Alma Mater Studiorum – Università di Bologna

DOTTORATO DI RICERCA IN

ECONOMIA

Ciclo 30

Settore Concorsuale: 13/A1

Settore Scientifico Disciplinare: SECS-P/01

Essays on Financial Crises

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Esame finale anno 2018

In memory of my father, Håkan Karlström.

Abstract

Chapter 1 studies the relationship between income inequality and the occurrence of banking crises for 33 advanced countries between 1970-2011. Differently from other empirical studies, the focus of this study is on levels rather than growth rates of income inequality. A statistically significant and positive relationship is found between the value of the Gini index and the probability of banking crises. This result is confirmed when income distribution is summarized by the top 1% income share[1].

Chapter 2 investigates whether macroprudential policies have been effective to address booms in 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 results show that an aggregate index including five different macroprudential policy instruments is negatively and significantly associated with domestic bank credit booms. The results for aggregate indexes are robust to the inclusion of country and year fixed effects. Moreover, macroprudential policies are also found to be effective to reduce the likelihood of booms in household credit. Finally, this study shows that macroprudential policies are effective to address specifically those credit booms that are followed by systemic banking crises.

Chapter 3 examines the impact of macroprudential policies on banks' systemic risk in advanced and developing countries during the period 2000-2015. The main findings suggest that a tighter macroprudential policy stance in a country is negatively and significantly associated with the level of systemic risk for banks. Moreover, tighter conditions for concentration limits seem to reduce the growth rate of systemic risk. Finally, the results also show that tightenings of macroprudential policies were negatively associated with the growth rate of systemic risk for banks prior to the Global Financial Crisis.

[1] This chapter is titled "Income Inequality and Banking Crises: Testing the Level Hypothesis Directly" and has been accepted for publication in the Journal of Macroeconomics. The paper is available on the following website: https://doi.org/10.1016/j.jmacro.2018.08.007.

Acknowledgements

I am greatly indebted to Gabriella Chiesa and Paolo Manasse for their guidance. Moreover, I'm grateful for the comments of Guglielmo Barone, Nicola Brugali, Valentina Bruno, Julián Caballero, Eugenio Cerutti, Milenko Fadic, Nicola Gennaioli, Roberto Golinelli, James Hamilton, Marcus Ingholt, Elena Lucchese, Salvatore Morelli, Efşan Nas Özen, Norhan Ossama, Sergio Pastorello, Henriëtte Prast, Sven Schreiber, Moritz Schularick and Andrea Teglio.

I would also like to thank participants at the following conferences and workshops: First Behavioral Macroeconomics Workshop (University of Bamberg), 32nd Annual Irish Economic Association Conference 2018 (Central Bank of Ireland), International Days of Macroeconomics and Finance 2018 (Bank Al-Maghrib), BoMoPaV Economics Meetings 2018 (University of Padova), 4th International Conference on Applied Theory, Macro and Empirical Finance (University of Macedonia), 11th RGS Doctoral Conference in Economics (University of Duisburg-Essen), International Rome Conference on Money, Banking and Finance (LUMSA University), Trends in Inequality (Istituto Carlo Cattaneo), and Finance and Economic Growth in the Aftermath of the Crisis (University of Milan).

Finally, I'm very grateful for the support I've received during the PhD program from Karla Gonzalez Ramos, Marie-Louise Karlström and Thomas Karlström.

Income Inequality and Banking Crises: Testing the Level Hypothesis Directly

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June 2018

Abstract

We perform an empirical analysis to investigate the relationship between income inequality and the occurrence of banking crises on a panel of 33 advanced countries in the period 1970-2011. Differently from other empirical studies, we focus on levels rather than growth rates of income inequality. We find a statistically significant and positive relationship between the value of the Gini index and the probability of banking crises. This result is confirmed when income distribution is summarized by the top 1% income share.

JEL codes: D310, G010

Keywords: Income inequality; Banking crises; Credit booms

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1 Introduction

In recent years, it has been claimed by some prominent scholars that income inequality may be responsible for financial crises. This point of view is well summarized in the influential book by Rajan (2010, p. 43), according to whom "growing economic inequality in the United States led to political pressures for more housing credit. This pressure created a serious fault line that distorted lending in the financial sector". While the argument is not fully new (see Galbraith, 1954, for instance), other researchers (e.g., Krugman, 2007, Fitoussi and Saraceno, 2009 and Stiglitz, 2012, among others) have endorsed what is now referred to as the "Rajan hypothesis", linking income inequality to the surge in household indebtedness which has been found to be a major predictor of banking crises.[1]

The hypothesis put forward by Rajan and other scholars has triggered a vigorous debate (see the exhaustive and updated surveys by Van Treeck, 2014 and Bazillier and Hericourt, 2017), and a relatively small group of studies have tried to investigate empirically the relationship between income inequality and the occurrence of banking or financial crises. We aim at participating to this growing debate by means of an econometric analysis that tests the link between levels of income inequality and the probability of banking crises. Differently from other scholars (see in particular Bordo and Meissner, 2012 and Perugini, Hölscher and Collie, 2016) we test this link directly. Our study encompasses a panel of 33 advanced countries in the period 1970-2011. The main finding of our paper is that the level of gross income inequality (measured by either the Gini index or the top 1% income share) is positively associated with the occurrence of banking crises. Furthermore, we find that the effect of an increase in the level of income inequality is sizable. In addition, the effect seems to be larger for countries that already have an elevated level of income inequality. Finally, the results hold for a series of robustness checks, such as, among the others, the rare events small sample bias, the inclusion of regional and time fixed effects, the exclusion of various country groups.

There are several reasons to claim that the relevant measure of income inequality is the level and not the growth rate when investigating the association between income inequality and the likelihood of banking crises. First of all, the theoretical literature by Iacoviello (2008) and Kumhof, Ranciere and Winant (2015) emphasizes the existence of a long-run relation between household debt and income inequality. As a consequence, the use of the growth rate of income inequality that removes the long-run trend as in the studies by Bordo and Meissner (2012) and Kirschenmann, Malinen and Nyberg (2016) seems problematic. In fact, the use of the growth rate of income inequality will lead to biased estimates if a long-run relation exists between income inequality and household debt as emphasized by Klein (2015). Iacoviello (2008) argues that

[1] See also Kirschenmann, Malinen and Nyberg (2016). Iacoviello (2008) shows that in the U. S. the prolonged rise of the 1980s and the 1990s in household debt can be quantitatively explained only by the concurrent increase in income inequality. See also Roy and Kemme (2012).

short-term movements in household debt can be explained by business cycle fluctuations while the connection between household debt and income inequality is a long-term one. Klein (2015) uses panel cointegration techniques, and shows that a long-run relation exists between income inequality and household debt. This result is consistent with Malinen (2016), who also finds a long-run steady-state relationship between the top 1% income share and domestic bank credit. In short, both the theoretical and empirical literature emphasize that income inequality is related to household debt only in the long-run, which suggests that the level of income inequality (rather than the growth rate) is the suitable measure in this study.

This paper is organized as follows. Section 2 reviews the related literature and places our analysis in perspective with respect to other empirical studies. Section 3 describes the dataset and variables. In Section 4 we provide a description of our empirical approach and the statistical model (4.1) followed by a discussion of our findings (4.2) and their robustness (4.3). Section 5 concludes.

2 Related literature

The first paper that investigates directly the relationship between income inequality and banking crises is Atkinson and Morelli (2011). Their approach is purely descriptive and focusses on the presence of a link between increases in income disparity (as measured by the Gini index as well as the top 1% income share) and the occurrence of banking crises in 25 countries between 1911 and 2010. They fail to detect any meaningful link between increases in income inequality before the occurrence of banking crises and the occurrence itself.

A similar conclusion is reached by Bordo and Meissner (2012) in a paper which became a benchmark for the subsequent literature. They test the Rajan hypothesis for a sample of 14 advanced countries between 1870 and 2008 and find that a credit boom increases the probability of a banking crisis.[2] However, they cannot detect any evidence that a rise in top income shares accelerates the boom. The strategy employed by Bordo and Meissner consists in investigating whether credit growth influences the likelihood of banking crises, and then verifying if a change in income inequality is associated with higher credit growth. In the first step, logit and OLS estimations are conducted with a binary banking crisis dependent variable and lagged real credit growth as independent variable. They show that credit growth in the previous two to five years is strongly and positively associated to a crisis. In the second step, the top 1% income share is regressed against cumulative growth in credit during the previous five-year period. They reject any relationship between credit growth and the growth in top income share.

Gu and Huang (2014) use data similar to Bordo and Meissner (2012), but reach different results, possibly because cross-section heterogeneity is taken into account by including countries that can be considered to be

[2]A similar conclusion is reached by Schularick and Taylor (2012). Using a new historical dataset for 14 countries over the years 1870-2008, they conclude that credit growth is a powerful predictor of financial crises.

outliers. Kirschenmann, Malinen and Nyberg (2016) perform logit estimations to investigate the existence of a direct link between changes in top income share and the likelihood of banking crises. Again, the primary dataset is the same as Bordo and Meissner (2012). The year-on-year change in income inequality is found to have some predictive power both in-sample and out-of-sample. Income inequality turns out to have substantial predictive power over and above credit booms and has a distinct role as a driver of financial crises that remains when controlling for credit growth. These results suggest that the empirical strategy employed by Bordo and Meissner might be unsuitable to detect the link between income inequality and banking crises.

Bellettini and Delbono (2013) were the first ones to investigate directly the "level" hypothesis to see whether persistently high levels of Gini values relate to banking crises. The quantitative analysis is descriptive and the association seems weak, although non-negligible. They make a remark on the geography of such association (see also Atkinson and Morelli (2015, p. 49)) to stress that its assessment should be primarily focused on the crisis-originator countries (e.g., US and UK for the 2008 banking crises) where the link between growing income inequality and banking crises seems pretty robust (see, for instance, Gu and Huang, 2014).

Atkinson and Morelli (2015) test statistically both the "growth" and the "level" hypothesis relying on an updated version of their previous database (Atkinson and Morelli, 2014). The authors find no clear-cut conclusion for the relationship between growing or high levels of economic inequality (summarized by different indexes) and the occurrence of banking crises in the period 2000-2012.

Perugini, Hölscher and Collie (2016) also test the "level" hypothesis by means of an econometric analysis where high levels of top income shares are shown to be robustly correlated to private sector indebtedness which in turn is a significant predictor of systemic banking risk.[3] The econometric analysis is performed on a panel of 18 OECD countries for the years 1970-2007. They explicitly take into account endogeneity and reverse causation issues by using IV and GMM-sys methodology. As in Bordo and Meissner's paper, private sector credit is found to be a significant predictor of financial crises. However, it is worth stressing that Perugini, Hölscher and Collie (2016) do not investigate the presence of a direct link between income inequality and financial crises that is not explained by credit growth.

As for the choice of credit measures, Perugini, Hölscher and Collie (2016) consider both household and corporate credit, but try to control for this by including investment as a percentage of GDP. This is the same route followed by Bordo and Meissner (2012). However, notice that retained profits are also often used to finance investments, which implies that the ratio between investments and GDP may be a suboptimal proxy for credit. The main features of the above mentioned literature are summarized in Table 1 below.

[3] Klein (2015) detects a long-run relationship between income inequality and household debt. He uses different measures of income inequality for 9 advanced countries in the period 1953-2008 and finds that inequality and leverage are cointegrated.

Table 1: Main features of some related empirical papers

	Atkinson and Morelli (2011)	Bordo and Meissner (2012)	Bellettini and Delbono (2013)	Gu and Huang (2014)	Atkinson and Morelli (2015)	Perugini, Hölscher and Collie (2016)	Kirschenmann, Malinen and Nyberg (2016)
Period	1911-2010	1928-2008	1980-2010	1928-2008	1900-2012	1970-2007	1870-2008
Number of countries	25	14 advanced countries	14 or 18	14 advanced countries	25	18 OECD countries	14 advanced countries
Measure of income inequality	Gini and top 1% income share	Top 1% income share	Gini	Top 1% income share	Many	Top income shares	Top 1% income share
Growth or Levels	Growth	Growth	Levels	Growth	Growth and Levels	Levels	Growth
Relationship between income inequality and banking crises	Ambiguous	Ambiguous	Weak	Strong in Anglo-saxon countries	Ambiguous	Strong*	Strong

* Between income inequality and private sector indebtedness.

3 Data and descriptive statistics

The dataset consists of yearly data for 33 advanced countries during the period 1970-2011.[4] A description of variable definitions and sources is provided in Tables A1 and A2 in the Appendix.[5] Data on the binary variable banking crisis has been compiled by 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). Our dataset includes a total of 123 country-year banking crisis observations distributed across 33 banking crisis episodes.

The income inequality measures are the Gini index and the top 1% income share before taxes and transfers. Data on the gross Gini index have been collected from the Standardized World Income Inequality

[4]The list of countries is: Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hong Kong, Iceland, Ireland, Israel, Italy, Japan, Latvia, Lithuania, Luxembourg, Netherlands, New Zealand, Norway, Portugal, Singapore, Slovak Republic, Slovenia, South Korea, Spain, Sweden, Switzerland, United Kingdom and United States.

[5]The control variables shown in Tables A1 and A2 were constructed using data from the World Bank Databank, International Financial Statistics (IMF), BIS total credit statistics, Economic Freedom of the World Database (Fraser institute) and OECD.

Database (SWIID) compiled by Solt (2016). The latest version of the SWIID database contains two collections of Gini indexes. The first one consists of the gross income inequality series from the Luxembourg Income Study (LIS) database. The second collection includes data from national statistical offices, cross-national income inequality databases, and academic articles (Solt, 2016).

Data for the top 1% income share before taxes and transfers have been collected from the World Top Incomes Database (WTID) which is based on historical income tax records. Accurate information about measures such as the mean household income is necessary to compute the Gini index. These measures can be unreliable since they are based on data affected by country-dependent inconsistencies (Kirschenmann, Malinen and Nyberg, 2016). However, the top 1% income share measure is computed using the same procedure and raw data for all countries (Piketty, 2007). In addition, data for the top 0.1%, 5% and 10% income shares is exploited to perform robustness tests.

Other related papers used disposable (or after tax) income to compute Gini indexes and/or top income shares. Our choice of gross incomes seems reasonable for at least three reasons. First, data on net income shares over time are currently very limited. Similarly, data on net Gini indexes are also limited relative to the gross ones. Finally, gross and net income shares tend to mimic similar developments in the distribution of income (see Malinen, 2016, p. 312, fn. 3).

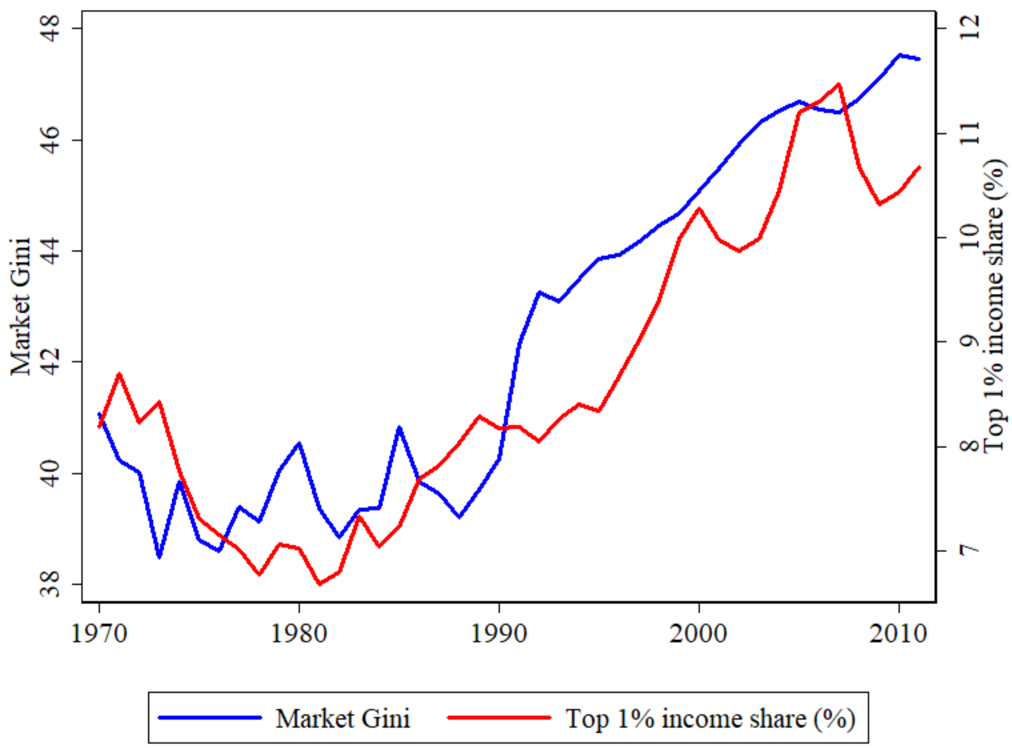
Figure 1 illustrates the average gross (or market) Gini index and the top 1% income share over the period 1970-2011 for 33 advanced countries. The general trend for both measures of income inequality is characterized by a steady increase since the 1980s.

The behavior of the average Gini index, the top 1% income share and the ratio of household credit to GDP around a banking crisis episode is illustrated in Figures 2 and 3. Figure 2 shows that the level of the Gini index (average for 27 advanced countries) is higher at the beginning of the banking crisis (vertical line) than during the previous 15 years. Moreover, the top 1% income share (average for 14 advanced countries) is also at its peak on the eve of the crisis compared to the preceding years as shown in Figure 3.

Household credit (as a percentage of GDP) is included in these figures because the main theoretical argument used to support the connection between income inequality and banking crises is based on the expansion of household credit. The ratio of household credit to GDP (average for 21 advanced countries) almost doubles during the 15 years before the banking crisis and then falls back to its previous level once the crisis has started.

The United States is a "crisis originator" country and is an especially important case when investigating the link between income inequality and banking crises. Figures 4 and 5 display the behavior of the average Gini index, the top 1% income share and household credit (as a percentage of GDP) around the two banking

Figure 1: Market Gini index and top 1% income share (average of 33 countries)



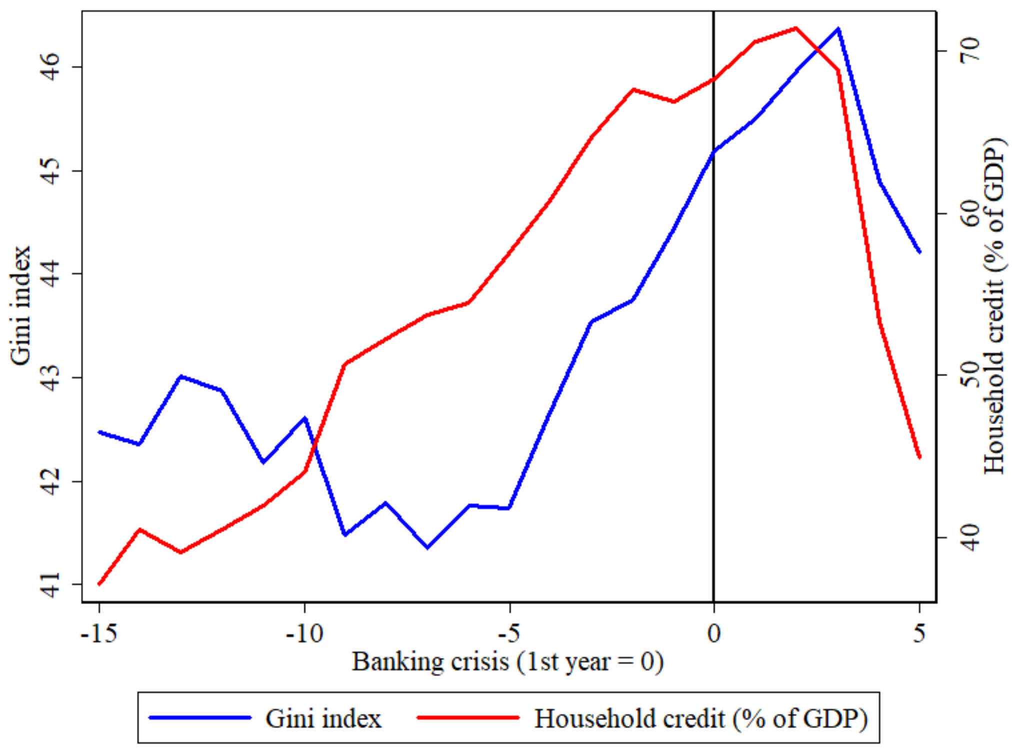
crises that started in 1988 and 2007 in the United States.[6]

Figure 4 shows that the Gini index was higher in the United States on the eve of the banking crisis compared to a decade earlier. Moreover, the Gini index and the ratio of household credit to GDP tend to move in tandem during the run-up to the crisis (the correlation is 0.83). Finally, the top 1% income share doubled during the 15 years before the crisis and then dropped once the crisis started, as shown in Figure 5. The co-movement between the top 1% income share and household credit (as a percentage of GDP) in the United States is even stronger than for the Gini index (the correlation is 0.92).

