.

Furthermore, the empirical literature clearly shows that household credit is more important for the occurrence and severity of financial crises compared to corporate credit. This implies that it is essential to examine the effectiveness of macroprudential policies on household credit and not only on the aggregate measure with domestic bank credit. The results show that macroprudential policies are negatively linked to the likelihood of household credit booms.

The findings also suggest that the effect of an increase in the aggregate macroprudential index (including all instruments) on the likelihood of bank credit booms is relatively large in economic terms.

Several robustness tests are conducted to check if the results are reliable for example using different boom thresholds, time periods and country groups. In addition, estimations with an alternative method to identify credit booms and including additional control variables provide further support for that macroprudential policies are effective to address credit booms.

Finally, this study also suggests that the macroprudential policy stance is negatively associated with the level of systemic risk for banks. This association seems to be more pronounced for banks' systemic risk at upper quantiles.

References

Acharya, V., Engle, R., Richardson, M., 2012. "Capital Shortfall: A New Approach to Ranking and Regulating Systemic Risks", American Economic Review, 102(3): 59-64

Akinci, O., Olmstead-Rumsey, J., 2018. "How effective are macroprudential policies? An empirical investigation", Journal of Financial Intermediation, Vol. 33, pp. 33-57

Alter, A., Feng, A., Valckx, N. 2018. "Understanding the Macro-Financial Effects of Household Debt: A Global Perspective", IMF Working Paper WP/18/76

Altunbas, Y., Binici, M., Gambacorta, L., 2018. "Macroprudential policy and bank risk", Journal of International Money and Finance, 81, 203-220

Beck, T., Büyükkarabacak, B., Rioja, F., Valev, N., 2012. "Who Gets the credit? Household vs. Firm Lending Across Countries", The B.E. Journal of Macroeconomics: Vol. 12: Iss. 1 (Contributions), Article 44.

Basel Committee on Banking Supervision. 2014. "Supervisory Framework for Measuring and Controlling Large Exposures", April.

Benoit, S., Colliard, J-E., Hurlin, C., Pérignon, C., 2017. "Where the Risks Lie: A Survey on Systemic Risk", Review of Finance, 109-152

Bergant, K., Grigoli, F., Hansen, N-J., Sandri, D., 2020. "Dampening Global Financial Shocks: Can Macroprudential Regulation Help (More than Capital Controls)?", IMF Working Paper WP/20/106

Bernanke B, Gertler M. 2001. "Should central banks respond to movements in asset prices?", American Economic Review 91:253–57

Bianchi, J., 2011. "Overborrowing and Systemic Externalities in the Business Cycle", American Economic Review. Vol 101 (December 2011): 3400-3426

Borio, C., 2003. "Towards a macroprudential framework for financial supervision and regulation?", BIS Working Paper No. 128, February

Brownlees, D., Engle, R.F., 2017. "SRISK: A Conditional Capital Shortfall Measure of Systemic Risk", Review of Financial Studies, 30(1), 48-79

Bruno, V., Shim, I., Shin, H.S., 2017. “Comparative assessment of macroprudential policies”, Journal of Financial Stability, 28, 183-202

Buch, C.M., Goldberg, L.S., 2017. “Cross-Border Prudential Spillovers: How Much? How Important? Evidence from the International Banking Research Network”, International Journal of Central Banking

Büyükkarabacak, B., Valev N.T., 2010. “The role of business and household credit in banking crises”, Journal of Banking and Finance, Volume 34, Issue 6, 1247-1256.

Caballero J.A., 2016. “Do Surges in International Capital Inflows Influence the Likelihood of Banking Crises?”, The Economic Journal, Volume 125, Issue 591, 281-316

Calderón, C., Kubota, M., 2012. “Gross Inflow Gone Wild”, World Bank Policy Research Working Paper WPS6270

Cerutti, E., Claessens, S., Laeven, L., 2017a. ”The use and effectiveness of macroprudential policies: New evidence”, Journal of Financial Stability, 28, 203-224

Cerutti, E., Correa, R., Fiorentino, E., Segall, E., 2017b. “Changes in Prudential Policy Instruments – A New Cross-Country Database”, International Journal of Central Banking, Vol 13(1), pp. 477-503