Descriptive statistics for the banking crisis variable, income inequality measures (Gini index and top income share) and the control variables are shown in Table A3 in the Appendix. It should be emphasized that data availability for the Gini index is considerably larger than for the top income share. The average value for the market Gini index is around 0.43 with a maximum of 0.58 for Hong Kong in 2002 and a minimum of 0.245 for Latvia in 1990. The top 1% income share has a mean value of 0.09. The highest

[6]The control variables shown in Tables A1 and A2 were constructed using data from the World Bank Databank, International Financial Statistics (IMF), BIS total credit statistics, Economic Freedom of the World Database (Fraser institute) and OECD.

Figure 2: Gini index and household credit (% of GDP) around banking crisis

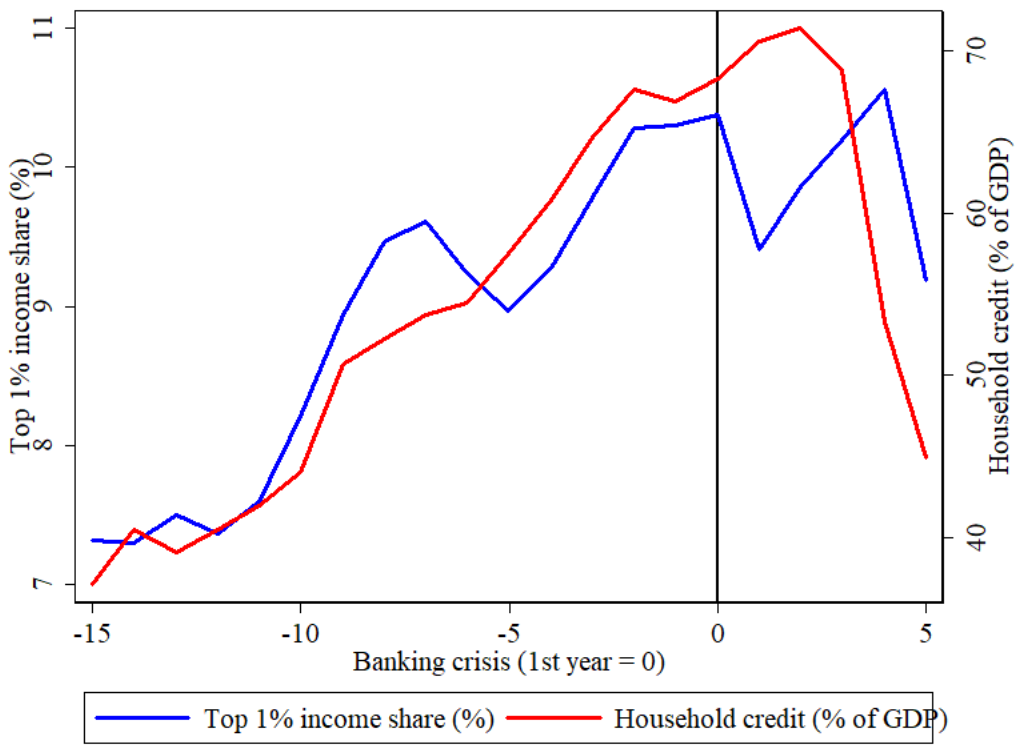


value (0.23) for the top 1 percent income share is observed in the United States in 2007, while Portugal had the lowest value (0.04) in 1981. Finally, on average around one third of all gross income goes to the top 10 percent of income earners and one fourth of this amount is earned by the top 1 percent.

4 Empirical analysis

The empirical approach employed in this paper follows Demigürç-Kunt and Detragiache (2005). We estimate both a baseline and an extended specification using logit regressions. For all countries and years, the binary dependent variable equals one if a banking crisis occurs and zero otherwise. The measures of income inequality level (gross Gini index and the top 1% of gross income share) are lagged from one up to three periods to avoid simultaneity issues. The baseline and extended specifications include a set of explanatory variables that are commonly found in the literature to control for macroeconomic fundamentals, monetary conditions and the global environment. More precisely, the baseline specification includes the real growth of GDP, the change in terms of trade, depreciation of the nominal exchange rate, the real interest rate, inflation, and GDP per capita. The extended specification instead includes all control variables of the baseline model,

Figure 3: Top 1% income share and household credit (% of GDP) around banking crisis



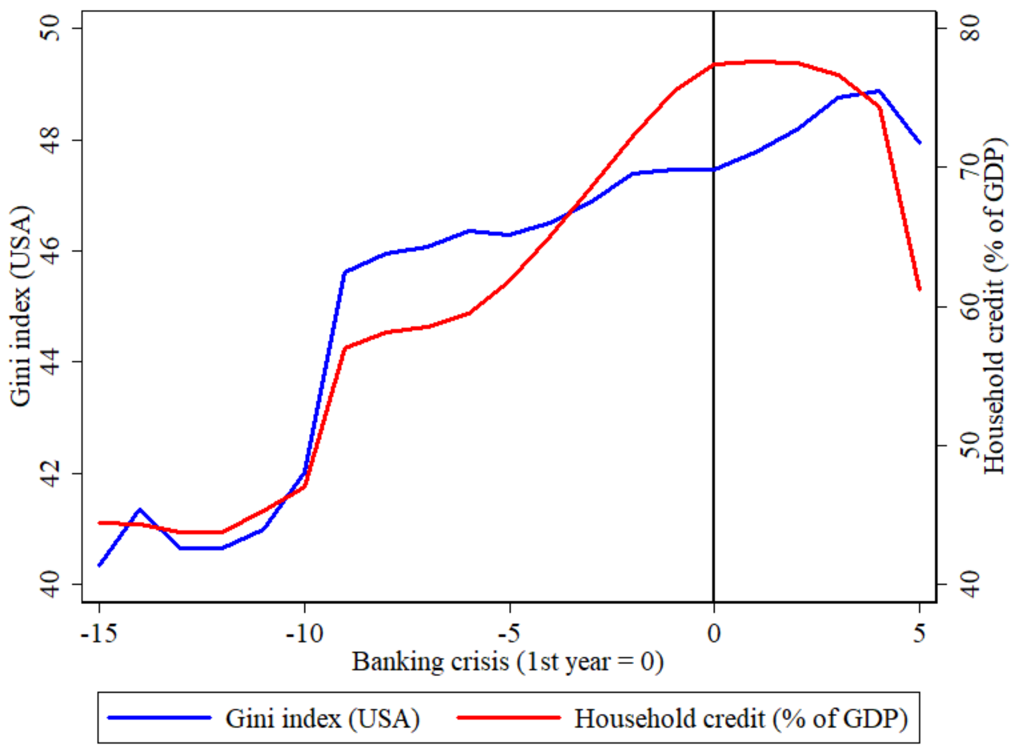
but also the ratio of broad money (M2) to international reserves, the ratio of domestic bank credit to GDP and the lagged growth rate of domestic bank credit.

The macroeconomic fundamentals are real GDP growth, inflation and nominal depreciation. A slowdown in GDP growth is likely to be associated with a banking crisis since lower economic growth negatively affects banks balance sheets by increasing the share of non-performing loans. An elevated inflation rate may be a sign of macroeconomic mismanagement which often precede banking crises (Duttagupta and Cashin, 2011).

In addition, banking crises have been found to often follow or coincide with currency crises. Consequently, nominal depreciation is employed as a proxy for high volatility in the nominal exchange rate that typically characterizes currency crises. However, even in the absence of a currency crisis, a nominal depreciation could potentially cause a banking crisis due to foreign exchange risk (Duttagupta and Cashin, 2011). Finally, GDP per capita (divided by one thousand to ease interpretation) is used as a proxy for institutional and economic development (Demigürç-Kunt and Detragiache, 2005).

Monetary conditions are proxied by the real interest rate in both the baseline and the extended specification. An increase in the real interest rate is a proxy for a tightening of financial conditions which is likely

Figure 4: Gini index and household credit (% of GDP) around banking crisis (USA)



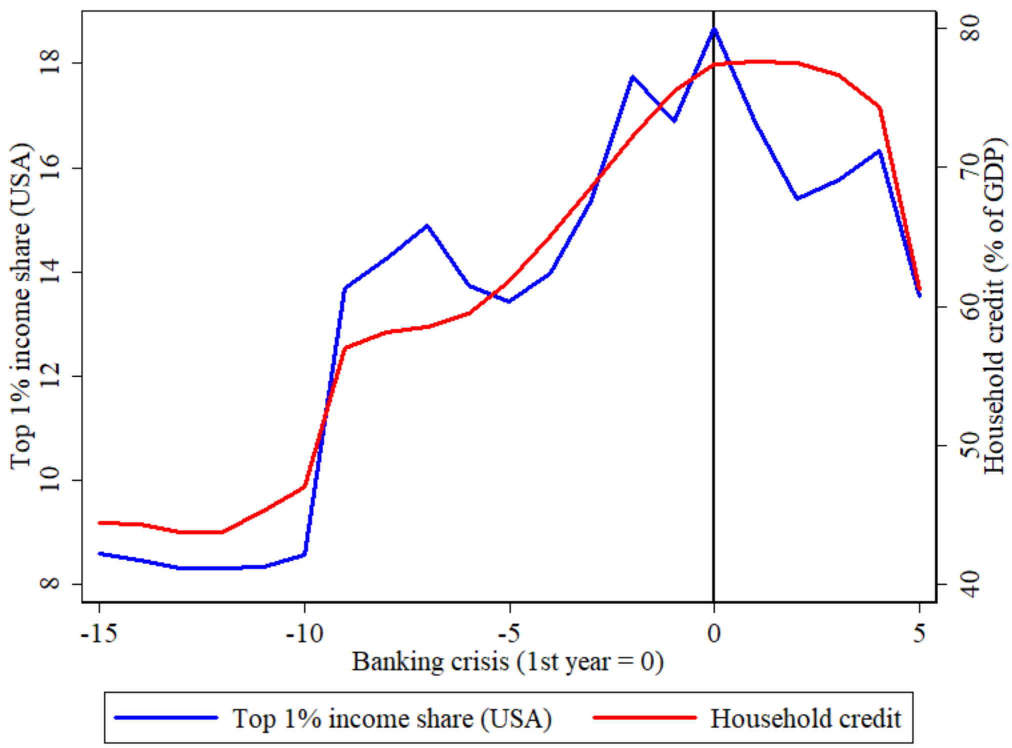
to squeeze banks balance sheets and increase the probability of a banking crisis (Duttagupta and Cashin, 2011).

The extended specification includes additional variables that are ignored in the baseline model. The ratio of private sector bank credit to GDP is used as a measure of the size of financial markets and institutions (financial deepness). Perugini, Hölscher and Collie (2016) argue that excessive levels of credit are associated with financial crises according to the literature and emphasize that the effect of stronger credit growth on the probability of financial crises depends on the level of credit to GDP. The lagged growth rate of real domestic credit is included as a proxy for credit booms that often precede banking crises (Schularick and Taylor, 2012).

Another variable, added to the extended specification, is the ratio of broad money (M2) to foreign exchange reserves. This variable measures a countrys vulnerability to currency crises which often coincide with banking crises. This variable was divided by one thousand to ease interpretation.

The global environment is proxied by the change in terms of trade in both the baseline and the extended specification. This variable has been divided by one trillion to ease interpretation of the coefficient. The

Figure 5: Top 1% income share and household credit (% of GDP) around banking crisis (USA)



change in terms of trade is likely to affect GDP growth and consequently the stability of the banking sector (Duttagupta and Cashin, 2011). Finally, the occurrence of a crisis is likely to affect the future path of the explanatory variables, which would generate endogeneity issues. To mitigate this problem, five observations are dropped after the first year of crisis, which implies that all crisis observations except the first year are dropped. In addition, White-Huber robust standard errors clustered by country are used throughout the paper except for the results presented in Tables A12-A13.

4.1 The statistical model

The main purpose of this paper is to investigate whether the level of income inequality is associated with the occurrence of banking crises. To this end, we model the probability of a banking crisis using a multivariate logit model. Formally, let y_{it} be a binary variable equal to 1 if a banking crisis occurs in country i during year t, and 0 otherwise, and let x_{it} be a vector of K explanatory variables. We assume that the probability of observing a crisis depends on x_{it} through the following expression:

$$\text{Prob}(y_{it} = 1|x_{it}) = \pi_{it}(\beta) = \frac{1}{1 + \exp\left(-x'_{it}\beta\right)},$$

where β is a vector of K unknown parameters to be estimated. The nonlinearity of the this expression implies that, contrary to the linear regression model, the parameters β do not measure the effect on the probability of a crisis of a change in one of the explanatory variables. Indeed, it is easy to check that for a continuous explanatory variable $x_{k,it}$ the marginal effect on the probability of a crisis is given by:

$$\frac{\partial \text{Prob}(y_{it} = 1|x_{it})}{\partial x_{k,it}} = \pi_{it}(\beta)[1 - \pi_{it}(\beta)]\beta_k,$$

where β_k is the coefficient that multiplies $x_{k,it}$ in the definition of $\pi_{it}(\beta)$. Thus, unlike the linear regression model, the marginal effect of a change in one of the regressors varies across the observations, and depends on the original probabilities $\pi_{it}(\beta)$. In particular, the effect is shrunk to zero if the occurrence of a crisis is either extremely unlikely ($\pi_{it}(\beta) \approx 0$) or extremely likely ($\pi_{it}(\beta) \approx 1$), and will be highest for values of $\pi_{it}(\beta)$ close to 0.5. Note however that β_k is informative on the sign of the marginal effect, as the shrinking coefficient $\pi_{it}(\beta)[1 - \pi_{it}(\beta)]$ is positive by construction.

Given a sample of observations $\{(y_{it}, x_{it}),\ t = 1, 2, \ldots, T,\ i = 1, 2, \ldots, N_t\}$, the unknown parameters β can be estimated by maximizing the sample loglikelihood function of the model:

$$\log L(\beta) = \sum_{t=1}^{T} \sum_{i=1}^{N_t} \left[y_{it} \log \pi_{it}(\beta) + (1 - y_{it}) \log \left(1 - \pi_{it}(\beta)\right) \right].$$

Under suitable regularity conditions, and when the sample size grows to infinity, the resulting Maximum Likelihood Estimator converges to the true value of β and is normally distributed. In samples of finite size, its distribution will only be approximately Gaussian. Its variance matrix is readily provided by any econometric package.

4.2 Results

If a higher level of gross income inequality is associated with the occurrence of banking crises, we would expect the coefficients of the lagged Gini index to be positive and significant. The results displayed in Table 2 show that the coefficients of the Gini index have the expected positive sign and are statistically significant at the 1 percent level. Moreover, the Gini coefficients are positive and highly significant for all lags in both the baseline and the extended model. Consequently, the significance of the Gini index is not sensitive to the specific choice of the number of lags or to the inclusion of measures of the level and growth rate of domestic credit to the private sector.

The baseline estimation for the Gini index covers 33 countries and 24 crisis episodes for the period 1970-2011. Due to data limitations for domestic credit and the ratio of M2 to international reserves, the extended estimation includes 28 countries and 20 crisis episodes for the same period.

Table 2: Results for logit estimations with Gini index, period 1970-2011

Variables	(1) crisis	(2) crisis	(3) crisis	(4) crisis	(5) crisis	(6) crisis
gdp_growth	−0.181***	−0.177***	−0.177***	−0.265***	−0.274***	−0.257***
	(0.0515)	(0.0514)	(0.0507)	(0.0620)	(0.0613)	(0.0630)
totchange	0.0622***	0.0613***	0.0565***	0.0845***	0.0858***	0.0813***
	(0.0131)	(0.0130)	(0.0125)	(0.0211)	(0.0204)	(0.0190)
depreciation	−0.0739***	−0.0738***	−0.0736***	−0.0885***	−0.0884***	−0.0873***
	(0.0154)	(0.0155)	(0.0155)	(0.0196)	(0.0206)	(0.0214)
realinterest	0.0306	0.0416	0.0372	0.0616	0.0660	0.0488
	(0.0743)	(0.0752)	(0.0724)	(0.115)	(0.119)	(0.130)
inflation	0.0664	0.0743	0.0734	0.0311	0.0360	0.0116
	(0.0621)	(0.0624)	(0.0597)	(0.0574)	(0.0557)	(0.0594)
gdp_pc	0.0293***	0.0295***	0.0285***	0.0500***	0.0507***	0.0508***
	(0.00856)	(0.00878)	(0.00897)	(0.0115)	(0.0121)	(0.0122)
m2_reserves				0.0107	0.0107	0.0101
				(0.0139)	(0.0146)	(0.0156)
credit_gdp				0.0123**	0.0130**	0.0120**
				(0.00505)	(0.00533)	(0.00549)
L2.credit_growth				0.0175	0.0162	1.622
				(0.0218)	(0.0230)	(2.552)
L.gini_market	0.118***			0.180***		
	(0.0390)			(0.0586)		
L2.gini_market		0.118***			0.188***	
		(0.0383)			(0.0574)	
L3.gini_market			0.106***			0.180***
			(0.0379)			(0.0550)
Observations	588	575	566	417	413	406
No. crises	24	24	24	20	20	20
% Total Correct	96.09	95.83	95.94	96.40	96.13	96.06
% Crises Correct	8.333	8.333	8.333	25	20	20
% No−Crises Correct	99.82	99.64	99.82	100	100	100
Pseudo R−sq	0.178	0.178	0.175	0.275	0.277	0.276
Chi−sq	35.72	35.44	34.75	44.16	44.28	43.96
p−value	8.20e−06	9.22e−06	1.25e−05	3.08e−06	2.93e−06	3.35e−06
AIC	180.8	180	179.9	138.4	137.8	137.5

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

The Gini index is a useful measure of total income inequality in a country, but it can be integrated with additional information. To this end, we can use the top 1% income share (before taxes and transfers) similarly to Atkinson and Morelli (2015).

Table 3 shows the results for the baseline and extended estimations with the top 1% income share. The coefficient multiplying the top 1% income share is positive and significant at the 1% and 5% level for the

Table 3: Results for logit estimation with top 1% income share, period 1970-2011

Variables	(1) crisis	(2) crisis	(3) crisis	(4) crisis	(5) crisis	(6) crisis
gdp_growth	−0.308***	−0.291***	−0.312***	−0.275***	−0.239**	−0.264***
	(0.105)	(0.107)	(0.0955)	(0.0913)	(0.101)	(0.0833)
totchange	0.0630***	0.0665***	0.0198	0.0583***	0.0651***	0.0308
	(0.0128)	(0.0125)	(0.0169)	(0.0108)	(0.0119)	(0.0197)
depreciation	−0.0689***	−0.0741***	−0.0588***	−0.0727***	−0.0813***	−0.0670***
	(0.0176)	(0.0156)	(0.0165)	(0.0224)	(0.0220)	(0.0254)
realinterest	0.0823	0.0839	0.0148	0.155	0.172	0.0804
	(0.0684)	(0.0762)	(0.0767)	(0.0998)	(0.124)	(0.142)
inflation	−0.0692	−0.0651	−0.125*	0.0233	0.0359	−0.0405
	(0.0761)	(0.0790)	(0.0749)	(0.0863)	(0.109)	(0.117)
gdp_pc	0.0369***	0.0379***	0.0241*	0.0426***	0.0473***	0.0330***
	(0.0137)	(0.0137)	(0.0123)	(0.0117)	(0.0120)	(0.0111)
m2_reserves				0.00229	−0.00249	0.000922
				(0.0101)	(0.0196)	(0.0110)
credit_gdp				0.0159*	0.0163*	0.0129*
				(0.00826)	(0.00912)	(0.00776)
L2.credit_growth				−0.00640	−0.00698	3.298
				(0.0198)	(0.0229)	(4.457)
L.topincomep99	12.82***			19.55***		
	(4.289)			(7.405)		
L2.topincomep99		13.30***			21.12**	
		(4.536)			(8.334)	
L3.topincomep99			4.077			12.10*
			(5.271)			(7.175)
Observations	408	402	392	324	321	317
No. crises	15	15	15	14	14	14
% Total Correct	96.57	96.52	96.17	96.30	96.26	95.90
% Crises Correct	6.667	6.667	0	14.29	14.29	7.143
% No−Crises Correct	100	100	100	100	100	100
Pseudo R−sq	0.195	0.202	0.145	0.223	0.238	0.178
Chi−sq	25.04	25.82	18.43	25.74	27.40	20.37
p−value	0.000748	0.000542	0.0102	0.00411	0.00225	0.0260
AIC	119.5	118.3	124.9	111.6	109.7	116.4

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

first and second. However, the top 1% income share is not significant at lag three in the baseline model, and is only significant at the 10% level in the extended model.