Chamberlin, J., Ricker-Gilbert, J., 2016. ”Participation in Rural Land Rental Markets in Sub-Saharan Africa: Who Benefits and by How Much? Evidence from Malawi and Zambia”. American Journal of Agricultural Economics, Vol. 98(5), 1507-1528

Chari, A., Dilts-Stedman, K., Forbes, K., 2022. ”Spillovers at the extremes: The macroprudential stance and vulnerability to the global financial cycle”, Journal of International Economics, Vol. 136

Cordella, T., Federico, P., Vegh, C., Vuletin, G., 2014. “Reserve requirements in the brave macroprudential world”, World Bank Policy Research Working Paper No. WPS6793

Dell’Ariccia G., Igan, D., Laeven, L. 2012b. ”Credit Booms and Lending Standards: Evidence from the Subprime Mortgage Market”, Journal of Money, Credit and Banking, Vol 44, Issue 2-3, 367-384

Dell'Ariccia G., Igan, D., Laeven, L., Tong, H. 2016. "Credit Booms and Macrofinancial Stability", Economic Policy, 31(86), 299-355

De Nicolò, G., Favara, G., Ratnovski, L., 2012. "Externalities and Macroprudential Policy", Staff Position Note, (Washington, DC: International Monetary Fund).

Drehmann, M., Borio, C., Tsatsaronis K., 2012. "Characterising the financial cycle: Don't lose sight of the medium term!", BIS Working Papers, no 380, June

Galati, G., Moessner, R., 2018. "What Do We Know About the Effects of Macroprudential Policy?", Economica, Vol 85, Issue 340, pp. 735-770

Gehrig, T, Iannino, M.C., 2021. "Did the Basel Process of capital regulation enhance the resiliency of European banks?", Journal of Financial Stability, Vol 55

Gorton, G., Ordoñez, G., 2016. "Good Booms, Bad Booms", NBER Working Paper No. 22008 Hamilton, J.D., 2017. "Why You Should Never Use the Hodrick-Prescott Filter", Review of Economics and Statistics forthcoming

Jordà, Ò., Schularick, T., Taylor, A.M., 2016. "The great mortgaging: housing finance, crises and business cycles", Economic Policy, Volume 31, Issue 85, pages 107-152

Jappelli, T., Pagano, M., 1994. "Saving, growth and liquidity constraints", Quarterly Journal of Economics 109, 83–109.

Karolyi, G.A., Sedunov, J., Taboada, A.G., 2018. "Cross-Border Bank Flows and Systemic Risk", Working Paper

Kirschenmann, K., Malinen, T., Nyberg, H., 2016. "The risk of financial crises: Is there a role for income inequality", Journal of International Money and Finance, 58, 161-180

Knyazeva, A., Kynazeva, D., Stiglitz, J., 2009. "Ownership changes and access to external financing", Journal of Banking and Finance 33, 1804–1816.

Kuttner, K.N., Shim, I., 2013. "Can non-interest rate policies stabilize housing markets? Evidence from a panel of 57 economies", BIS Working Papers No 433.

Laeven, L., Valencia, F., 2013. "Systemic Banking Crises Database", IMF Economic Review, 61, 225-270.

Lim, C.H., Columba, F., Costa, A., Kongsamut, P., Otani, A., Saiyid, M., Wezel, T., Wu, X., 2011. "Macroprudential Policy: What Instruments and How to Use Them? Lessons from Country Experiences", IMF Working Paper No. 11/238 (Washington, DC: International Monetary Fund).

Mendoza, E., Terrones, M., 2008. "An anatomy of credit booms: evidence from macro aggregates and micro data", NBER Working Paper, 1449

Merrouche, O., Nier, E., 2010. "What Caused the Global Financial Crisis? – Evidence on the Drivers of Financial Imbalances 1999-2007", IMF Working Paper No. 10/265

Mian, A., Sufi, A., 2010. "The Great Recession: Lessons from Microeconomic Data", American Economic Review, 100(2): 51-56.

Mian, A., Sufi, A., 2014. "House of Debt: How They (and You) Caused the Great Recession, and How We Can Prevent It from Happening Again", University of Chicago Press.

Parente, P.M.D.C., Santos Silva, J.M.C., 2016. "Quantile Regression with Clustered Data", Journal of Econometric Methods 5(1), 1-15

Rajan, R.G., 1994. "Why Bank Credit Policies Fluctuate: A Theory and Some Evidence", Quarterly Journal of Economics, Vol. 109, No. 2, pp. 399-441.

Rancière, R., Tornell, A., Westermann, F., 2008. "Systemic Crises and Growth", Quarterly Journal of Economics, Vol. 123, No. 1, pp. 359-406.

Reinhart, D., Sowerbutts, R., 2015. "Regulatory arbitrage in action: evidence from banking flows and macroprudential policy", Bank of England Staff Working Paper No. 546

Reinhart, C.M., Rogoff, K.S., 2011. "From Financial Crash to Debt Crisis", American Economic Review 101: 1676-1706

Richter, B., Schularick, M., Wachtel, P., 2017. "When to lean against the wind", CEPR Discussion Paper DP12188

Roy, S., Kemme, D., 2012. "Causes of Banking Crises: Deregulation, Credit Booms and Asset Bubbles", International Review of Economics and Finance, 24, 270-94.

Schularick, M., Taylor, A.M., 2012. "Credit Booms Gone Bust: Monetary Policy, Leverage Cycles and Financial Crises", American Economic Review, 102, 1029-61.

Sedunov, J., 2021. "Federal reserve intervention and systemic risk during financial crises", Journal of Banking and Finance, Vol. 133

Wooldridge, J.M., 2010. "Econometric Analysis of Cross Section and Panel Data, 2nd Edition. Cambridge, MA: MIT Press

Appendix

Table A1: 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 A2: Definitions and sources for macroprudential policy 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 A3: 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 A4: Correlation between MAPP 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 A5: 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 A6: 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 domestic 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 clustered by country are reported for Logit estimations without country fixed effects. All independent variables are lagged one quarter.

Table A7: 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 domestic 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 A8: Aggregate macroprudential policy 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 indexes 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 A9: 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 clustered by country for Logit estimations. All independent variables are lagged one quarter.

Table A10: Estimations for different time periods

Variables	2000Q1-2006Q4 Logit (1)	LPM (2)	Firth logit (3)	2007Q1-2014Q4 Logit (4)	LPM (5)	Firth logit (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 clustered by country for Logit estimations. All independent variables are lagged one quarter.

Table A11: Estimations for different country samples

Variables	Advanced countries Logit	LPM	Firth logit	Developing countries Logit	LPM	Firth logit
	(1)	(2)	(3)	(4)	(5)	(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 clustered by country for Logit estimations. All independent variables are lagged one quarter.

Table A12: 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 clustered by country for Logit and LPM estimations. All independent variables are lagged one quarter.

Table A13: Estimations with bank-capital-based prudential policies

	Hodrick-Prescott filter			Hamilton filter		
Variables	Logit	LPM	Firth logit	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 A14: 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 Finanical Development Database
Concentration	The assets of the three largest commenrcial 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 A15: 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 A16: Estimations with macroprudential policy 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 include 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 A17: List of countries for 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 A18: 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 boom episodes