Overall, these results suggest that a higher level of the top 1% income share is associated with a higher probability of banking crises. This finding reinforces the results found for the Gini index, even though statistical significance is generally weaker for the top 1% income share. The baseline model estimation is based on a sample containing 15 banking crises in 19 countries, while the sample used to estimate the extended model contains 14 banking crises distributed across 18 countries. Turning the attention to macroeconomic fundamentals, we note that the coefficient of contemporaneous real GDP growth is negative and highly significant in all estimations. This finding is consistent with Demigürç-Kunt and Detragiache (2005) and suggests that lower GDP growth precede or coincide with the onset of banking crises. In addition, the coefficient of GDP per capita is positive and significant.

The estimate of the inflation rate coefficient is positive but insignificant in Table 2, and insignificant with a fluctuating sign in Table 6; this is different from Demigürç-Kunt and Detragiache (2005), who find the inflation rate coefficient to be positive and significant for 94 advanced and developing countries. It should be emphasized that our paper only includes advanced countries for which the volatility of the inflation rate is typically lower than for developing countries. Finally, the coefficient of nominal depreciation is found to be negative and highly significant in all specifications.

Concerning monetary conditions, the real interest rate has a positive but insignificant coefficient in all estimations reported in Tables 2 and 3. Furthermore, the estimates of the credit to GDP coefficient is positive and significant in all specifications. This result is in line with the findings in Perugini, Hölscher and Collie (2016).

Among the global conditions, the coefficient of the change in terms of trade is estimated to be positive and highly significant. Finally, the coefficient for the ratio of broad money (M2) to foreign exchange reserves is insignificant in all estimations.

The results above clearly show that a higher level of income inequality is associated with a higher probability of a banking crisis occurrence. The question is, how large is the effect of the level of income inequality on the probability of a banking crisis. We follow the approach by Kirschenmann, Malinen and Nyberg (2016) and calculate the average marginal effects for the Gini index and the top 1% income share.

Table 4 shows the average marginal effects of the Gini index and the top 1% income share for columns 1 and 4 in Tables 2 and 3. The average level of the Gini index for the extended model and the full sample has a standard deviation of about 5.87. An increase in the level of the Gini index (lagged 1 period) by one standard deviation raises the likelihood of a banking crisis by 3.81 percentage points. An increase in the probability of a banking crisis by 3.81 percentage points is economically a large effect given that the frequency of a crisis episode is only 4.8 percent in the full sample.

Furthermore, the standard deviation is around 0.03 for the average level of the top 1% income share in the extended model for the full sample, meaning that an increase of one standard deviation in the level of the top 1% income share raises the probability of a banking crisis by 2.21 percentage points (the frequency of a crisis is 4.3% in this sample).

Table 4: Average marginal effects of Gini index and top 1% income share

	Baseline			Extension		
Variable	Full sample	>50%	>75%	Full sample	>50%	>75%
L1.Gini	0.0041***	0.0058*	0.0131***	0.0065***	0.0120**	0.0171***
	(0.0014)	(0.0030)	(0.0041)	(0.0022)	(0.0047)	(0.0055)
Observations	588	316	168	417	223	117
Countries	33	31	25	28	25	18
Crises	24	16	11	20	14	10
Std. Dev.	3.1269	1.5216	1.2988	3.0268	1.3066	1.0691
L1. Top 1% income	0.4038***	0.6073***	0.7452***	0.6888***	1.4458***	2.0375**
	(0.1534)	(0.2050)	(0.2476)	(0.2610)	(0.3452)	(0.9283)
Observations	408	210	119	324	172	95
Countries	19	16	14	18	16	13
Crises	15	8	5	14	8	4
Std. Dev.	0.0190	0.0170	0.0157	0.0191	0.0179	0.0160

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

It could be of interest to examine whether an increase in the level of income inequality depends on the initial level of inequality. The 50th and 75th percentile for the Gini index and the top 1% income share are computed based on the full sample in the baseline and extended specification respectively. The standard deviation is around 3.9 for the Gini index for countries above the 75th percentile in the extended model. An increase of one standard deviation in the level of the Gini index for countries above the 75th percentile increases the probability of a crisis by 6.60 percentage points. Consequently, the effect of an increase in the level of income inequality on the likelihood of crisis is higher if the country already has a high level of income inequality.

To conclude, the results show that the level of income inequality before taxes and transfers is positively and significantly associated with banking crises. Moreover, the effect of an increase in the level of income inequality on the probability of occurrence of a banking crisis is relatively large in economic terms. Finally, the results suggest that an increase in the level of income inequality has a bigger effect on the probability of banking crises if the country already has an high level of income inequality.

4.3 Robustness and sensitivity analysis

We now estimate a set of different specifications to test the robustness of the results illustrated in the previous section.

4.3.1 Bias-corrected estimation results

Maximum likelihood estimates of the parameters of a logistic regression model are consistent but only asymptotically unbiased. King and Zeng (2001) point out that the finite sample bias is exacerbated when events are rare, i.e. when the frequency of observation of the rarer of the two outcomes is very small. More specifically, the bias can lead to a sharp underestimation of the probability of the rarer event. Since in our full sample we observe 33 banking crisis events for the 33 countries over the interval 1970-2011, it is important to investigate whether the results discussed in section 4.2 are driven by the bias due to the rare events phenomenon.[7]

Using an extensive Monte Carlo analysis, Leitgöb (2013) compares the bias in ML estimates with the bias in three alternative estimation approaches: Exact Logistic Regression (Cox and Snell, 1989), the Bias Correction Method by King and Zeng (2001), and the Penalized Maximum Likelihood (PML) approach by Firth (1993). His conclusions are that PML seems to be the best available option to overcome the small sample bias problem, because it appears to be essentially unbiased and easy to apply.[8] PML estimates are computed by maximizing the sum of the likelihood function and a penalty function equal to one-half the log of the determinant of the information matrix.[9]

Table 5 shows the PML estimation results for the baseline and extended specifications of Table 2, which includes the lagged Gini index. In both specifications, the Gini coefficient estimates have the expected sign and are significant at the 5% level at all lags, instead of the 1% level as in Table 2. This difference appears to be due mainly to an increase in the estimated standard errors, rather than to a change in parameter estimates, at least for the baseline specifications. Table 6 reports the PML estimation results for the baseline and extended specifications of Table 3. The conclusions are qualitatively the same as for the previous table, but the decrease in accuracy arising from shifting from ML to PML implies that the top 1% income share variable is not statistically significant anymore, except for the extended specifications which include its first two lags, and even though the point estimates of the parameters do not change much. Overall, our conclusion is that the results in section 4.2 are robust w.r.t. the rare events small sample bias, at least when inequality is measured using the Gini index.

4.3.2 Including regional and time fixed effects

The next issue we consider is whether the results still hold when models include country fixed effects. One way to check if this is the case amounts to estimating logit regressions with country fixed effects. However,

[7]We are grateful to an anonymous referee for raising this point.

[8]See also Alter, Feng and Valckx (2018) and Arnold and Nguyen Long (2018) for an application of PML to logistic regression with rare events.

[9]PML estimates can be computed in Stata using the `firthlogit` package (see Coveney, 2015).

Table 5: PML results for the Gini index

Variables	(1) crisis	(2) crisis	(3) crisis	(4) crisis	(5) crisis	(6) crisis
gdp_growth	-0.179***	-0.175***	-0.176***	-0.231***	-0.240***	-0.234***
	(0.059)	(0.059)	(0.058)	(0.077)	(0.078)	(0.078)
totchange	0.065**	0.064**	0.059**	0.075**	0.076**	0.072**
	(0.028)	(0.027)	(0.026)	(0.037)	(0.036)	(0.035)
depreciation	-0.066***	-0.066***	-0.066***	-0.070***	-0.070***	-0.070***
	(0.021)	(0.021)	(0.021)	(0.027)	(0.026)	(0.027)
realinterest	0.033	0.043	0.039	0.026	0.032	0.035
	(0.071)	(0.072)	(0.072)	(0.120)	(0.122)	(0.122)
inflation	0.081	0.089	0.087	0.025	0.033	0.040
	(0.071)	(0.072)	(0.073)	(0.123)	(0.124)	(0.125)
gdp_pc	0.029**	0.029**	0.028**	0.042***	0.043***	0.042***
	(0.011)	(0.011)	(0.011)	(0.015)	(0.015)	(0.015)
m2_reserves				0.014*	0.014*	0.014*
				(0.008)	(0.008)	(0.008)
credit_gdp				0.010	0.011*	0.012*
				(0.006)	(0.007)	(0.007)
L2.credit_growth				2.382	2.063	1.671
				(3.648)	(3.594)	(3.604)
L.gini_market	0.114**			0.150**		
	(0.052)			(0.075)		
L2.gini_market		0.113**			0.156**	
		(0.050)			(0.074)	
L3.gini_market			0.102**			0.151**
			(0.049)			(0.072)
Observations	588	575	566	416	412	406
No. crises	24	24	24	20	20	20
% Total Correct	96.09	96	95.94	95.19	96.12	96.06
% Crises Correct	4.17	4.17	4.17	20	20	20
% No-Crises Correct	100	100	100	100	100	100
Pseudo R-sq	0.241	0.240	0.238	0.443	0.444	0.446
Chi-sq	29.22	29.20	29.06	27.80	27.67	27.87
p-value	0.0001	0.0001	0.0001	0.0019	0.0020	0.0019
AIC	130.133	129.299	129.176	75.587	75.202	74.999

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

this procedure implies that the number of available observations in the specifications shown in Tables 2 and 3 drop by at least one third. Consequently, we include macro-region fixed effects, following Magud and Vesperoni (2015) and Hutchinson (2002). These dummy variables control for region-specific unobservable time-invariant characteristics, and are essentially equivalent to an aggregated form of fixed effects analysis (Magud and Vesperoni, 2015). Accordingly, the 33 advanced countries in the dataset were divided in six different geographic regions.[10]

[10]The 33 countries are divided into the following 6 regions: North America and Australasia (Australia, Canada, New Zealand and the United States), South Europe (Israel, Italy, Portugal and Spain), East and Southeast Europe (Czech Republic, Estonia, Greece, Latvia, Lithuania, Slovak Republic and Slovenia), Nordic countries (Denmark, Finland, Iceland, Norway and Sweden),

Table 6: PML results for the top 1% income share

Variables	(1) crisis	(2) crisis	(3) crisis	(4) crisis	(5) crisis	(6) crisis
gdp_growth	-0.306***	-0.289**	-0.304***	-0.268**	-0.238**	-0.254**
	(0.117)	(0.116)	(0.110)	(0.120)	(0.120)	(0.114)
totchange	0.064**	0.062*	0.043	0.053*	0.051	0.049
	(0.029)	(0.032)	(0.046)	(0.032)	(0.038)	(0.048)
depreciation	-0.057**	-0.062**	-0.052*	-0.058**	-0.062**	-0.059*
	(0.026)	(0.027)	(0.028)	(0.029)	(0.030)	(0.031)
realinterest	0.080	0.078	0.019	0.103	0.114	0.071
	(0.100)	(0.102)	(0.103)	(0.133)	(0.139)	(0.135)
inflation	-0.033	-0.036	-0.089	0.038	0.042	0.016
	(0.096)	(0.100)	(0.094)	(0.140)	(0.158)	(0.150)
gdp_pc	0.036**	0.037**	0.025	0.040**	0.043**	0.032*
	(0.018)	(0.017)	(0.017)	(0.019)	(0.020)	(0.019)
m2_reserves				0.012	0.012	0.011
				(0.009)	(0.009)	(0.008)
credit_gdp				0.012	0.012	0.012
				(0.011)	(0.010)	(0.010)
L2.credit_growth				3.614	2.769	3.361
				(4.753)	(4.927)	(4.627)
L.topincomep99	12.214			16.113*		
	(7.611)			(8.873)		
L2.topincomep99		12.322			16.733*	
		(7.647)			(9.196)	
L3.topincomep99			4.310			11.614
			(8.199)			(9.871)
Observations	408	402	392	323	320	317
No. crises	15	15	15	14	14	14
% Total Correct	95.57	96.52	96.17	96.28	96.25	95.9
% Crises Correct	7.14	7.12	0	16.67	16.67	7.69
% No-Crises Correct	100	100	100	100	100	100
Pseudo R-sq	0.273	0.280	0.196	0.398	0.409	0.309
Chi-sq	18.67	19.17	14.75	18.44	19.44	16.39
p-value	0.0093	0.0077	0.0394	0.0480	0.0351	0.0889
AIC	83.966	83.259	90.663	62.410	61.731	68.697

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

Table 7 shows the estimation results of the baseline and extended specifications including regional dummy variables and the Gini index. In the baseline model, the Gini coefficient has the expected sign and is significant at the 10% level for the first and second lag of the Gini index. In comparison to the specifications without regional dummies, the third lag of the Gini index is no longer significant. All lags of the Gini coefficient are significant at the 5% level in the extended specification. Finally, the coefficient for the top 1% income share is significant at the 1% level in both the baseline and extended estimations shown in Table 8.

Similarly to Magud and Vesperoni (2015) as well as Bordo and Meissner (2012), we include yearly dummy

Asia (Hong Kong, Japan, South Korea, and Singapore) and Western Europe (Austria, Belgium, France, Germany, Ireland, Luxembourg, Netherlands, Switzerland and the United Kingdom).

Table 7: Results for Gini index including regional dummies

Variables	(1) crisis	(2) crisis	(3) crisis	(4) crisis	(5) crisis	(6) crisis
gdp_growth	−0.172***	−0.170***	−0.171***	−0.371***	−0.386***	−0.390***
	(0.0593)	(0.0596)	(0.0597)	(0.0774)	(0.0785)	(0.0809)
totchange	0.0721***	0.0721***	0.0689***	0.123***	0.129***	0.128***
	(0.0160)	(0.0163)	(0.0156)	(0.0295)	(0.0300)	(0.0291)
depreciation	−0.0695***	−0.0688***	−0.0689***	−0.0806***	−0.0799***	−0.0782***
	(0.0153)	(0.0153)	(0.0154)	(0.0186)	(0.0192)	(0.0212)
realinterest	0.0391	0.0494	0.0463	0.123	0.127	0.0865
	(0.0843)	(0.0863)	(0.0861)	(0.112)	(0.117)	(0.148)
inflation	0.0624	0.0700	0.0705	0.0356	0.0438	0.00360
	(0.0692)	(0.0695)	(0.0675)	(0.0795)	(0.0803)	(0.0732)
gdp_pc	0.0308***	0.0308***	0.0301***	0.0592***	0.0613***	0.0637***
	(0.0107)	(0.0106)	(0.0104)	(0.0182)	(0.0195)	(0.0208)
d_NA_Australasia	−1.055	−1.047	−1.075	−0.535	−0.508	−0.580
	(0.968)	(0.973)	(0.977)	(1.029)	(1.033)	(0.955)
d_South_Europe	0.364	0.365	0.355	0.718**	0.760**	0.615
	(0.485)	(0.501)	(0.489)	(0.364)	(0.379)	(0.488)
d_East_Europe	0.317	0.285	0.260	−	−	−
	(0.964)	(0.994)	(1.001)	(−)	(−)	(−)
d_Nordic	−0.669	−0.642	−0.706	−0.791	−0.833	−1.121
	(0.464)	(0.466)	(0.478)	(0.501)	(0.534)	(0.752)
d_Asia	−1.291*	−1.286*	−1.346*	−1.484**	−1.584**	−1.619**
	(0.783)	(0.768)	(0.752)	(0.666)	(0.635)	(0.651)
d_Western_Europe	−	−	−	−	−	−
	(−)	(−)	(−)	(−)	(−)	(−)
m2_reserves				0.00641	0.00550	0.00196
				(0.0197)	(0.0216)	(0.0249)
credit_gdp				0.0109**	0.0122**	0.00958*
				(0.00516)	(0.00560)	(0.00539)
L2.credit_growth				0.0441*	0.0455*	4.541
				(0.0263)	(0.0274)	(4.449)
L.gini_market	0.0749*			0.161**		
	(0.0427)			(0.0812)		
L2.gini_market		0.0765*			0.172**	
		(0.0438)			(0.0801)	
L3.gini_market			0.0661			0.174**
			(0.0441)			(0.0758)
Observations	588	575	566	403	399	392
No. crises	24	24	24	20	20	20
% Total Correct	96.09	96	96.11	96.03	95.99	95.92
% Crises Correct	4.167	8.333	8.333	20	20	20
% No−Crises Correct	100	99.82	100	100	100	100
Pseudo R−sq	0.200	0.199	0.198	0.307	0.310	0.318
Chi−sq	40.16	39.77	39.41	48.81	49.28	50.21
p−value	0.00013	0.00015	0.00017	0.00004	0.00003	0.00002
AIC	186.4	185.7	185.3	140.3	139.4	137.8

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

Table 8: Results for the top 1% income share including regional dummies

Variables	(1) crisis	(2) crisis	(3) crisis	(4) crisis	(5) crisis	(6) crisis
gdp_growth	−0.338***	−0.305**	−0.324***	−0.308**	−0.258**	−0.293**
	(0.130)	(0.133)	(0.125)	(0.120)	(0.130)	(0.118)
totchange	0.101***	0.111***	0.0897***	0.0923***	0.112***	0.0940***
	(0.0201)	(0.0181)	(0.0325)	(0.0205)	(0.0239)	(0.0337)
depreciation	−0.0579***	−0.0653***	−0.0534***	−0.0698***	−0.0805***	−0.0734**
	(0.0168)	(0.0145)	(0.0170)	(0.0239)	(0.0249)	(0.0302)
realinterest	0.129*	0.125	0.0865	0.187**	0.229*	0.166
	(0.0671)	(0.0832)	(0.0720)	(0.0924)	(0.135)	(0.141)
inflation	−0.0349	−0.0216	−0.0932	0.00697	0.0558	0.00295
	(0.0790)	(0.0891)	(0.0827)	(0.0926)	(0.134)	(0.127)
gdp_pc	0.0254*	0.0250*	0.0123	0.0343**	0.0393**	0.0252*
	(0.0149)	(0.0148)	(0.0121)	(0.0165)	(0.0176)	(0.0136)
d_NA_Australasia	−2.227***	−2.363***	−1.960**	−1.838**	−2.209***	−1.978**
	(0.821)	(0.777)	(0.831)	(0.881)	(0.819)	(0.944)
d_South_Europe	0.261	0.0578	0.0643	0.472	0.369	0.210
	(0.489)	(0.514)	(0.342)	(0.499)	(0.565)	(0.403)
d_East_Europe	−	−	−	−	−	−
	(−)	(−)	(−)	(−)	(−)	(−)
d_Nordic	−0.154	−0.265	−0.414	0.0515	0.0634	−0.111
	(0.439)	(0.462)	(0.346)	(0.505)	(0.601)	(0.500)
d_Asia	−2.165***	−2.345***	−2.525***	−1.739**	−1.872**	−2.071***
	(0.750)	(0.695)	(0.628)	(0.746)	(0.748)	(0.608)
d_Western_Europe	−	−	−	−	−	−
	(−)	(−)	(−)	(−)	(−)	(−)
m2_reserves				0.00597	−0.00863	0.00605
				(0.0113)	(0.0408)	(0.0117)
credit_gdp				0.00794	0.00823	0.00533
				(0.00655)	(0.00881)	(0.00689)
L2.credit_growth				−0.00210	−0.00311	2.118
				(0.0268)	(0.0319)	(4.394)
L.topincomep99	26.53***			28.68***		
	(7.930)			(9.440)		
L2.topincomep99		26.94***			33.42***	
		(7.949)			(11.19)	
L3.topincomep99			15.07***			23.42***
			(5.719)			(8.825)
Observations	408	402	392	324	321	317
No. crises	15	15	15	14	14	14
% Total Correct	96.81	96.77	96.43	96.30	96.26	95.90
% Crises Correct	13.33	13.33	6.667	14.29	14.29	7.143
% No−Crises Correct	100	100	100	100	100	100
Pseudo R−sq	0.255	0.267	0.208	0.267	0.290	0.227
Chi−sq	32.84	34.14	26.46	30.77	33.34	26.08
p−value	0.00180	0.00114	0.0147	0.0144	0.00665	0.0529
AIC	119.7	117.9	124.9	114.6	111.7	118.6

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

variables to control for unobservable time effects. In the Appendix we show the results for the Gini index and top 1% income share including both region- and decade- (1980s, 1990s and 2000s) fixed effects. The estimated coefficient of the Gini index is insignificant for all lags in the baseline specification in Table A4 in the Appendix. However, the estimated Gini coefficients are positive and significant at the 10% level in the extended model. Moreover, the coefficient for the top 1% income share is generally highly significant in both the baseline and extended model shown in Table A5.