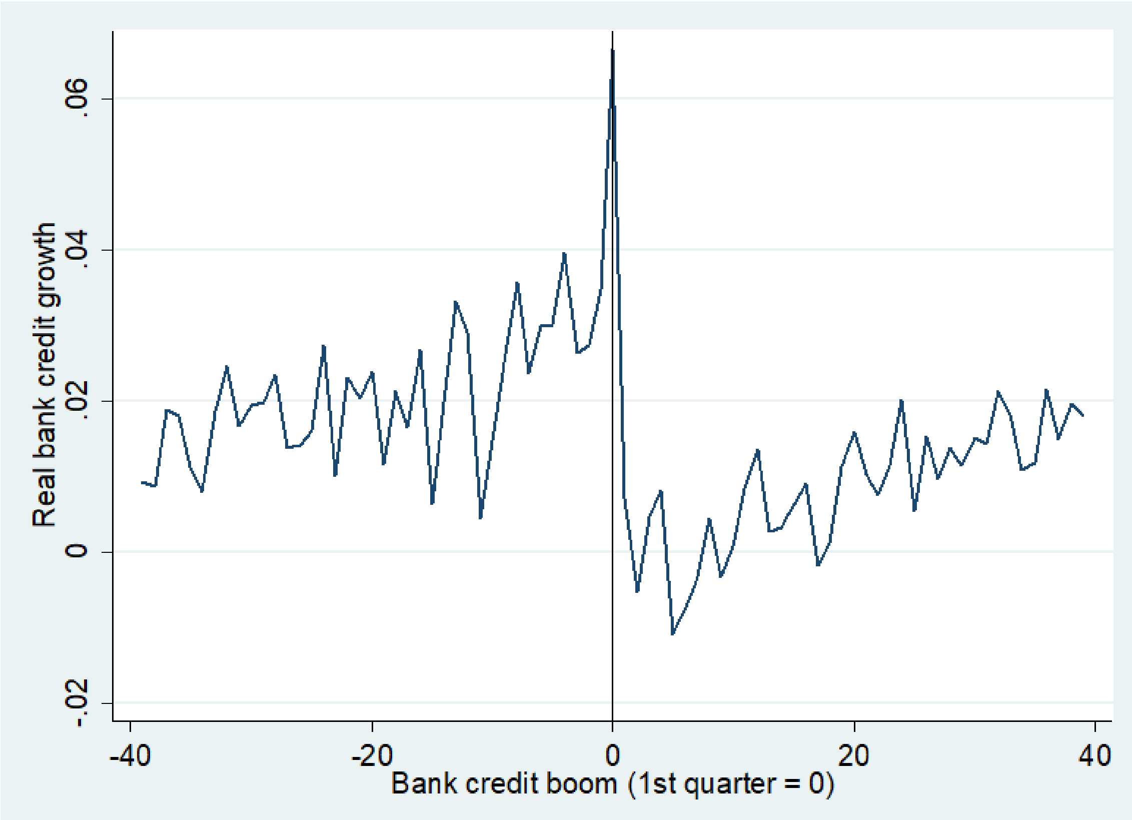


Figure A2: Average real growth rate of GDP around good boom episodes

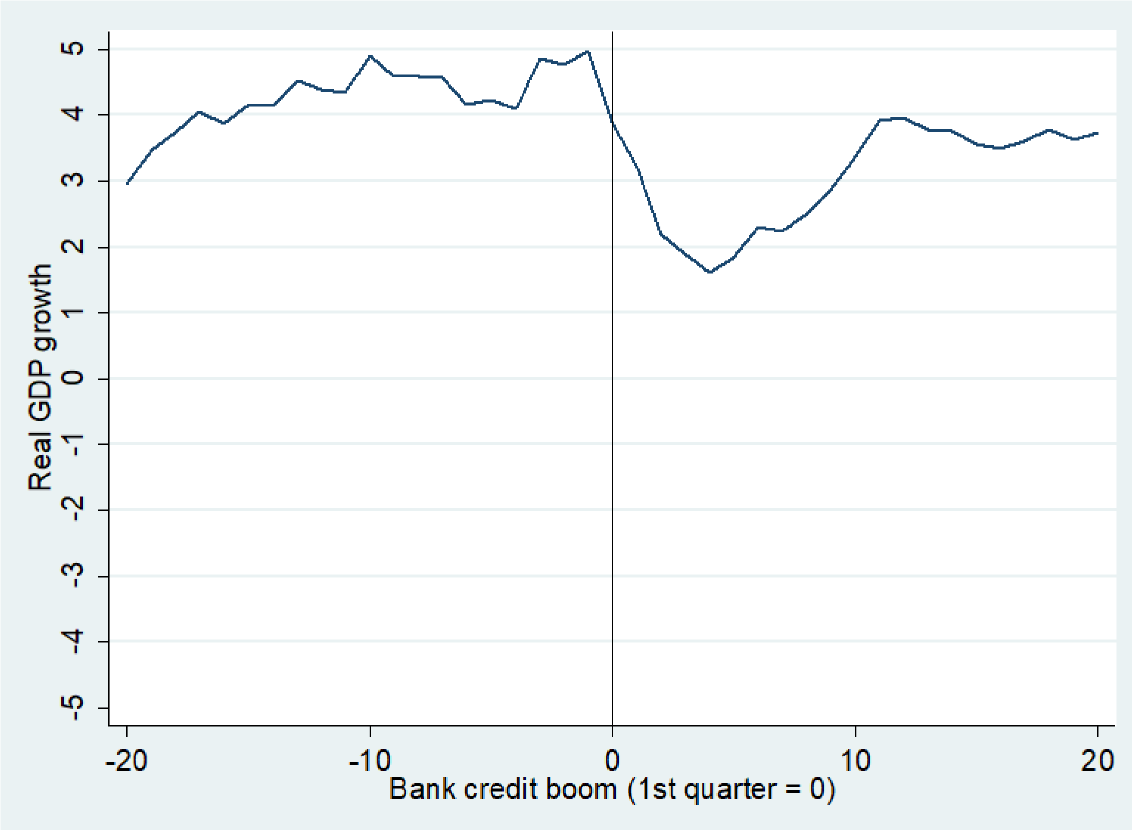