Furthermore, to test the robustness of the results for the top 1% income share, we re-estimate the baseline and extended specification for the top 0.1%, 5% and 10% income shares, including regional fixed effects. Table A6 in the Appendix shows that the coefficients for top 0.1%, 5% and 10% income shares are positive and highly significant.

4.3.3 Estimation on selected subsamples

To test whether the significance of the results depends on a specific region, we estimate the extended model with one lag for the Gini index and the top 1% income share excluding one region at a time. The Gini index is significant when excluding any of the six different regions shown in Table A7. However, the results are only significant at the 10% level when excluding North America and Australasia or Western Europe. Moreover, the coefficient for the top 1% income share is significant under the exclusion of any region with the exception of North America and Australasia or Western Europe, as shown in Table A8.

4.3.4 Alternative total credit definitions

Bordo and Meissner (2012) argue that domestic bank credit may not be a a good proxy for total credit if substantial amounts of credit are provided by non-bank institutions. For example, in the United States banks only account for 30% of total credit, while bank credit in countries like Germany or Greece can be around 90% of total credit (Dembiermont, Drehmann and Muksakunratana, 2013). Table A3 shows that the median level of total credit as a percentage of GDP is 117% compared to 69% for domestic bank credit. Consequently, the specifications are re-estimated including a measure for total credit which may also include cross-border credit and domestic credit from other financial institutions.

Table A9 in the Appendix shows the results for the Gini index and the top 1% income shares including the broader measure of total credit. Both the Gini index and the top 1% income share (columns 1 and 4) are highly statistically significant. Moreover, the coefficient estimate for the level of total credit (as a percentage of GDP) is positive and significant, while that of the growth rate of total credit is statistically insignificant.

Furthermore, Perugini, Hölscher and Collie (2016) consider aggregate measures of credit that include both household credit (the relevant type of credit according to the literature) and credit to firms. Moreover, the average correlation between the real growth rate in firm and household credit is only 40% across countries (Dembiermont, Drehmann and Muksakunratana, 2013). Columns 2-3 and 5-6 in Table A9 show the results for estimations including household and firm credit separately. The Gini index and the top 1% income share are both positive and highly statistically significant when including household or firm credit. Interestingly, both the level of household credit to GDP and the lagged growth rate of household credit are highly significant in the specifications that include the Gini index (column 2). However, both the level and growth rate of firm credit are not significant in any specification (columns 3 and 6). This result is consistent with the findings by Büyükkarabacak and Valev (2010). Consequently, household credit seems to be more important for financial stability compared to firm credit.

4.3.5 Lagged control variables

For the results presented in the previous Section all control variables except credit growth are contemporaneous, which may lead to endogeneity issues. To check if the coefficients are influenced by endogeneity we lag all control variables one period. Table A10 shows that the coefficients for the Gini index are highly significant when all control variables are lagged one period in the baseline specification. In addition, Table A11 shows that the significance of the top 1% income share is robust to lagging the control variables one period.

Among the lagged control variables, the coefficients of GDP per capita and the change in terms of trade typically remain positive and significant. The level of credit to GDP is highly significant and positive in all estimations with the Gini index. This finding reinforces the importance of the level of credit to GDP as a determinant of banking crises.

Interestingly, the coefficient of the growth rate of GDP switches to a positive sign and is highly significant as shown in Table A10. Consequently, the negative estimated coefficient of contemporaneous GDP growth shown in Tables 7 and 8 may be a consequence of the onset of the banking crisis rather than a cause of the crisis. Furthermore, the coefficient of nominal depreciation is not significant when lagged one period, which once again may be a consequence of endogeneity. In addition, the real interest rate becomes significant and positive when lagged one period, contrary to previous results.

4.3.6 Alternative robust standard errors

Logit estimations with robust standard errors that are not clustered by country are shown in Table A12. The coefficient estimates for the Gini index in the baseline and extended model remain significant. Moreover, Table A13 shows that the coefficients for the Gini index are also positive and significant for probit regressions. In addition, the sign and significance of the critical coefficients seem quite stable with respect to the omission/inclusion of the additional regressors.

4.3.7 Including measures of the quality of institutions and market conditions

It is important to control for the quality of institutions and market regulations across countries. Estimations including regulation indices from the Fraser Institute in the Economic Freedom of the World database can be found in the Appendix (see Tables A14-A16). All regulation indexes take values between 0 and 10, and a higher number implies more deregulation. The credit regulation index (code 5A) is a summary measure of (i) ownership of banks (ii) foreign bank competition (iii) private sector credit and (iv) interest rates controls/negative interest rates.

Furthermore, it is important to account for the institutional setting of labor and product markets. Labor market regulation (code 5B) includes information about (i) hiring regulations for temporary workers and minimum wage, (ii) hiring and firing regulations, (iii) centralized collective bargaining, (iv) hours regulation and (v) conscription and mandated costs of dismissal. In addition, the business regulation index encompasses information on (i) price controls, (ii) administrative requirements, (iii) bureaucracy costs, (iv) time and money required to start a business, (v) extra payments or bribes, (vi) licensing costs and (vii) cost of tax compliance. These measures have been used previously in the empirical literature for example by Perugini, Hölscher and Collie (2016) and Giannone, Lenza, and Reichlin (2011).

Table A14 reports results from Logit estimations including each regulation index separately and all together. First, we can see that the coefficients for both the Gini index and the top 1% income share are positive and significant in all estimations. Second, the business regulation index (business_reg) is negative and highly significant, while the credit regulation index (credit_reg) and the labor regulation index (labour_reg) are not. These findings suggest that a more deregulated product market seems to lower the probability of banking crises. To conclude, the previous finding that the Gini index and top 1% income share are positively associated with the likelihood of banking crises seems robust with respect to the inclusion of regulation indices for credit, labor and product markets.

According to Piketty and Saez (2013), a booming stock market both increases top income shares (via higher capital gains) and enhances financial fragility. Stock market conditions are proxied by a share price index collected from the OECD database. If the contemporaneous level of the share price index is included, its coefficient is insignificant. Moreover, the contemporaneous coefficient for the growth rate of the share price index is negative and significant at the 1% level. This result is expected since banking crises often coincide with a collapse in stock prices.

Tables A15 and A16 show results for the top 1% income share when the level and growth rate of the share price index are lagged one period. The lagged coefficients for both the level and growth rate of the share price index and the top 1% income share are positive and typically significant. In short, results suggest that the positive association between the top 1% income share and the likelihood of banking crises previously found is not simply a correlation caused by a booming stock market.

5 Conclusions

This paper is one of the first to empirically investigate whether the level of income inequality is directly linked to the occurrence of banking crises. Previous empirical literature examining the "level" hypothesis either used descriptive statistics (for example Atkinson and Morelli, 2015), or investigated the indirect link between income inequality and banking crises via the level of credit in the economy (Perugini, Hölscher and Collie, 2016).

We conduct an econometric analysis based on logit regressions to estimate the relationship between the level of the Gini index or top 1% income shares (both before taxes and transfers) and banking crises. Using a panel dataset of 33 advanced countries over the period 1970-2011, we find strong evidence for a positive association between the probability of banking crises and the level of income inequality. In addition, the results successfully pass a battery of robustness tests, such as for example the inclusion of the level and growth rate of domestic bank credit and the exclusion of various groups of countries.

Furthermore, we find that the effect of an increase in the level of inequality on the probability of the occurrence of a banking crisis is relatively large in economic terms, and that the size of the effect seems to increase with the level of income inequality.

Although income inequality could influence the probability of a banking crisis through several channels, to set up a fully-fledged theoretical model supporting our empirical findings goes beyond the scope of this paper.[11]

A possible mechanism, consistent with our empirical findings, that links income inequality and banking crises is the following. Persistently high levels of (*before*-tax) income inequality may induce policy makers to increase redistribution through large public expenditure and taxation mechanisms like those pioneered by Meltzer and Richard (1981), and later extended to growth by Alesina and Rodrik (1994) and Persson and Tabellini (1994). Worsening public deficits and debts (and rising interest rates), such policies may depress growth and ultimately deteriorate banks stability.

To conclude, it is worth mentioning that almost all biggest economies of our samples display a positive association between persistently high levels of income inequality and the occurrence of banking crises. Insofar as high levels of income inequality are associated to banking crises in large economies, inequality should be

[11] With the exception of Kumhof, Ranciere and Winant (2015), we are not aware of theoretical contributions displaying a neat relationship between income inequality and financial crises. Kirschenmann, Malinen and Nyberg (2016) discuss the literature and describe some of these channels.

taken very seriously at the international level as financial integration might easily give rise to epidemic contagion worldwide.

Acknowledgement

We thank conference audiences in Rome and Palermo (Money, Banking and Finance, December 2017), Milan (Finance and Economic Growth in the Aftermath of the Crisis, September 2017) and Bologna (Trends in Inequality: Social, Economic and Political Issues, November 2017). We also thank Gabriella Chiesa, Henriette Prast, and Paolo Manasse for helpful comments on earlier drafts. The usual disclaimer applies.

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Appendix

Table A1: Definitions and sources of main variables

Variable	Definition	Source
crisis	A binary variable equal to 1 in the first year of a banking crisis, 0 otherwise.	Laeven and Valencia (2013).
gini_gross	Market Gini index pre-tax and pre-transfer.	Standard World Income Inequality Database (SWIID) version 5.1.
topincomep99	The income share of top 1% pre-tax and pre-transfer	World Top Incomes Database.
gdp_growth	Growth rate of real GDP.	World Bank WDI.
totchange	Change in terms of trade.	World Bank WDI.
realinterest	Nominal interest rate minus contemporaneous inflation.	The nominal interest rate is from IFS: (i) treasure bill rate or (ii) discount/bank rate or (iii) the deposit rate. The GDP deflator based Inflation is from World Bank WDI.
inflation	Rate of change of GDP deflator.	World Bank WDI.
m2_reserves	Ratio of M2 to international reserves.	M2 (money plus quasi-money in local currency) that is converted to US$ and divided by total foreign exchange reserves of the central bank. All data is from IMF IFS.
depreciation	Rate of depreciation.	USD/LCU exchange rate (IMF IFS).
gdp1_pc	Real GDP per capita.	Constant 1995 in thousands of US$ (World Bank WDI).
credit_gdp	Ratio of private sector bank credit to GDP.	Adjusted domestic bank credit to the private non-financial sector divided by GDP (BIS total credit statistics). Otherwise depository corporations domestic claims on private sector (IMF IFS) divided by nominal GDP (World Bank WDI). All in LCU.
credit_growth	Growth rate of real domestic bank credit to the private sector.	Adjusted domestic bank credit to the private non-financial sector (BIS total credit statistics), otherwise depository corporations domestic claims on private sector (IMF IFS); divided by the GDP deflator (World Bank WDI). All in LCU.

Table A2: Definitions and sources of additional variables used in robustness tests

Variable	Definition	Source
totalcredit_gdp	Ratio of private sector total credit to GDP. This variable includes domestic bank credit, cross-border credit and domestic credit from other financial institutions.	Adjusted total credit to the private non-financial sector divided by GDP (BIS total credit statistics).
totalcredit_growth	Growth rate of real total credit to the private sector. This variable includes domestic bank credit, cross-border credit and domestic credit from other financial institutions.	Adjusted total credit to the private non-financial sector (BIS total credit statistics); divided by the GDP deflator (World Bank WDI). All in LCU.
hhcredit_gdp	Ratio of private sector household credit to GDP.	Adjusted household credit to the private non-financial sector divided by GDP (BIS total credit statistics).
hhcredit_growth	Growth rate of real household credit to the private sector.	Adjusted household credit to the private non-financial sector (BIS total credit statistics); divided by the GDP deflator (World Bank WDI). All in LCU.
firmcredit_gdp	Ratio of private sector firm credit to GDP.	Adjusted firm credit to the private non-financial sector divided by GDP (BIS total credit statistics).
firmcredit_growth	Growth rate of real firm credit to the private sector.	Adjusted firm credit to the private non-financial sector (BIS total credit statistics); divided by the GDP deflator (World Bank WDI). All in LCU.
credit_reg	Credit regulation index taking values from 0 to 10. A higher number implies more deregulation.	Economic Freedom of the World database (Fraser institute).
labor_reg	Labor market regulation index taking values from 0 to 10. A higher number implies more deregulation.	Economic Freedom of the World database (Fraser institute).
business_reg	Business regulation index taking values from 0 to 10. A higher number implies more deregulation.	Economic Freedom of the World database (Fraser institute).
house_index	Real house price index	OECD
share_index	Share price index	OECD
topincomep999	The income share of top 0.1% pre-tax and pre-transfer.	World Top Incomes Database.
topincomep95	The income share of top 5% pre-tax and pre-transfer.	World Top Incomes Database.
topincomep90	The income share of top 10% pre-tax and pre-transfer.	World Top Incomes Database.

Table A3: Descriptive statistics

Variable	Mean	Median	Std. Dev.	Min	Max	Obs.
Bank crisis	0.09	0	0.15	0	1	1386
Market Gini index	43.41	44.20	6.08	24.47	58.59	1040
Top 0.1% income share	0.03	0.02	0.02	0.01	0.12	595
Top 1% income share	0.09	0.08	0.03	0.04	0.23	662
Top 5% income share	0.21	0.21	0.04	0.12	0.37	665
Top 10% income share	0.32	0.31	0.05	0.19	0.47	659
GDP growth	3.35	3.21	3.41	-14.81	16.16	1217
Change in terms of trade	1.20×10^{12}	0	6.82×10^{12}	-3.26×10^{13}	6.97×10^{13}	1201
Depreciation	7.88	-0.06	257.10	-99.29	7533.67	861
Real interest rate	1.25	1.35	3.97	-19.43	20.11	745
Inflation	7.24	4.02	16.87	-9.69	390.68	1217
GDP per capita	31381.71	29192	16752.88	1960.36	110001.1	1227
Ratio M2 to Inter. Res.	123602.6	66.84	2130872	0.90	4.22×10^{7}	623
Credit to GDP	76.58	68.58	34.37	20.7	312.12	1071
Credit growth	0.06	0.05	0.07	-0.21	0.60	1032
Total credit to GDP	123.21	117.43	49.51	29.3	421.43	1043
Total credit growth	0.06	0.05	0.06	-0.13	0.78	999
Household credit to GDP	50.12	46.89	24.52	5.93	137.95	774
Household credit growth	0.07	0.06	0.07	-0.20	0.61	747
Firm credit to GDP	83.73	79.58	36.17	26.13	369.23	752
Firm credit growth	0.05	0.04	0.07	-0.15	0.92	730
Credit regulation index	8.72	9.26	1.50	0	10	566
Labour regulation index	5.97	5.7	1.70	2.62	9.46	529
Business regulation index	6.79	6.78	0.92	3.91	9.5	424
Real house price index	75.17	72.18	31.18	24.10	188.54	890
Share price index	66.19	47.82	78.37	0.01	1246.92	947

Table A4: Results for Gini index including regional and period dummies

Variables	(1) crisis	(2) crisis	(3) crisis	(4) crisis	(5) crisis	(6) crisis
gdp_growth	−0.191***	−0.191***	−0.191***	−0.364***	−0.378***	−0.374***
	(0.0664)	(0.0663)	(0.0663)	(0.0794)	(0.0800)	(0.0818)
totchange	0.0570***	0.0565***	0.0546***	0.141***	0.144***	0.143***
	(0.0201)	(0.0203)	(0.0194)	(0.0482)	(0.0502)	(0.0481)
depreciation	−0.0661***	−0.0661***	−0.0659***	−0.0832***	−0.0818***	−0.0822***
	(0.0155)	(0.0155)	(0.0160)	(0.0229)	(0.0227)	(0.0246)
realinterest	0.0352	0.0397	0.0366	0.0470	0.0566	0.0363
	(0.0965)	(0.0949)	(0.0989)	(0.187)	(0.182)	(0.208)
inflation	0.101	0.104	0.103	−0.0653	−0.0553	−0.0559
	(0.0769)	(0.0749)	(0.0749)	(0.0939)	(0.0963)	(0.0978)
gdp_pc	0.0227**	0.0228**	0.0225**	0.0671**	0.0681**	0.0661**
	(0.0105)	(0.0103)	(0.0102)	(0.0300)	(0.0300)	(0.0289)
d_NA_Australasia	−1.012	−1.032	−1.055	−0.333	−0.319	−0.332
	(1.073)	(1.098)	(1.097)	(1.050)	(1.069)	(1.015)
d_South_Europe	0.106	0.104	0.109	0.885	0.902	0.814
	(0.501)	(0.514)	(0.506)	(0.577)	(0.570)	(0.555)
d_East_Europe	−0.00757	−0.0270	−0.0283	–	–	–
	(0.953)	(0.959)	(0.955)	(–)	(–)	(–)
d_Nordic	−0.655	−0.644	−0.681	−0.847	−0.880	−0.850
	(0.435)	(0.450)	(0.456)	(0.743)	(0.783)	(0.763)
d_Asia	−1.363	−1.367	−1.402*	−1.685**	−1.757**	−1.926***
	(0.857)	(0.846)	(0.839)	(0.751)	(0.715)	(0.710)
d_Western_Europe	–	–	–	–	–	–
	(–)	(–)	(–)	(–)	(–)	(–)
d_1980s	13.24***	13.66***	13.81***	271.2	290.0	16.15***
	(1.235)	(1.183)	(1.197)	(344.9)	(378.2)	(2.275)
d_1990s	14.91***	15.34***	15.38***	269.6	288.7	14.39***
	(1.153)	(1.297)	(1.252)	(344.0)	(377.3)	(1.172)
d_2000s	14.66***	15.07***	15.09***	269.7	288.7	14.44***
	(1.127)	(1.253)	(1.208)	(344.0)	(377.3)	(0.829)
m2_reserves				0.00170	0.00100	0.00279
				(0.0332)	(0.0333)	(0.0329)
credit_gdp				0.0136**	0.0141**	0.0157**
				(0.00675)	(0.00640)	(0.00702)
L2.credit_growth				3.393	3.636	2.975
				(4.403)	(4.831)	(4.570)
L.gini_market	0.0514			0.203*		
	(0.0513)			(0.108)		
L2.gini_market		0.0519			0.211*	
		(0.0523)			(0.112)	
L3.gini_market			0.0459			0.208*
			(0.0532)			(0.107)
Observations	588	575	566	403	399	392
No. crises	24	24	24	20	20	20
% Total Correct	96.26	96.17	96.11	95.78	95.99	95.92
% Crises Correct	8.333	8.333	8.333	20	20	20
% No−Crises Correct	100	100	100	99.74	100	100
Pseudo R−sq	0.230	0.229	0.227	0.331	0.333	0.335
Chi−sq	46.17	45.67	45.13	52.69	52.83	52.89
p−value	9.16e−05	0.000110	0.000133	5.22e−05	4.97e−05	4.87e−05
AIC	186.4	185.8	185.5	142.4	141.9	141.1