Figure A3: Average real growth rate of GDP around bad boom episodes

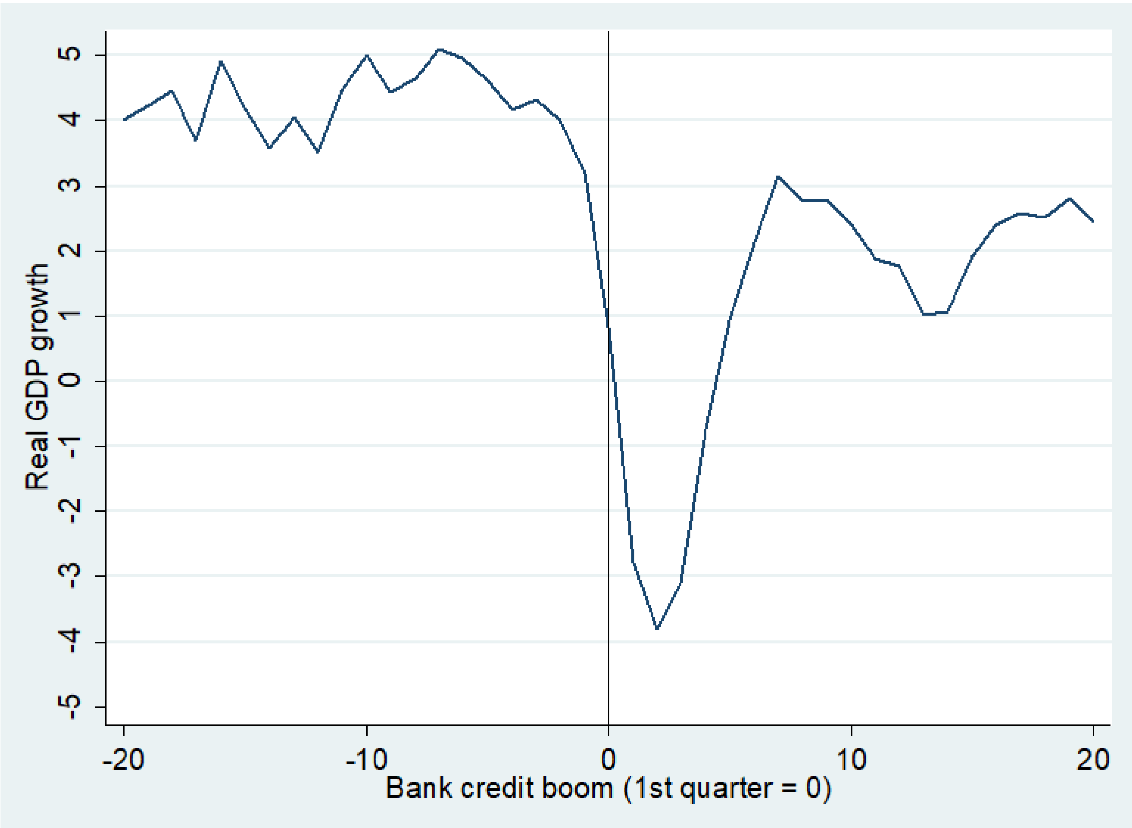


Figure A4: Median ratio of household and firm credit (% of GDP) around good booms

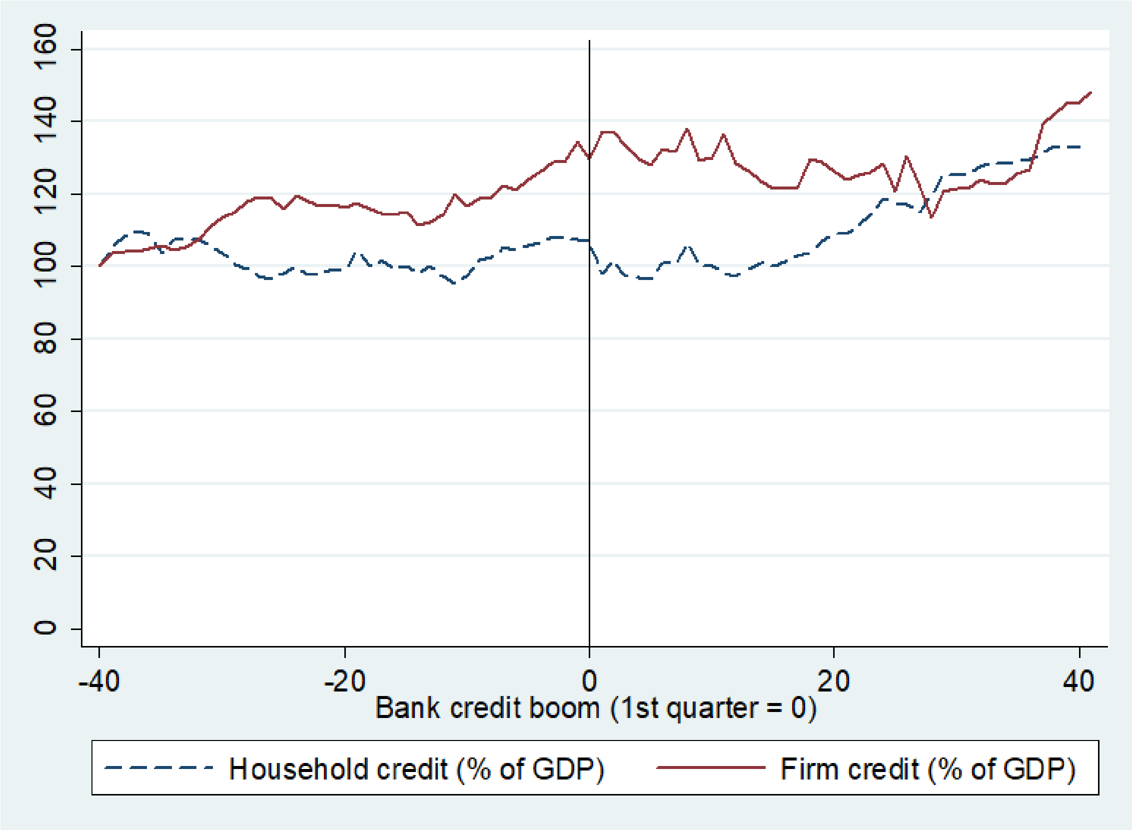


Figure A5: Median ratio of household and firm credit (% of GDP) around bad booms