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

Table A5: Results for top 1% income share including regional and period dummies

Variables	(1) crisis	(2) crisis	(3) crisis	(4) crisis	(5) crisis	(6) crisis
gdp_growth	−0.335**	−0.306**	−0.333**	−0.304***	−0.253**	−0.298**
	(0.135)	(0.146)	(0.149)	(0.111)	(0.119)	(0.131)
totchange	0.0936***	0.104***	0.0775**	0.0970***	0.118***	0.0827**
	(0.0222)	(0.0193)	(0.0340)	(0.0326)	(0.0311)	(0.0346)
depreciation	−0.0550***	−0.0608***	−0.0494***	−0.0684***	−0.0827***	−0.0688**
	(0.0158)	(0.0145)	(0.0163)	(0.0239)	(0.0230)	(0.0273)
realinterest	0.126	0.127	0.109	0.166	0.189	0.176
	(0.0854)	(0.0967)	(0.0999)	(0.119)	(0.140)	(0.137)
inflation	−0.0130	0.0111	−0.0250	−0.0492	−0.0179	0.00851
	(0.140)	(0.148)	(0.167)	(0.109)	(0.132)	(0.143)
gdp_pc	0.0207	0.0194	0.00718	0.0331*	0.0379**	0.0251*
	(0.0177)	(0.0184)	(0.0145)	(0.0183)	(0.0181)	(0.0134)
d_NA_Australasia	−2.056***	−2.244***	−1.856*	−1.763*	−2.203***	−1.652*
	(0.759)	(0.741)	(0.948)	(0.901)	(0.849)	(0.935)
d_South_Europe	0.271	0.0888	0.0461	0.500	0.407	0.421
	(0.566)	(0.607)	(0.410)	(0.600)	(0.660)	(0.413)
d_East_Europe	−	−	−	−	−	−
	(−)	(−)	(−)	(−)	(−)	(−)
d_Nordic	0.0139	−0.0503	−0.206	0.0782	0.105	0.164
	(0.489)	(0.532)	(0.288)	(0.643)	(0.730)	(0.492)
d_Asia	−2.051***	−2.237***	−2.251***	−1.845**	−2.036***	−1.992***
	(0.719)	(0.678)	(0.701)	(0.731)	(0.700)	(0.723)
d_Western_Europe	−	−	−	−	−	−
	(−)	(−)	(−)	(−)	(−)	(−)
d_1980s	13.62***	13.10***	14.94***	91.41	59.82	24.42*
	(1.920)	(1.931)	(2.668)	(471.4)	(438.8)	(14.52)
d_1990s	14.28***	13.97***	16.12***	90.37	58.58	23.88
	(1.115)	(1.135)	(1.307)	(471.1)	(438.7)	(15.07)
d_2000s	14.19***	13.74***	16.11***	90.76	58.86	24.31
	(0.800)	(0.872)	(1.102)	(471.2)	(438.8)	(15.01)
m2_reserves				0.00855	−0.0248	0.0703
				(0.0832)	(0.0693)	(0.0709)
credit_gdp				0.00808	0.00927	0.00764
				(0.00888)	(0.0109)	(0.00702)
L2.credit_growth				1.061	0.660	−1.044
				(6.023)	(5.611)	(4.391)
L.topincomep99	24.44***			28.05***		
	(7.838)			(9.753)		
L2.topincomep99		25.91***			33.96***	
		(8.567)			(12.05)	
L3.topincomep99			13.60*			23.31**
			(7.107)			(9.947)
Observations	408	402	392	324	321	317
No. crises	15	15	15	14	14	14
% Total Correct	96.81	96.77	96.43	96.30	96.26	95.90
% Crises Correct	13.33	13.33	6.667	14.29	14.29	7.143
% No−Crises Correct	100	100	100	100	100	100
Pseudo R−sq	0.266	0.279	0.229	0.281	0.304	0.247
Chi−sq	34.23	35.78	29.12	32.42	34.97	28.31
p−value	0.00506	0.00311	0.0231	0.0280	0.0141	0.0776
AIC	124.3	122.3	114.2	118.9	116.1	122.4

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

Table A6: Results for the top 0.1%, 5% and 10% income shares including regional dummies

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	crisis	crisis	crisis	crisis	crisis	crisis
gdp_growth	−0.296**	−0.250***	−0.324***	−0.263**	−0.224**	−0.298***
	(0.144)	(0.0943)	(0.120)	(0.127)	(0.0902)	(0.114)
totchange	0.0865***	0.0952***	0.102***	0.0776**	0.0921***	0.101***
	(0.0184)	(0.0153)	(0.0193)	(0.0328)	(0.0174)	(0.0215)
depreciation	−0.0578***	−0.0573***	−0.0567***	−0.0783**	−0.0725***	−0.0675***
	(0.0201)	(0.0165)	(0.0156)	(0.0336)	(0.0239)	(0.0222)
realinterest	0.150**	0.122*	0.0895	0.241**	0.175*	0.140*
	(0.0732)	(0.0653)	(0.0607)	(0.0951)	(0.0941)	(0.0833)
inflation	0.00115	0.00646	−0.0657	0.0759	0.0426	−0.0353
	(0.0843)	(0.0780)	(0.0770)	(0.0846)	(0.0822)	(0.0967)
gdp_pc	0.0166	0.0376**	0.0333*	0.0214	0.0497***	0.0478**
	(0.0119)	(0.0173)	(0.0182)	(0.0160)	(0.0179)	(0.0209)
d_NA_Australasia	−2.281**	−1.738**	−1.624**	−1.850*	−1.478*	−1.274
	(0.938)	(0.739)	(0.816)	(1.009)	(0.837)	(0.888)
d_South_Europe	0.431	0.340	0.181	0.524	0.565	0.494
	(0.451)	(0.542)	(0.555)	(0.578)	(0.552)	(0.600)
d_East_Europe	−	−	−	−	−	−
	(−)	(−)	(−)	(−)	(−)	(−)
d_Nordic	−0.284	−0.423	−0.0113	−0.0507	−0.197	0.264
	(0.354)	(0.659)	(0.477)	(0.403)	(0.839)	(0.640)
d_Asia	−1.717**	−2.099***	−2.623***	−1.233	−1.838***	−2.403***
	(0.705)	(0.643)	(0.625)	(0.909)	(0.649)	(0.665)
d_Western_Europe	−	−	−	−	−	−
	(−)	(−)	(−)	(−)	(−)	(−)
m2_reserves				−0.0208	0.00277	0.00692
				(0.144)	(0.0156)	(0.0101)
credit_gdp				0.00812	0.00804	0.00721
				(0.00787)	(0.00902)	(0.00758)
L2.credit_growth				−0.0122	−0.00374	0.0156
				(0.0281)	(0.0292)	(0.0266)
L.topincomep999	47.83***			49.65***		
	(14.31)			(13.16)		
L.topincomep95		16.25***			20.38**	
		(5.999)			(8.681)	
L.topincomep90			12.47**			15.91**
			(5.660)			(8.006)
Observations	366	410	408	287	326	324
No. crises	13	14	15	12	13	14
% Total Correct	96.72	96.83	96.81	96.17	96.32	96.30
% Crises Correct	7.692	7.143	13.33	8.333	7.692	14.29
% No−Crises Correct	100	100	100	100	100	100
Pseudo R−sq	0.241	0.208	0.234	0.250	0.224	0.249
Chi−sq	27.05	25.41	30.08	24.91	24.44	28.67
p−value	0.0123	0.0204	0.00459	0.0715	0.0804	0.0263
AIC	109.3	120.7	122.5	102.8	114.8	116.7

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

Table A7: Results for Gini index, excluding one region at a time

	Excluding NA-Australasia	Excluding South Europe	Excluding East Europe	Excluding Nordic	Excluding Asia	Excluding Western Europe
Variables	crisis	crisis	crisis	crisis	crisis	crisis
gdp_growth	−0.286***	−0.264***	−0.334***	−0.295***	−0.240***	−0.209***
	(0.0687)	(0.0659)	(0.0707)	(0.0789)	(0.0708)	(0.0624)
totchange	0.0689**	0.145***	0.0883***	0.0997***	−2.459	0.0813**
	(0.0317)	(0.0445)	(0.0199)	(0.0287)	(2.838)	(0.0325)
depreciation	−0.104***	−0.0929***	−0.0853***	−0.0821***	−0.0740***	−0.112***
	(0.0253)	(0.0196)	(0.0190)	(0.0206)	(0.0214)	(0.0259)
realinterest	0.0287	0.219***	0.0851	−0.118	0.0366	0.143
	(0.152)	(0.0750)	(0.105)	(0.143)	(0.129)	(0.151)
inflation	0.00762	0.0535	0.0412	0.0177	−0.0212	0.0595
	(0.0545)	(0.0646)	(0.0544)	(0.0975)	(0.0692)	(0.130)
gdp_pc	0.0438**	0.0913***	0.0491***	0.0582***	0.0437***	0.0470***
	(0.0173)	(0.0292)	(0.0105)	(0.0173)	(0.0120)	(0.00993)
m2_reserves	0.0199	−0.0430	0.0119	0.00781	0.0125	0.0197**
	(0.0277)	(0.0267)	(0.0108)	(0.0186)	(0.0149)	(0.0100)
credit_gdp	0.0136**	0.00912	0.0118**	0.0141**	0.0154**	0.00922
	(0.00606)	(0.00580)	(0.00488)	(0.00631)	(0.00677)	(0.00621)
L2.credit_growth	0.00611	−0.00959	0.0270	0.0285	1.595	0.0134
	(0.0428)	(0.598)	(0.0196)	(0.0193)	(3.120)	(0.0314)
L.gini_market	0.152*	0.246***	0.177***	0.232***	0.212***	0.185*
	(0.0824)	(0.0895)	(0.0565)	(0.0726)	(0.0651)	(0.112)
Observations	300	378	403	368	322	314
No. crises	18	16	20	17	18	11
% Total Correct	95	97.09	96.28	96.20	95.65	97.13
% Crises Correct	27.78	31.25	25	17.65	22.22	18.18
% No−Crises Correct	99.29	100	100	100	100	100
Pseudo R−sq	0.302	0.316	0.281	0.284	0.241	0.305
Chi−sq	41.10	41.88	44.68	39.12	33.41	29.09
p−value	1.08e−05	7.87e−06	2.48e−06	2.42e−05	0.000233	0.00120
AIC	117.1	112.6	136.4	120.6	127.4	88.25

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

Table A8: Results for top 1% income share, excluding one region at a time

	Excluding NA-Australasia	Excluding South Europe	Excluding East Europe	Excluding Nordic	Excluding Asia	Excluding Western Europe
Variables	crisis	crisis	crisis	crisis	crisis	crisis
gdp_growth	−0.359***	−0.249**	−0.275***	−0.264**	−0.273**	−0.215*
	(0.0973)	(0.0981)	(0.0913)	(0.105)	(0.115)	(0.123)
totchange	0.0529***	0.0657***	0.0583***	0.0594***	−1.577	0.0631**
	(0.0172)	(0.0144)	(0.0108)	(0.0113)	(2.333)	(0.0291)
depreciation	−0.0863***	−0.0720***	−0.0727***	−0.0665***	−0.0478**	−0.101***
	(0.0311)	(0.0244)	(0.0224)	(0.0222)	(0.0227)	(0.0306)
realinterest	0.204*	0.182*	0.155	0.0656	0.0932	0.191
	(0.106)	(0.0978)	(0.0998)	(0.122)	(0.126)	(0.136)
inflation	0.0663	0.0138	0.0233	0.0242	−0.0610	0.0189
	(0.0690)	(0.0974)	(0.0863)	(0.0901)	(0.124)	(0.119)
gdp_pc	0.0396***	0.0502***	0.0426***	0.0420**	0.0283*	0.0508***
	(0.0149)	(0.0139)	(0.0117)	(0.0179)	(0.0151)	(0.0179)
m2_reserves	0.0108	0.00518	0.00229	0.00368	−0.00716	−0.0291
	(0.0613)	(0.00964)	(0.0101)	(0.00978)	(0.0248)	(0.117)
credit_gdp	0.0133	0.0132*	0.0159*	0.0198**	0.0144	0.0168
	(0.0105)	(0.00801)	(0.00826)	(0.00994)	(0.00881)	(0.0165)
L2.credit_growth	−0.00711	−0.0282	−0.00640	−0.00783	3.268	−0.00916
	(0.0250)	(0.0809)	(0.0198)	(0.0183)	(4.705)	(0.0269)
L.topincomep99	22.56	19.62***	19.55***	23.93***	18.92**	17.22
	(19.02)	(7.604)	(7.405)	(9.287)	(8.095)	(10.79)
Observations	202	299	324	287	251	257
No. crises	12	12	14	12	12	8
% Total Correct	95.05	96.66	96.30	96.52	95.62	96.89
% Crises Correct	16.67	16.67	14.29	16.67	8.333	12.50
% No−Crises Correct	100	100	100	100	100	99.60
Pseudo R−sq	0.246	0.232	0.223	0.238	0.179	0.263
Chi−sq	22.41	23.31	25.74	23.75	17.22	18.71
p−value	0.0131	0.00966	0.00411	0.00828	0.0697	0.0441
AIC	90.62	99.38	111.6	97.93	101.2	74.55

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

Table A9: Income inequality and different measures of credit

Variables	(1) crisis	(2) crisis	(3) crisis	(4) crisis	(5) crisis	(6) crisis
gdp_growth	−0.307***	−0.324***	−0.322***	−0.237**	−0.279***	−0.251***
	(0.0732)	(0.0709)	(0.0730)	(0.101)	(0.0982)	(0.0846)
totchange	0.0746***	0.0832***	0.0748***	0.0517***	0.0613***	0.0472***
	(0.0222)	(0.0216)	(0.0232)	(0.0110)	(0.0126)	(0.0149)
depreciation	−0.0815***	−0.0878***	−0.0844***	−0.0789***	−0.0855***	−0.0898***
	(0.0209)	(0.0193)	(0.0197)	(0.0249)	(0.0211)	(0.0226)
realinterest	0.0557	0.0686	0.0357	0.156	0.128	0.128
	(0.122)	(0.118)	(0.107)	(0.104)	(0.0903)	(0.0862)
inflation	0.0124	−0.0176	−0.0549	0.0191	−0.0521	−0.0563
	(0.0640)	(0.0704)	(0.0683)	(0.0926)	(0.0804)	(0.0948)
gdp_pc	0.0243	0.0416***	0.0386**	0.0302**	0.0437***	0.0446**
	(0.0151)	(0.00867)	(0.0178)	(0.0127)	(0.0167)	(0.0210)
m2_reserves	0.00626	0.0151*	0.00919	−0.00272	0.00353	0.00192
	(0.0206)	(0.00904)	(0.0136)	(0.0228)	(0.00845)	(0.0117)
totalcredit_gdp	0.0105**			0.0193**		
	(0.00515)			(0.00945)		
L2.totalcredit_growth	0.00926			−0.0110		
	(0.0170)			(0.0173)		
hhcredit_gdp		0.0283***			0.0270*	
		(0.00907)			(0.0157)	
L2.hhcredit_growth		0.0532**			0.0171	
		(0.0239)			(0.0292)	
firmcredit_gdp			0.00270			0.0156
			(0.00592)			(0.0101)
L2.firmcredit_growth			0.000698			−0.00740
			(0.0272)			(0.0132)
L.gini_market	0.154***	0.140**	0.132**			
	(0.0528)	(0.0544)	(0.0567)			
L.topincomep99				17.03***	9.210**	16.34***
				(5.132)	(4.068)	(6.145)
Observations	409	388	372	324	298	289
No. crises	19	19	19	14	14	14
% Total Correct	96.33	95.88	95.70	96.30	95.97	95.85
% Crises Correct	21.05	15.79	15.79	14.29	14.29	14.29
% No−Crises Correct	100	100	100	100	100	100
Pseudo R−sq	0.256	0.271	0.234	0.236	0.241	0.229
Chi−sq	39.39	41.05	35.14	27.20	27.22	25.66
p−value	2.17e−05	1.11e−05	0.000118	0.00242	0.00240	0.00422
AIC	136.3	132.6	136.9	110.2	107.7	108.4

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

Table A10: Gini index, all control variables are lagged 1 period

Variables	(1) crisis	(2) crisis	(3) crisis	(4) crisis	(5) crisis	(6) crisis
L.gdp_growth	0.141***	0.143***	0.143***	0.260**	0.236**	0.220**
	(0.0513)	(0.0521)	(0.0513)	(0.103)	(0.0989)	(0.0989)
L.totchange	0.0888***	0.0899***	0.0872***	0.145***	0.147***	0.148***
	(0.0182)	(0.0182)	(0.0176)	(0.0374)	(0.0395)	(0.0391)
L.depreciation	−0.0215	−0.0226	−0.0233	−0.0478	−0.0506	−0.0503
	(0.0218)	(0.0223)	(0.0226)	(0.0327)	(0.0337)	(0.0342)
L.realinterest	0.178**	0.181**	0.186**	0.378***	0.407***	0.423***
	(0.0831)	(0.0815)	(0.0804)	(0.102)	(0.120)	(0.130)
L.inflation	0.101	0.103	0.110	0.0488	0.0614	0.0742
	(0.0729)	(0.0733)	(0.0718)	(0.104)	(0.108)	(0.109)
L.gdp_pc	0.0343***	0.0345***	0.0343***	0.0687**	0.0705**	0.0716**
	(0.0128)	(0.0129)	(0.0130)	(0.0283)	(0.0303)	(0.0307)
d_NA_Australasia	−1.366	−1.339	−1.323	−0.834	−0.879	−0.807
	(1.053)	(1.038)	(1.022)	(1.280)	(1.293)	(1.220)
d_South_Europe	0.376	0.340	0.319	1.861***	1.871***	1.879***
	(0.823)	(0.833)	(0.829)	(0.586)	(0.576)	(0.566)
d_East_Europe	0.409	0.443	0.468	−	−	−
	(0.752)	(0.751)	(0.732)	(−)	(−)	(−)
d_Nordic	−0.539	−0.529	−0.558	−0.706	−0.897	−0.971
	(0.525)	(0.531)	(0.541)	(0.549)	(0.637)	(0.700)
d_Asia	−2.017	−2.040	−2.032	−2.163*	−2.253*	−2.293*
	(1.250)	(1.277)	(1.291)	(1.243)	(1.284)	(1.314)
d_Western_Europe	−	−	−	−	−	−
	(−)	(−)	(−)	(−)	(−)	(−)
L.m2_reserves				−0.0188	−0.0198	−0.0196
				(0.0269)	(0.0289)	(0.0290)
L.credit_gdp				0.0156***	0.0164***	0.0168***
				(0.00399)	(0.00411)	(0.00438)
L.credit_growth				−4.416	−4.813	−4.969
				(3.428)	(3.650)	(3.824)
L.gini_market	0.0892**			0.184**		
	(0.0369)			(0.0922)		
L2.gini_market		0.0939**			0.173**	
		(0.0378)			(0.0874)	
L3.gini_market			0.0891**			0.172**
			(0.0406)			(0.0787)
Observations	569	563	550	391	386	379
No. crises	24	24	24	20	20	20
% Total Correct	95.96	95.91	95.82	95.65	95.60	95.51
% Crises Correct	4.167	4.167	4.167	15	15	15
% No−Crises Correct	100	100	100	100	100	100
Pseudo R−sq	0.145	0.147	0.145	0.270	0.272	0.274
Chi−sq	28.92	29.16	28.63	42.60	42.80	42.84
p−value	0.00671	0.00620	0.00739	0.000321	0.000300	0.000296
AIC	196	195.2	194.6	145.3	144.6	143.8

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

Table A11: Top 1% income share, all control variables are lagged 1 period

Variables	(1) crisis	(2) crisis	(3) crisis	(4) crisis	(5) crisis	(6) crisis
L.gdp_growth	0.0837	0.119	0.112	0.224	0.284**	0.267**
	(0.0762)	(0.0833)	(0.0836)	(0.138)	(0.130)	(0.124)
L.totchange	0.0997***	0.122***	0.0808**	0.0998***	0.126***	0.0895**
	(0.0162)	(0.0203)	(0.0359)	(0.0162)	(0.0220)	(0.0377)
L.depreciation	−0.0261	−0.0217	−0.0298	−0.0363	−0.0324	−0.0356
	(0.0342)	(0.0333)	(0.0338)	(0.0373)	(0.0366)	(0.0359)
L.realinterest	0.270***	0.273***	0.218**	0.462***	0.426***	0.418***
	(0.0967)	(0.0924)	(0.0889)	(0.150)	(0.127)	(0.129)
L.inflation	0.0718	0.0972	0.0510	0.172	0.181	0.186
	(0.0741)	(0.0774)	(0.0796)	(0.132)	(0.125)	(0.143)
L.gdp_pc	0.0408*	0.0394*	0.0331*	0.0395*	0.0365	0.0350*
	(0.0228)	(0.0238)	(0.0198)	(0.0217)	(0.0233)	(0.0197)
d_NA_Australasia	−2.383***	−2.585***	−2.138***	−1.867**	−2.096**	−1.929**
	(0.725)	(0.674)	(0.756)	(0.877)	(0.833)	(0.923)
d_South_Europe	1.012	0.898	1.056**	1.611*	1.425	1.535**
	(0.621)	(0.669)	(0.532)	(0.946)	(0.960)	(0.767)
d_East_Europe	−	−	−	−	−	−
	(−)	(−)	(−)	(−)	(−)	(−)
d_Nordic	−0.715	−0.758	−0.888	0.405	0.372	0.274
	(0.890)	(0.907)	(0.758)	(0.846)	(0.887)	(0.718)
d_Asia	−2.191**	−2.723**	−2.377**	−2.153**	−2.907**	−2.614**
	(0.933)	(1.222)	(0.989)	(0.911)	(1.418)	(1.332)
d_Western_Europe	−	−	−	−	−	−
	(−)	(−)	(−)	(−)	(−)	(−)
L.m2_reserves				0.0134	0.00854	0.0125
				(0.0146)	(0.0183)	(0.0127)
L.credit_gdp				0.0203*	0.0173	0.0183**
				(0.0115)	(0.0113)	(0.00911)
L.credit_growth				−6.574	−6.676	−6.627
				(5.588)	(5.405)	(5.076)
L.topincomep99	27.09***			33.02***		
	(7.588)			(9.172)		
L2.topincomep99		30.73***			35.90***	
		(9.277)			(10.78)	
L3.topincomep99			20.55**			30.57***
			(8.221)			(10.77)
Observations	395	392	386	316	314	307
No. crises	15	15	15	14	14	14
% Total Correct	96.20	96.43	96.11	96.20	96.50	95.77
% Crises Correct	0	6.667	0	14.29	21.43	7.143
% No−Crises Correct	100	100	100	100	100	100
Pseudo R−sq	0.192	0.216	0.154	0.235	0.255	0.208
Chi−sq	24.49	27.52	19.56	26.92	29.16	23.71
p−value	0.0269	0.0106	0.107	0.0423	0.0229	0.0961
AIC	127.1	123.8	131.3	117.7	115.3	120.1

Robust standard errors in parentheses.

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

Table A12: Logit results for income inequality, robust S.E. (not clustered by country)

Variables	(1) crisis	(2) crisis	(3) crisis	(4) crisis	(5) crisis	(6) crisis
gdp_growth	−0.181***	−0.265***	−0.324***	−0.308***	−0.275***	−0.279***
	(0.0508)	(0.0579)	(0.0718)	(0.0953)	(0.0881)	(0.0967)
totchange	0.0622***	0.0845***	0.0832***	0.0630***	0.0583***	0.0613***
	(0.0171)	(0.0254)	(0.0286)	(0.0177)	(0.0192)	(0.0206)
depreciation	−0.0739***	−0.0885***	−0.0878***	−0.0689***	−0.0727***	−0.0855***
	(0.0178)	(0.0206)	(0.0208)	(0.0205)	(0.0193)	(0.0213)
realinterest	0.0306	0.0616	0.0686	0.0823	0.155	0.128
	(0.0766)	(0.121)	(0.128)	(0.0859)	(0.117)	(0.123)
inflation	0.0664	0.0311	−0.0176	−0.0692	0.0233	−0.0521
	(0.0663)	(0.0751)	(0.0923)	(0.0840)	(0.101)	(0.0996)
gdp_pc	0.0293***	0.0500***	0.0416***	0.0369**	0.0426**	0.0437**
	(0.00989)	(0.0153)	(0.0140)	(0.0147)	(0.0180)	(0.0190)
m2_reserves		0.0107	0.0151*		0.00229	0.00353
		(0.0140)	(0.00866)		(0.0101)	(0.00894)
credit_gdp		0.0123**			0.0159	
		(0.00618)			(0.0122)	
L2.credit_growth		0.0175			−0.00640	
		(0.0228)			(0.0218)	
hhcredit_gdp			0.0283**			0.0270
			(0.0137)			(0.0189)
L2.hhcredit_growth			0.0532*			0.0171
			(0.0278)			(0.0323)
L.gini_market	0.118**	0.180**	0.140*			
	(0.0471)	(0.0713)	(0.0792)			
L.topincomep99				12.82	19.55*	9.210
				(8.785)	(11.77)	(7.648)
Observations	588	417	388	408	324	298
No. crises	24	20	19	15	14	14
% Total Correct	96.09	96.40	95.88	96.57	96.30	95.97
% Crises Correct	8.333	25	15.79	6.667	14.29	14.29
% No−Crises Correct	99.82	100	100	100	100	100
Pseudo R−sq	0.178	0.275	0.271	0.195	0.223	0.241
Chi−sq	35.72	44.16	41.05	25.04	25.74	27.22
p−value	8.20e−06	3.08e−06	1.11e−05	0.000748	0.00411	0.00240
AIC	180.8	138.4	132.6	119.5	111.6	107.7

Robust standard errors in parentheses.

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

Table A13: Probit results for income inequality, robust S.E. (not clustered by country)

Variables	(1) crisis	(2) crisis	(3) crisis	(4) crisis	(5) crisis	(6) crisis
gdp_growth	−0.0946***	−0.140***	−0.171***	−0.156***	−0.139***	−0.145***
	(0.0272)	(0.0353)	(0.0445)	(0.0507)	(0.0493)	(0.0539)
totchange	0.0309***	0.0432***	0.0402***	0.0321***	0.0295***	0.0302***
	(0.00904)	(0.0132)	(0.0143)	(0.0102)	(0.0104)	(0.0105)
depreciation	−0.0356***	−0.0451***	−0.0471***	−0.0325***	−0.0381***	−0.0458***
	(0.00882)	(0.0101)	(0.0108)	(0.0102)	(0.00956)	(0.0110)
realinterest	0.0263	0.0508	0.0425	0.0427	0.0868	0.0669
	(0.0357)	(0.0534)	(0.0582)	(0.0399)	(0.0552)	(0.0561)
inflation	0.0398	0.0215	−0.00898	−0.0258	0.0137	−0.0236
	(0.0301)	(0.0369)	(0.0423)	(0.0390)	(0.0450)	(0.0444)
gdp_pc	0.0147***	0.0269***	0.0212***	0.0186**	0.0221**	0.0214**
	(0.00529)	(0.00778)	(0.00759)	(0.00769)	(0.00914)	(0.00992)
m2_reserves		0.00584	0.00769		0.00111	0.00159
		(0.00591)	(0.00482)		(0.00416)	(0.00395)
credit_gdp		0.00575*			0.00739	
		(0.00311)			(0.00537)	
L2.credit_growth		0.0123			−8.97e−05	
		(0.00899)			(0.00891)	
hhcredit_gdp			0.0144**			0.0133
			(0.00654)			(0.00863)
L2.hhcredit_growth			0.0294**			0.0138
			(0.0122)			(0.0123)
L.gini_market	0.0560***	0.0857**	0.0630*			
	(0.0212)	(0.0343)	(0.0359)			
L.topincomep99				6.244	9.160*	4.913
				(4.122)	(5.161)	(3.778)
Observations	588	417	388	408	324	298
No. crises	24	20	19	15	14	14
% Total Correct	96.26	96.16	95.62	96.57	96.30	95.97
% Crises Correct	8.333	20	15.79	6.667	14.29	14.29
% No−Crises Correct	100	100	99.73	100	100	100
Pseudo R−sq	0.181	0.275	0.274	0.197	0.224	0.244
Chi−sq	36.29	44.12	41.52	25.36	25.90	27.60
p−value	6.39e−06	3.14e−06	9.13e−06	0.000656	0.00388	0.00209
AIC	180.3	138.4	132.2	119.2	111.5	107.4

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

Table A14: Extended estimation including credit, labor and business regulation indices

Variables	(1) crisis	(2) crisis	(3) crisis	(4) crisis	(5) crisis	(6) crisis	(7) crisis	(8) crisis
gdp_growth	−0.252***	−0.254***	−0.271***	−0.301***	−0.316***	−0.310***	−0.301***	−0.302***
	(0.0607)	(0.0648)	(0.0710)	(0.0792)	(0.0848)	(0.0822)	(0.112)	(0.113)
totchange	−0.0754	−0.0761	−0.0792	−0.126**	−0.00322	0.0127	−0.0194	−0.0338
	(0.0498)	(0.0557)	(0.0529)	(0.0564)	(0.0327)	(0.0255)	(0.0367)	(0.0404)
depreciation	−0.0872***	−0.0907***	−0.107***	−0.114***	−0.0705***	−0.0696***	−0.0814**	−0.0817***
	(0.0203)	(0.0196)	(0.0287)	(0.0273)	(0.0234)	(0.0236)	(0.0319)	(0.0296)
realinterest	−0.0536	−0.00458	−0.00581	0.0133	0.141	0.129	0.317	0.343
	(0.135)	(0.111)	(0.137)	(0.179)	(0.120)	(0.124)	(0.246)	(0.239)
inflation	−0.0907	−0.0430	−0.0728	−0.0179	0.0170	−0.00247	0.136	0.174
	(0.137)	(0.115)	(0.152)	(0.190)	(0.123)	(0.133)	(0.275)	(0.265)
gdp_pc	0.0529***	0.0520***	0.0674***	0.0739***	0.0419***	0.0395**	0.0561**	0.0578**
	(0.0118)	(0.0126)	(0.0162)	(0.0179)	(0.0161)	(0.0180)	(0.0229)	(0.0226)
credit_gdp	0.0138**	0.0134**	0.0197***	0.0202***	0.0251*	0.0249*	0.0305**	0.0311**
	(0.00631)	(0.00654)	(0.00744)	(0.00718)	(0.0129)	(0.0135)	(0.0131)	(0.0131)
L2.credit_growth	4.506	3.926	3.984	3.567	3.724	3.523	−1.194	−1.448
	(2.829)	(2.720)	(3.191)	(4.093)	(4.816)	(4.441)	(4.827)	(5.351)
credit_reg	−0.346			0.0308	−0.279			−0.0837
	(0.295)			(0.382)	(0.450)			(0.440)
labor_reg		0.00596		0.335*		−0.122		0.120
		(0.149)		(0.178)		(0.176)		(0.242)
business_reg			−1.299***	−1.681***			−1.485***	−1.597***
			(0.302)	(0.454)			(0.475)	(0.542)
L.gini_market	0.218**	0.236***	0.251**	0.288**				
	(0.0848)	(0.0805)	(0.102)	(0.127)				
L.topincomep99					27.17**	28.86**	32.30***	30.48***
					(10.62)	(12.01)	(8.676)	(10.19)
Observations	304	297	270	270	212	204	179	179
No. crises	16	16	16	16	10	10	10	10
% Total Correct	95.39	95.62	95.19	94.81	95.75	95.59	94.97	94.97
% Crises Correct	18.75	25	25	18.75	10	10	10	10
% No−Crises Correct	99.65	99.64	99.61	99.61	100	100	100	100
Pseudo R−sq	0.287	0.276	0.327	0.344	0.259	0.253	0.298	0.301
Chi−sq	36.04	34.39	39.69	41.78	20.88	20.19	23.02	23.22
p−value	8.30e−05	0.000159	1.92e−05	3.63e−05	0.0220	0.0275	0.0107	0.0259
AIC	111.3	112.2	103.8	105.7	81.73	81.62	76.11	79.91

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

Table A15: Estimation with the top 1% income share including the share price index (level)

Variables	(1) crisis	(2) crisis	(3) crisis	(4) crisis	(5) crisis	(6) crisis
L.gdp_growth	0.0102	0.0457	0.0159	−0.0581	−0.00603	0.0387
	(0.0878)	(0.0915)	(0.0910)	(0.138)	(0.142)	(0.130)
L.totchange	0.0648***	0.0732***	−0.0721*	0.150***	0.181***	0.101*
	(0.0171)	(0.0198)	(0.0413)	(0.0358)	(0.0400)	(0.0528)
L.depreciation	−0.0265	−0.0260	−0.0240	−0.0142	−0.0114	−0.0207
	(0.0291)	(0.0291)	(0.0253)	(0.0316)	(0.0315)	(0.0299)
L.realinterest	0.303***	0.308***	0.248***	0.405***	0.415***	0.315***
	(0.0811)	(0.0767)	(0.0804)	(0.116)	(0.104)	(0.0843)
L.inflation	0.210**	0.221**	0.181*	0.259*	0.268**	0.229*
	(0.0913)	(0.0876)	(0.0945)	(0.139)	(0.121)	(0.121)
L.gdp_pc	0.0412***	0.0412***	0.0266**	0.0218	0.0178	0.0118
	(0.0116)	(0.0123)	(0.0113)	(0.0136)	(0.0147)	(0.0133)
L.credit_gdp	0.0207*	0.0207**	0.0182**	0.0202*	0.0186*	0.0175*
	(0.0107)	(0.0105)	(0.00909)	(0.0110)	(0.00960)	(0.00894)
L2.credit_growth	−1.540	−1.669	−5.872	−7.285	−7.388	−8.269
	(4.757)	(4.515)	(6.047)	(5.286)	(4.905)	(5.720)
L.share_index	0.00990*	0.00950	0.0176**	0.0204***	0.0212***	0.0207***
	(0.00585)	(0.00600)	(0.00712)	(0.00771)	(0.00821)	(0.00713)
d_NA_Australasia				−1.533	−1.691*	−1.274
				(0.971)	(0.902)	(0.999)
d_South_Europe				0.718	0.493	0.685
				(0.588)	(0.648)	(0.547)
d_East_Europe				−	−	−
				(−)	(−)	(−)
d_Nordic				1.213	1.152*	0.919*
				(0.746)	(0.650)	(0.506)
d_Asia				−3.961***	−4.709***	−3.442***
				(1.286)	(1.519)	(1.217)
d_Western_Europe				−	−	−
				(−)	(−)	(−)
L.topincomep99	18.51***			30.09***		
	(7.117)			(11.15)		
L2.topincomep99		20.22**			31.79***	
		(8.835)			(10.97)	
L3.topincomep99			11.52			20.67*
			(8.438)			(10.66)
Observations	340	339	335	340	339	335
No. crises	15	15	15	15	15	15
% Total Correct	95.88	95.87	95.52	95.59	95.87	95.52
% Crises Correct	6.667	6.667	6.667	6.667	13.33	6.667
% No−Crises Correct	100	100	99.69	99.69	99.69	99.69
Pseudo R−sq	0.186	0.197	0.182	0.269	0.292	0.241
Chi−sq	22.92	24.17	22.35	33.12	35.84	29.52
p−value	0.0110	0.00717	0.0134	0.00711	0.00304	0.0206
AIC	122	120.7	122.2	119.8	117	123

Robust standard errors in parentheses
*** p¡0.01, ** p¡0.05, * p¡0.1

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

Table A16: Estimation with the top 1% income share including the share price index (growth rate)

Variables	(1) crisis	(2) crisis	(3) crisis	(4) crisis	(5) crisis	(6) crisis
L.gdp_growth	−0.0240	−0.0115	−0.0267	0.0105	0.0319	0.0290
	(0.102)	(0.0972)	(0.0970)	(0.123)	(0.119)	(0.116)
L.totchange	0.0697***	0.0812***	−0.000384	0.0958***	0.117***	0.0417
	(0.0157)	(0.0168)	(0.0344)	(0.0169)	(0.0178)	(0.0430)
L.depreciation	−0.0287	−0.0301	−0.0312	−0.0271	−0.0244	−0.0327
	(0.0316)	(0.0317)	(0.0312)	(0.0329)	(0.0331)	(0.0344)
L.realinterest	0.328***	0.339***	0.248***	0.428***	0.421***	0.339***
	(0.0982)	(0.0958)	(0.0845)	(0.114)	(0.0949)	(0.0923)
L.inflation	0.135	0.152	0.0601	0.172	0.184*	0.131
	(0.112)	(0.104)	(0.115)	(0.121)	(0.104)	(0.111)
L.gdp_pc	0.0386***	0.0412***	0.0232*	0.0335*	0.0306	0.0249
	(0.0124)	(0.0136)	(0.0125)	(0.0186)	(0.0213)	(0.0181)
L.credit_gdp	0.0282***	0.0285***	0.0270***	0.0208	0.0189	0.0175*
	(0.00982)	(0.00907)	(0.00894)	(0.0138)	(0.0132)	(0.0101)
L2.credit_growth	2.967	2.635	2.902	1.085	1.406	1.336
	(3.758)	(3.509)	(3.576)	(3.807)	(3.132)	(3.433)
L.share_index_growth	2.138*	2.480**	3.010**	1.800	2.145*	2.351
	(1.199)	(1.264)	(1.478)	(1.389)	(1.301)	(1.441)
d_NA_Australasia				−1.926**	−2.173**	−1.758*
				(0.925)	(0.873)	(0.902)
d_South_Europe				0.937	0.679	0.842
				(0.917)	(0.971)	(0.711)
d_East_Europe				−	−	−
				(−)	(−)	(−)
d_Nordic				0.174	0.128	−0.178
				(0.971)	(0.991)	(0.769)
d_Asia				−1.428**	−2.047*	−1.142***
				(0.596)	(1.068)	(0.408)
d_Western_Europe				−	−	−
				(−)	(−)	(−)
L.topincomep99	24.34***			34.16***		
	(6.465)			(9.450)		
L2.topincomep99		27.18***			37.68***	
		(7.574)			(10.06)	
L3.topincomep99			20.89***			27.62***
			(8.035)			(9.833)
Observations	337	336	332	337	336	332
No. crises	15	15	15	15	15	15
% Total Correct	95.85	96.13	95.78	95.85	96.43	96.08
% Crises Correct	6.667	13.33	6.667	6.667	20	13.33
% No−Crises Correct	100	100	100	100	100	100
Pseudo R−sq	0.173	0.189	0.149	0.222	0.246	0.192
Chi−sq	21.20	23.21	18.24	27.25	30.19	23.48
p−value	0.0197	0.00999	0.0510	0.0388	0.0170	0.102
AIC	123.5	121.4	126	125.4	122.4	128.7

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

Credit Booms, Macroprudential Policy and Financial Crises

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October 2018

Abstract

Credit booms have been found to be one of the best predictors of banking crises in both advanced and developing countries. Consequently, 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 results show that an aggregate index including five different macroprudential policy instruments is negatively and significantly associated with domestic bank credit booms. The results for aggregate indexes are robust to the inclusion of country and year fixed effects. Moreover, macroprudential policies are also found to be effective to reduce the likelihood of booms in household credit. Finally, this study shows that macroprudential policies are effective to address specifically those credit booms that are followed by systemic banking crises.

JEL codes: E58, G01, G18, G28

Keywords: Credit Booms, Macroprudential Policy, Banking Crises

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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 are 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 (2012) provide empirical evidence showing 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., 2016, pp. 319)".

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 policymakers 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.

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. Finally, chapter 7 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 macroprudential indexes measuring 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. 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. 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: "(1) 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%, or (2) the annual growth rate of the credit-to-GDP ratio exceeds 20 percent (Dell'Ariccia et al., 2016, pp. 341)". 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 macroprudential 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.

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 differs 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 discuss 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 A3 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 to 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% 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 countercyclical macroprudential tools. The GMPI survey asks respondents whether this tool has been used as a monetary policy instrument or a macroprudential policy tool which makes it possible to distinguish when the tool is used as a macroprudential instrument. 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 Table 1 and summary statistics are shown in Table 2.

Table 1. Variable definitions and sources

Variable	Definition	Source
LTV_CAP	Cumulative change (sum of easings net of tightenings) in the Loan-to-Value (LTV) cap.	Cerutti et al. (2017b)
IBEX	Cumulative change in the interbank exposure limit. Limits banks exposures to other banks.	Cerutti et al. (2017b)
CONCRAT	Cumulative change in concentration limits. Limits banks' exposures to specific borrowers or sectors.	Cerutti 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.	Cerutti 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.	Cerutti 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.	Cerutti et al. (2017b)
MAPP_B_FI	Sum of LTV_CAP, IBEX, and CONCRAT.	Cerutti 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.	Cerutti et al. (2017b)
CAP_REQ	Cumulative change in general capital requirements. This index measures regulatory changes in the Basel Accords.	Cerutti et al. (2017b)
SSCB	Cumulative change in sector-specific capital buffers.	Cerutti et al. (2017b)
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 2. Summary statistics of variables

	Mean	Median	Min	Max	Std. Dev.	Obs
Dependent variables						
Bank credit boom 1.5 s.d. (HP filter)	0.055	0	0	1	0.228	2448
Bank credit boom 1.75 s.d. (HP filter)	0.029	0	0	1	0.167	2448
Bank credit boom 2 s.d. (HP filter)	0.015	0	0	1	0.120	2448
Household credit boom 1.75 s.d. (HP filter)	0.026	0	0	1	0.160	2197
Bank credit boom 1.5 s.d. (Hamilton filter)	0.080	0	0	1	0.271	2421
Bank credit boom 1.75 s.d. (Hamilton filter)	0.041	0	0	1	0.198	2421
Bank credit boom 2 s.d. (Hamilton filter)	0.017	0	0	1	0.129	2421
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 show summary statistics for all observations between 2000Q1-2014Q4.

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) 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).