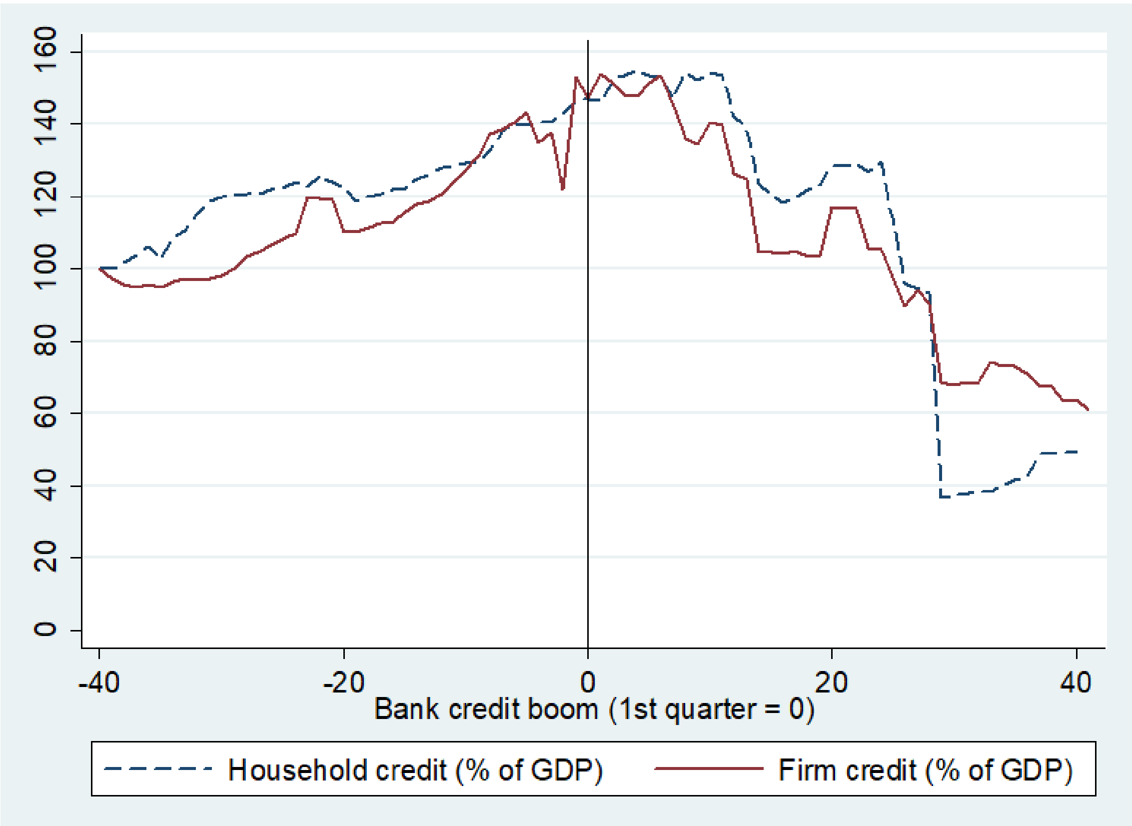


Figure A6: Distribution of credit booms with different thresholds between 2000Q1-2014Q4

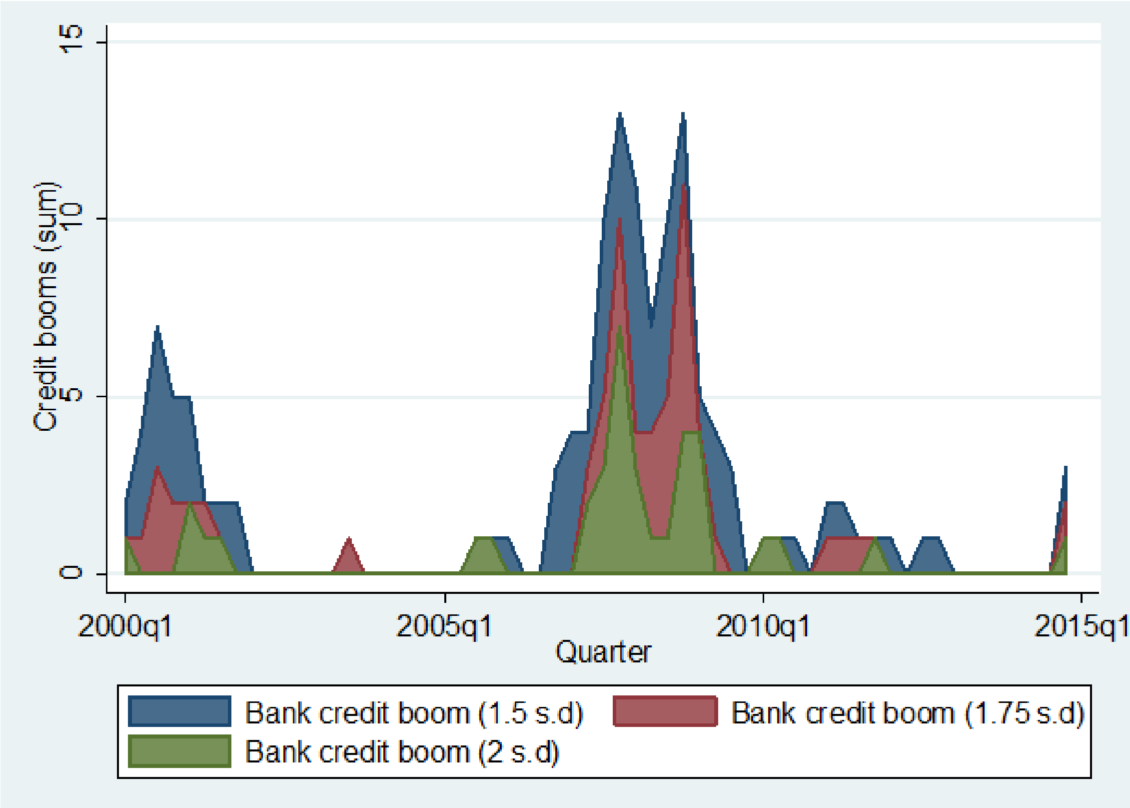


Figure A7: Macroprudential policy indexes (averages) in advanced countries

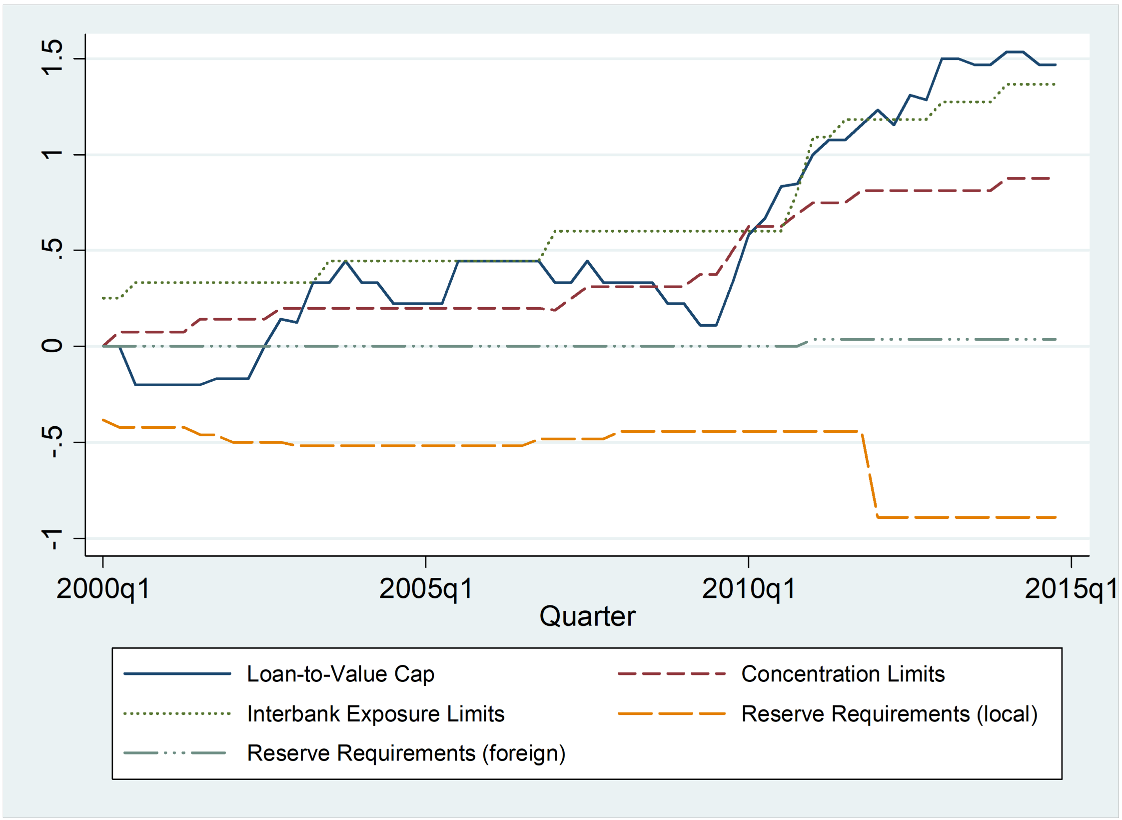


Figure A8: Macroprudential policy indexes (averages) in developing countries