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 A1 in the appendix show preliminary 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% of credit growth observations is found to be negative and highly significant shown in columns 1 and 5 in Table A1. Moreover, the interaction term with the dummy variable for the top 50% of credit growth observations is also found to be negative but only significant at the 10% level (column 2). However, the coefficients for interaction terms with the bottom 50% or 25% of credit growth observations are insignificant in all estimations shown in columns 3, 4 and 5. Moreover, the coefficient for interaction terms with the dummy variable for the top 25% of credit growth observations and sub-indexes MAPP_B_FI and MAPP_RR are also negative and significant shown in columns 6 and 8. 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).

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 & 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 & 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) display 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 3 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 show 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.

Figure 1. Aggregate macroprudential indexes (averages) and credit booms 2000Q1-2014Q4

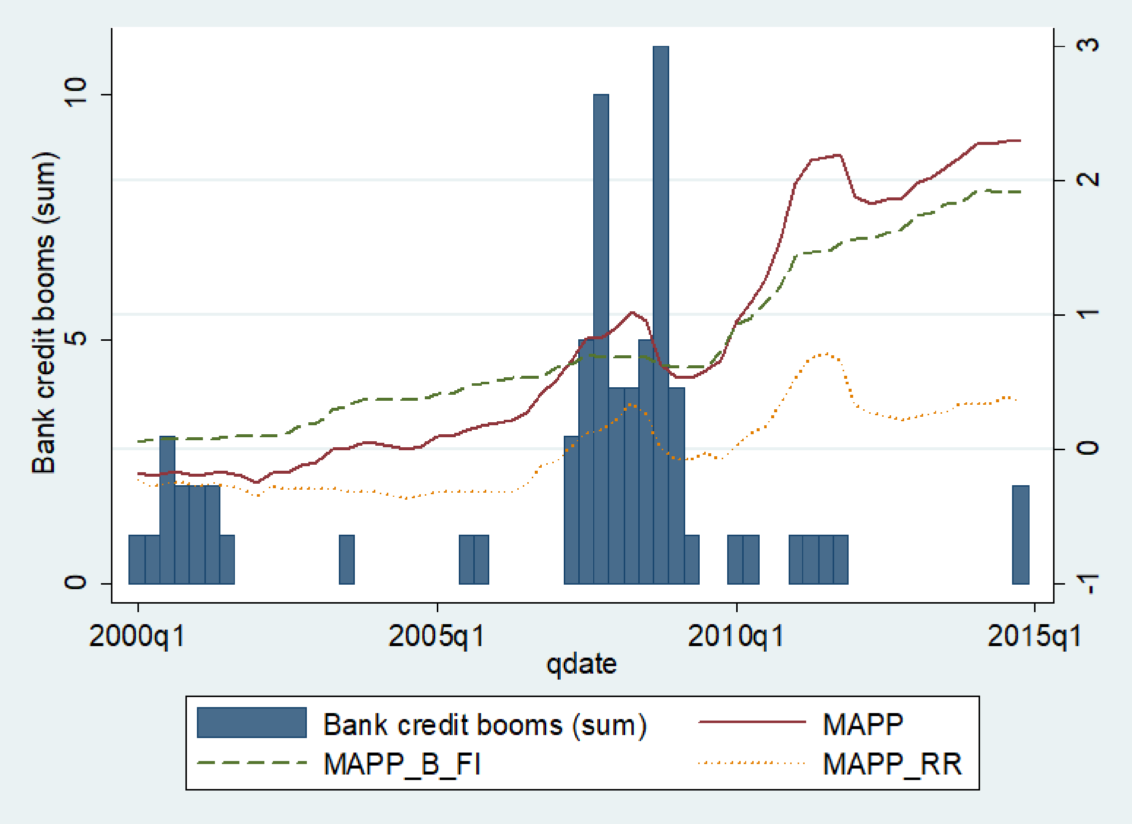


Table 3. Correlation between MAPP and other policies

	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.*

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.

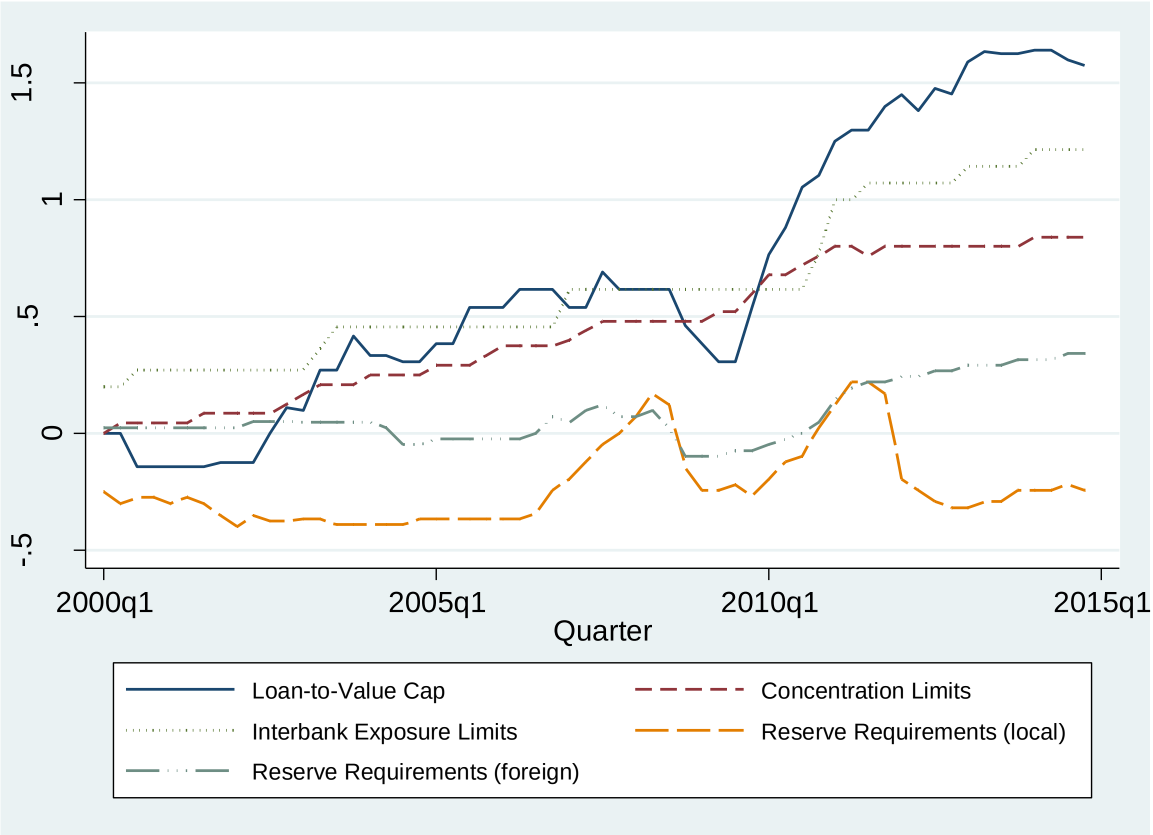
Table 4 show pairwise correlations between individual macroprudential policy instruments. Loan-to-Value caps (LTV_CAP) is positively correlated with all other individual policies. However, interbank exposure limits (IBEX) and concentration limits (CONCRAT) are weakly negatively correlated. In addition, the reserve requirement policies (RR_D and RR_FX) are positively correlated.

Table 4. 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.*

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 5. 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 estimations with country fixed effects (columns 5 and 7). However, the MAPP index is not significant in the LPM estimation with only year fixed effects (column 6). Finally, the MAPP index is also negative and significant in the Firth logit estimation shown in column 8.

The aggregate index MAPP_B_FI including LTV caps, concentration limits and interbank exposure limits has a negative and significant coefficient in all Logit, LPM, and Firth logit estimations (columns 1-4) shown in Table 6. 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 and LPM estimations (columns 5-7). However, index MAPP_RR is not significant in the Firth logit estimation (column 8). 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 7. The coefficients for Loan-to-Value caps (LTV_CAP) and interbank exposure limits (IBEX) are negative but not significant in any of the Logit, LPM or Firth logit estimations (columns 1-6). The coefficients for concentration limits (CONCRAT) are negative and significant at the 5% and 10% level in the LPM and Firth logit estimations (columns 8 and 9).

Furthermore, results for reserve requirement policies are shown in Table 8. Reserve requirements on local currency denominated accounts (RR_D) are found to be negative and significant at the 1% level both for Logit and LPM estimations 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 in the Logit estimation with country fixed effects.

Table 5. Aggregate macroprudential index (MAPP)

VARIABLES	Logit (1)	Logit (2)	Logit (3)	Logit (4)	LPM (5)	LPM (6)	LPM (7)	Firth logit (8)
Log (VIX)	1.464***	1.526***	2.873***	2.850***	0.047***	0.094***	0.091***	1.469***
	(0.404)	(0.407)	(0.669)	(0.798)	(0.011)	(0.027)	(0.021)	(0.384)
Real GDP growth	0.093*	0.254***	-0.050	0.020	0.005***	-0.001	0.001	0.090**
	(0.050)	(0.068)	(0.067)	(0.081)	(0.001)	(0.001)	(0.002)	(0.043)
Change CB policy rate	0.004	-0.001	0.008	0.004	0.000	0.001	0.000	0.005
	(0.004)	(0.016)	(0.005)	(0.018)	(0.001)	(0.000)	(0.001)	(0.012)
Inflation	0.145**	0.094	0.048	-0.062	0.001	0.001	-0.003	0.172**
	(0.060)	(0.158)	(0.064)	(0.150)	(0.003)	(0.002)	(0.003)	(0.072)
Log (real exchange rate)	-0.104	7.592**	-0.140	6.287**	0.149***	-0.003	0.137***	-0.088
	(0.131)	(3.083)	(0.135)	(3.136)	(0.050)	(0.002)	(0.052)	(0.093)
Bank credit (% of GDP)	-0.003	0.056***	-0.006	0.074***	0.001***	-0.000	0.002***	-0.003
	(0.004)	(0.017)	(0.005)	(0.024)	(0.000)	(0.000)	(0.000)	(0.004)
Log (GDP per capita)	0.670	6.789***	0.345	3.016	0.144***	0.006	0.124***	0.660***
	(0.443)	(2.239)	(0.465)	(2.064)	(0.035)	(0.008)	(0.037)	(0.234)
MAPP	-0.229***	-0.489***	-0.182**	-0.270**	-0.008***	-0.001	-0.005**	-0.220**
	(0.078)	(0.129)	(0.087)	(0.130)	(0.002)	(0.001)	(0.002)	(0.089)
Constant	-12.668***		-13.204***		-1.442***	-0.252**	-1.381***	-12.597***
	(2.971)		(3.395)		(0.307)	(0.103)	(0.320)	(2.251)
Country fixed effects	NO	YES	NO	YES	YES	NO	YES	NO
Year fixed effects	NO	NO	YES	YES	NO	YES	YES	NO
Observations	2171	1370	1284	1370	2171	2171	2171	2171
Credit booms	61	61	61	61	61	61	61	61
Countries	41	24	41	24	41	41	41	41
Pseudo R2 (LPM: R2)	0.0721	-	0.1717	-	-	0.0749	-	-
Chi-sq	56.70	61.65	124.39	151.76	-	-	-	34.00
Prob > chi-sq (LPM: F-test)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Robust standard errors in parentheses

*** 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 6. Aggregate macroprudential sub-indexes (MAPP_B_FI & MAPP_RR)

VARIABLES	Logit (1)	Logit (2)	LPM (3)	Firth logit (4)	Logit (5)	Logit (6)	LPM (7)	Firth logit (8)
Log (VIX)	1.357***	1.363***	0.044***	1.368***	1.480***	1.658***	0.050***	1.483***
	(0.402)	(0.403)	(0.011)	(0.383)	(0.413)	(0.408)	(0.011)	(0.383)
Real GDP growth	0.074*	0.213***	0.005***	0.072*	0.083*	0.241***	0.005***	0.080*
	(0.044)	(0.061)	(0.001)	(0.042)	(0.050)	(0.066)	(0.001)	(0.043)
Change CB policy rate	0.005	-0.001	0.000	0.006	0.004	-0.001	0.000	0.005
	(0.004)	(0.015)	(0.001)	(0.012)	(0.004)	(0.015)	(0.001)	(0.012)
Inflation	0.127**	0.081	0.001	0.155**	0.142**	0.106	0.001	0.168**
	(0.061)	(0.154)	(0.003)	(0.073)	(0.056)	(0.157)	(0.003)	(0.073)
Log (real exchange rate)	-0.097	5.393**	0.137***	-0.081	-0.118	5.720**	0.122**	-0.101
	(0.134)	(2.688)	(0.050)	(0.095)	(0.130)	(2.861)	(0.050)	(0.091)
Bank credit (% of GDP)	-0.004	0.057***	0.001***	-0.003	-0.004	0.049***	0.001***	-0.004
	(0.004)	(0.017)	(0.000)	(0.004)	(0.005)	(0.015)	(0.000)	(0.004)
Log (GDP per capita)	0.714*	4.876***	0.136***	0.706***	0.637	5.199**	0.116***	0.622***
	(0.406)	(1.891)	(0.034)	(0.230)	(0.446)	(2.038)	(0.033)	(0.237)
MAPP_B_FI	-0.306**	-0.582***	-0.014***	-0.290**				
	(0.128)	(0.208)	(0.004)	(0.127)				
MAPP_RR					-0.220*	-0.537***	-0.008***	-0.205
					(0.131)	(0.192)	(0.003)	(0.135)
Constant	-12.408***		-1.357***	-12.382***	-12.463***		-1.210***	-12.331***
	(2.711)		(0.301)	(2.212)	(2.937)		(0.297)	(2.238)
Country fixed effects	NO	YES	YES	NO	NO	YES	YES	NO
Year fixed effects	NO	NO	NO	NO	NO	NO	NO	NO
Observations	2171	1370	2171	2171	2171	1370	2171	2171
Credit booms	61	61	61	61	61	61	61	61
Countries	41	24	41	41	41	24	41	41
Pseudo R2 (LPM: R2)	0.0696	-	-	-	0.0630	-	-	-
Chi-sq	63.61	56.05	-	34.21	50.82	54.10	-	30.78
Prob > chi-sq (LPM: F-test)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0002

Robust standard errors in parentheses
*** 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 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 and LPM estimations without country fixed effects. All independent variables are lagged one quarter.

Table 7. Borrower- and financial institution-targeted macroprudential policies

VARIABLES	Logit (1)	LPM (2)	Firth logit (3)	Logit (4)	LPM (5)	Firth logit (6)	Logit (7)	LPM (8)	Firth logit (9)
Log (VIX)	1.367**	0.031*	1.405*	1.478***	0.033	1.462*	0.773	0.029**	0.796
	(0.660)	(0.016)	(0.731)	(0.466)	(0.021)	(0.822)	(0.479)	(0.014)	(0.494)
Real GDP growth	-0.061	0.001	-0.059	0.163*	0.003	0.141	0.170***	0.006***	0.164***
	(0.075)	(0.002)	(0.081)	(0.091)	(0.004)	(0.143)	(0.053)	(0.002)	(0.055)
Change CB policy rate	0.921***	0.017	0.981**	0.864*	0.019	0.644	0.001	0.000	0.002
	(0.271)	(0.012)	(0.436)	(0.474)	(0.016)	(0.822)	(0.003)	(0.001)	(0.012)
Inflation	-0.024	-0.004	-0.088	0.169	0.001	0.172	0.108	0.003	0.156
	(0.061)	(0.005)	(0.096)	(0.329)	(0.010)	(0.433)	(0.069)	(0.004)	(0.096)
Log (real exchange rate)	-0.102	0.109	-0.025	0.031	0.286	0.068	-0.170	0.054	-0.136
	(0.340)	(0.095)	(0.192)	(0.197)	(0.175)	(0.237)	(0.210)	(0.059)	(0.138)
Bank credit (% of GDP)	0.002	0.001	0.001	-0.001	0.000	0.000	-0.004	0.001***	-0.004
	(0.009)	(0.000)	(0.007)	(0.006)	(0.001)	(0.010)	(0.006)	(0.000)	(0.005)
Log (GDP per capita)	0.953**	0.124**	0.847**	0.850*	0.225	0.664	1.145**	0.075**	1.097***
	(0.293)	(0.061)	(0.421)	(0.496)	(0.137)	(0.738)	(0.558)	(0.037)	(0.311)
LTV_CAP	-0.158	-0.008	-0.141						
	(0.204)	(0.005)	(0.182)						
IBEX				-0.776	-0.001	-0.637			
				(0.500)	(0.014)	(0.465)			
CONCRAT							-0.647	-0.022**	-0.565*
							(0.454)	(0.011)	(0.306)
Constant	-14.820***	-1.160**	-13.841***	-14.272***	-1.937*	-12.720**	-13.738***	-0.746**	-13.488***
	(3.229)	(0.569)	(4.367)	(3.962)	(1.083)	(6.348)	(4.041)	(0.335)	(2.888)
Country fixed effects	NO	YES	NO	NO	YES	NO	NO	YES	NO
Year fixed effects	NO	NO	NO	NO	NO	NO	NO	NO	NO
Observations	807	807	807	645	645	645	1275	1275	1275
Credit booms	16	16	16	16	16	16	38	38	38
Countries	25	25	25	14	14	14	25	25	25
Pseudo R2 (LPM: R2)	0.1176	-	-	0.0691	-	-	0.0896	-	-
Chi-sq	31.65	-	15.26	34.53	-	6.49	43.08	-	21.94
Prob > chi-sq (LPM: F-test)	0.0001	0.0358	0.0544	0.0000	0.3971	0.5924	0.0000	0.0005	0.0050

Robust standard errors in parentheses
*** 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. 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 8. Reserve requirement policies

VARIABLES	Logit (1)	Logit (2)	LPM (3)	Firth logit (4)	Logit (5)	Logit (6)	LPM (7)	Firth logit (8)
Log (VIX)	1.478***	1.677***	0.051***	1.486***	1.389***	1.508***	0.047***	1.389***
	(0.412)	(0.410)	(0.011)	(0.383)	(0.403)	(0.402)	(0.011)	(0.378)
Real GDP growth	0.079*	0.241***	0.005***	0.076*	0.065	0.217***	0.005***	0.061
	(0.047)	(0.066)	(0.001)	(0.043)	(0.045)	(0.062)	(0.001)	(0.041)
Change CB policy rate	0.005	-0.001	0.000	0.006	0.005	-0.001	0.000	0.006
	(0.004)	(0.015)	(0.001)	(0.012)	(0.004)	(0.015)	(0.001)	(0.012)
Inflation	0.140**	0.114	0.002	0.167**	0.128**	0.087	0.002	0.152**
	(0.056)	(0.155)	(0.003)	(0.074)	(0.059)	(0.155)	(0.003)	(0.072)
Log (real exchange rate)	-0.113	5.700**	0.141***	-0.096	-0.130	4.565*	0.089*	-0.110
	(0.127)	(2.733)	(0.051)	(0.091)	(0.135)	(2.738)	(0.048)	(0.094)
Bank credit (% of GDP)	-0.004	0.049**	0.001***	-0.004	-0.005	0.050***	0.001***	-0.005
	(0.005)	(0.015)	(0.000)	(0.004)	(0.005)	(0.015)	(0.000)	(0.004)
Log (GDP per capita)	0.663	5.136***	0.130***	0.648***	0.653	4.232**	0.087***	0.647***
	(0.440)	(1.930)	(0.035)	(0.236)	(0.411)	(1.925)	(0.032)	(0.236)
RR_D	-0.215	-0.655***	-0.012***	-0.208				
	(0.145)	(0.245)	(0.004)	(0.147)				
RR_FX					-0.363	-1.613**	-0.009	-0.114
					(0.332)	(0.746)	(0.006)	(0.407)
Constant	-12.649***		-1.340***	-12.544***	-12.038***		-0.958***	-11.979***
	(2.893)		(0.313)	(2.244)	(2.836)		(0.281)	(2.196)
Country fixed effects	NO	YES	YES	NO	NO	YES	YES	NO
Year fixed effects	NO	NO	NO	NO	NO	NO	NO	NO
Observations	2171	1370	2171	2171	2171	1370	2171	2171
Credit booms	61	61	61	61	61	61	61	61
Countries	41	24	41	41	41	24	41	41
Pseudo R2 (LPM: R2)	0.0612	-	-	-	0.0588	-	-	-
Chi-sq	49.96	53.52	-	30.78	55.57	51.15	-	29.91
Prob > chi-sq (LPM: F-test)	0.0000	0.0000	0.0000	0.0002	0.0000	0.0000	0.0000	0.0002

Robust standard errors in parentheses

*** 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 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.

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 have 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 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 5 and 6. 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 9 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 (columns 5, 6 and 8) except LPM estimation with both country and year fixed effects (column 7). Moreover, the aggregate index MAPP is negative and significant in all estimations with good credit booms (columns 1-3) except for Firth logit (column 4). 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

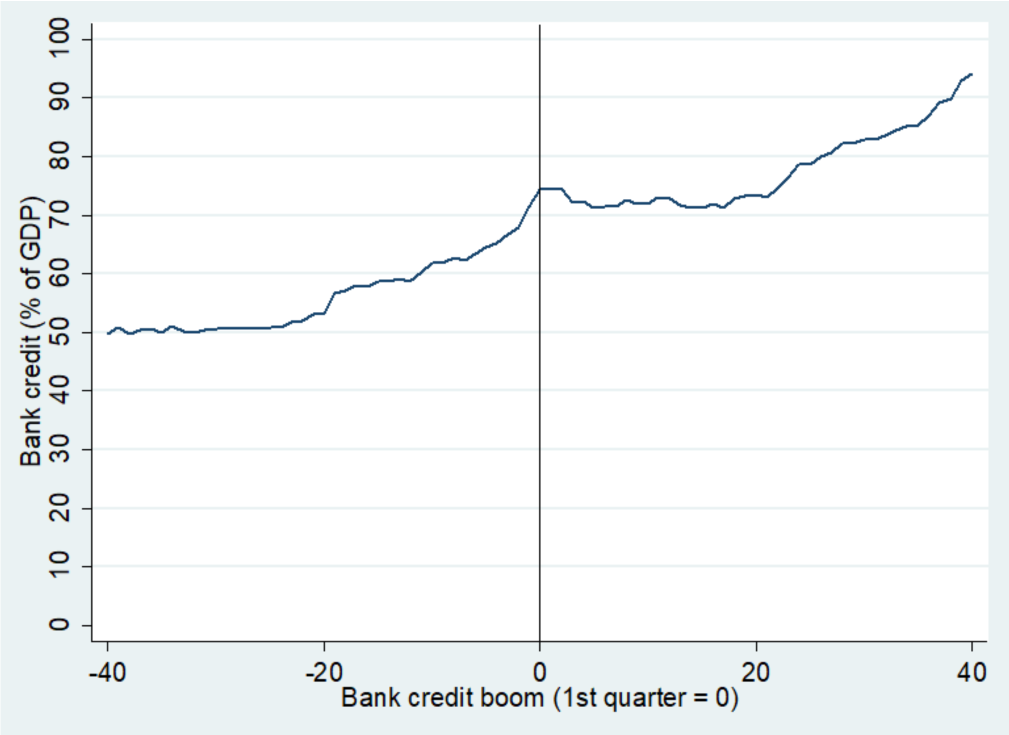


Figure 4. Average ratio of domestic bank credit to GDP around bad boom episodes

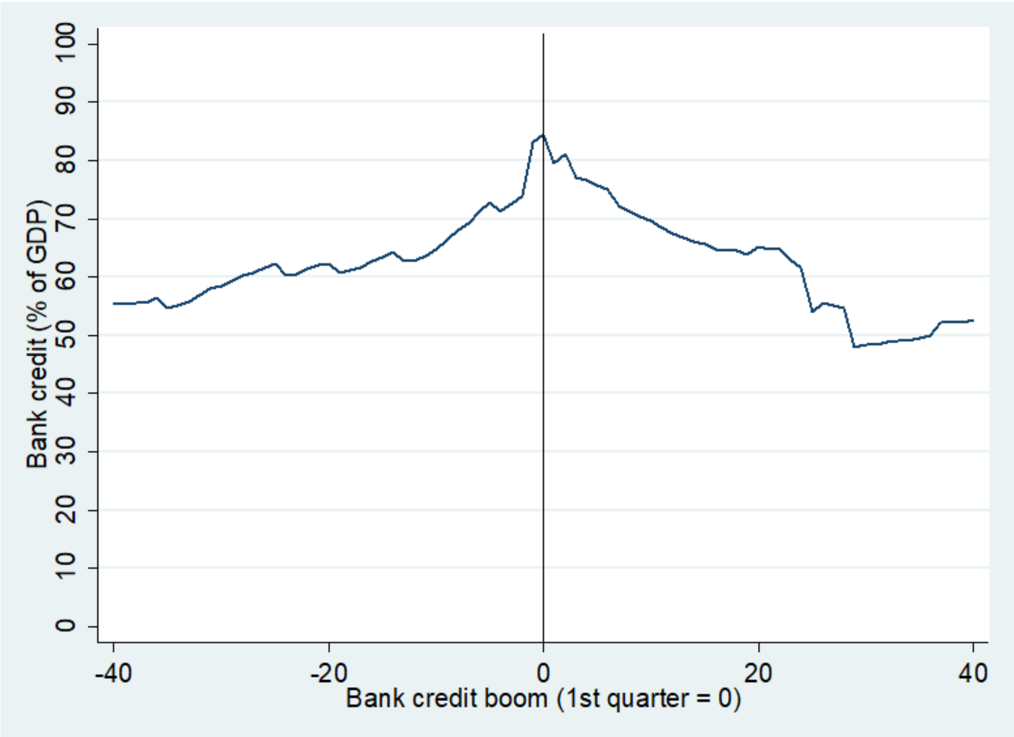


Figure 5. Average real growth rate of GDP around good boom episodes

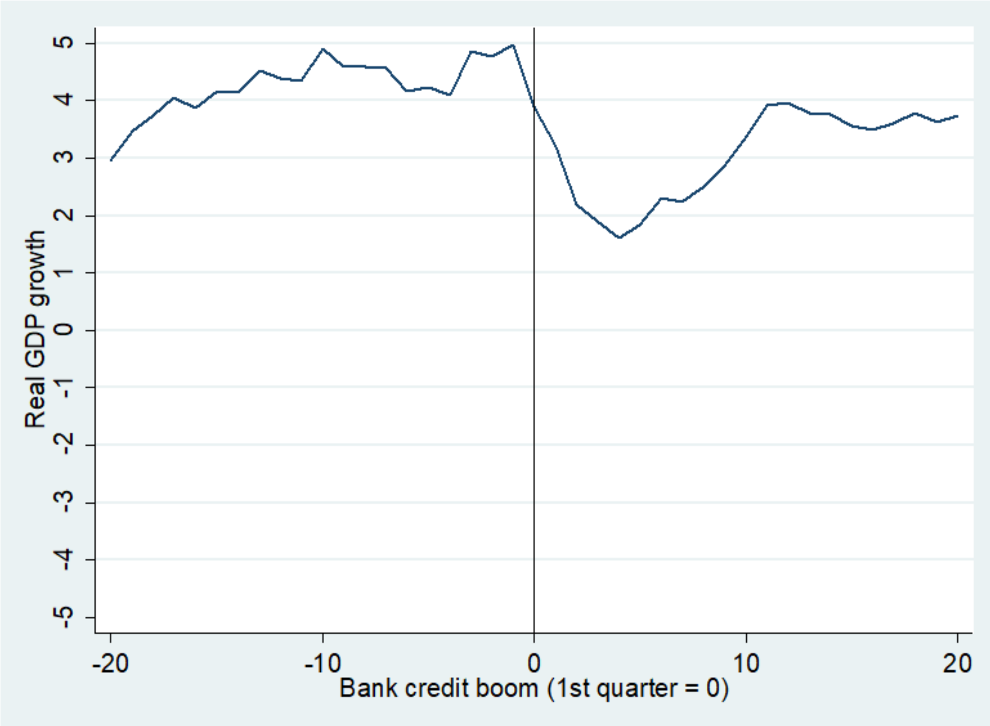


Figure 6. Average real growth rate of GDP around bad boom episodes

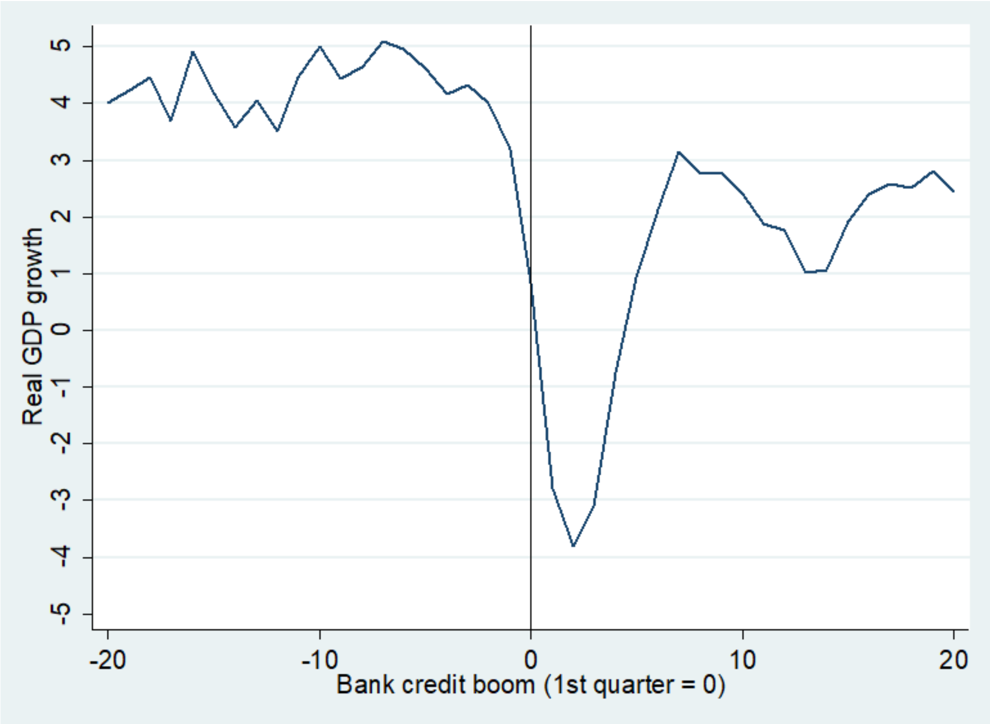


Table 9. Good and bad credit booms

	Good credit boom				Bad credit boom			
	Logit	LPM	LPM	Firth logit	Logit	LPM	LPM	Firth logit
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log (VIX)	1.216***	0.022***	0.039**	1.233**	1.456**	0.022***	0.059***	1.496**
	(0.413)	(0.008)	(0.016)	(0.514)	(0.614)	(0.007)	(0.013)	(0.628)
Real GDP growth	0.159***	0.004***	0.002*	0.154***	-0.023	0.001	-0.001	-0.036
	(0.039)	(0.001)	(0.001)	(0.056)	(0.070)	(0.001)	(0.001)	(0.071)
Change CB policy rate	0.001	0.000	0.000	0.004	0.017	0.000	0.000	0.019
	(0.002)	(0.001)	(0.001)	(0.013)	(0.014)	(0.001)	(0.001)	(0.014)
Inflation	0.086	0.001	-0.001	0.147	0.065	-0.001	-0.002	0.244**
	(0.125)	(0.003)	(0.003)	(0.103)	(0.130)	(0.002)	(0.002)	(0.116)
Log (real exchange rate)	-0.078	0.059	0.055	-0.057	-0.063	0.038	0.021	-0.020
	(0.212)	(0.040)	(0.042)	(0.108)	(0.250)	(0.031)	(0.032)	(0.165)
Bank credit (% of GDP)	-0.007	0.001**	0.001**	-0.006	0.005	0.001***	0.001***	0.005
	(0.006)	(0.000)	(0.000)	(0.005)	(0.008)	(0.000)	(0.000)	(0.006)
Log (GDP per capita)	0.494	0.050*	0.040	0.485*	1.448***	0.057***	0.047**	1.408***
	(0.743)	(0.027)	(0.030)	(0.284)	(0.320)	(0.021)	(0.023)	(0.442)
MAPP	-0.166**	-0.005***	-0.004**	-0.141	-0.515**	-0.002*	-0.000	-0.502***
	(0.081)	(0.002)	(0.002)	(0.098)	(0.203)	(0.001)	(0.001)	(0.157)
Constant	-11.075**	-0.537**	-0.484*	11.063***	-20.233***	-0.554***	-0.581***	-19.978***
	(4.928)	(0.243)	(0.259)	(2.769)	(3.093)	(0.189)	(0.199)	(4.125)
Country fixed effects	NO	YES	YES	NO	NO	YES	YES	NO
Year fixed effects	NO	NO	YES	NO	NO	NO	YES	NO
Observations	2145	2145	2145	2145	2131	2131	2131	2131
Credit booms	35	35	35	35	21	21	21	21
Countries	41	41	41	41	41	41	41	41
Pseudo R2 (LPM: R2)	0.0532	-	-	-	0.1586	-	-	-
Chi-sq	37.98	-	-	20.34	142.26	-	-	32.31
Prob > chi-sq (LPM: F-test	0.0000	0.0009	0.0000	0.0091	0.0000	0.0000	0.0000	0.0001

Robust standard errors in parentheses
*** 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 "good" according to this criterion are defined as "good". Robust standard errors clustered by country are reported for Logit and LPM estimations without country fixed effects. 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 7 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 8 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 A2 and A3 in the appendix show the behavior of both household credit 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 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.

Figure 7. Average household credit (% of GDP) around good credit booms

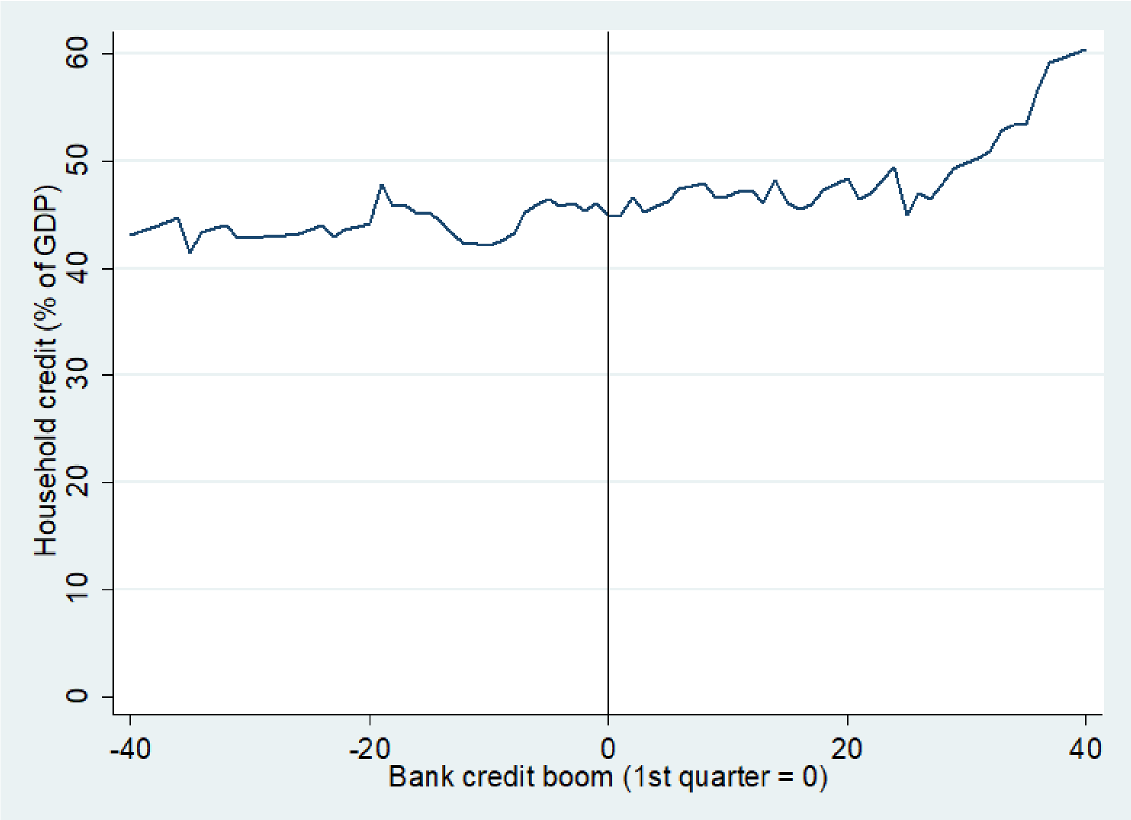


Figure 8. Average household credit (% of GDP) around bad credit booms

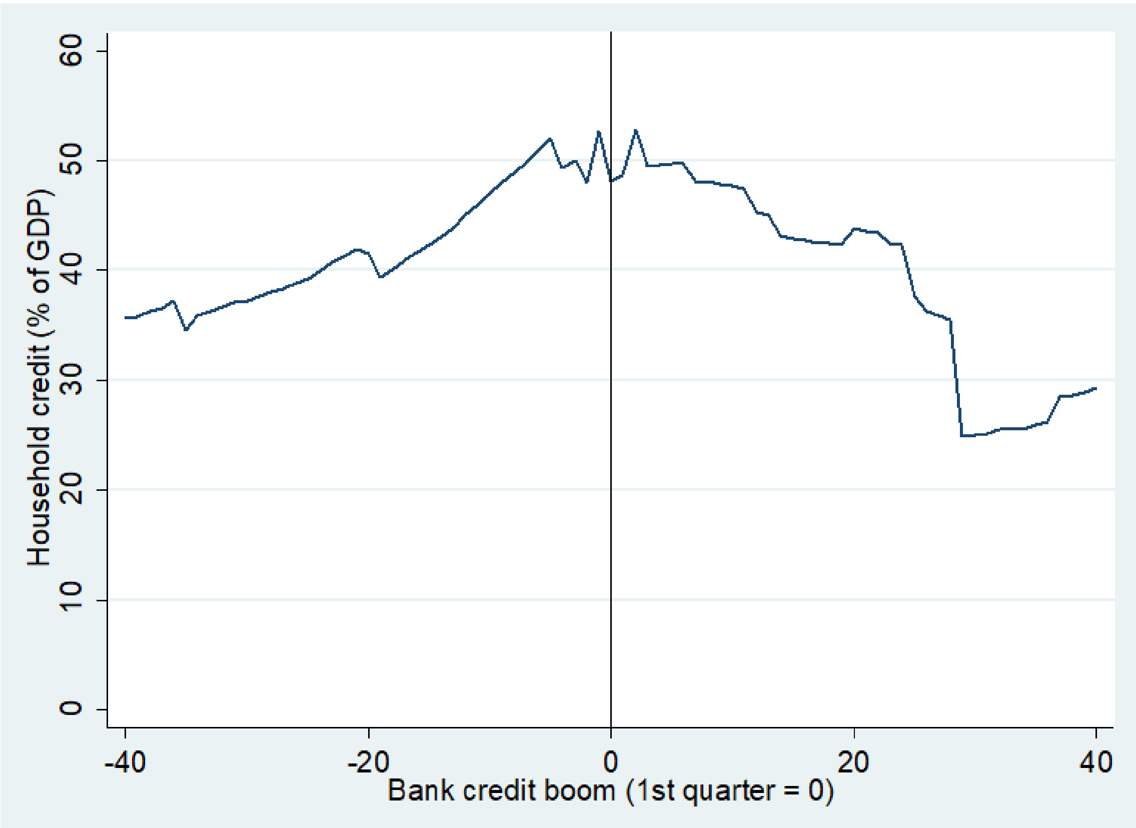


Table 10 shows the results for the MAPP index and household credit booms with threshold 1.75 standard deviations. The measure of household credit includes not only domestic bank credit but also credit from non-bank financial institutions and cross-border credit. Consequently, this credit measure is suitable 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 statistically significant in all estimations except for LPM with only year fixed effects.

The results for the macroprudential sub-indexes MAPP_B_FI and MAPP_RR are shown in Table 11. 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 6) 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.

Table 10. Aggregate macroprudential index (MAPP) and household credit booms

VARIABLES	Logit (1)	Logit (2)	Logit (3)	Logit (4)	LPM (5)	LPM (6)	LPM (7)	Firth logit (8)
Log (VIX)	0.020	0.064	1.594***	1.629*	0.006	0.041**	0.040**	0.039
	(0.624)	(0.527)	(0.609)	(0.989)	(0.011)	(0.018)	(0.020)	(0.474)
Real GDP growth	0.268***	0.482***	0.230**	0.431***	0.007***	0.003	0.006***	0.263***
	(0.072)	(0.095)	(0.114)	(0.123)	(0.001)	(0.002)	(0.002)	(0.051)
Change CB policy rate	-0.002	0.028	-0.002	-0.020	-0.000	0.000	-0.000	0.005
	(0.003)	(0.243)	(0.005)	(0.280)	(0.001)	(0.000)	(0.001)	(0.014)
Inflation	0.170*	0.214	0.128	0.128	0.000	0.001	0.000	0.219**
	(0.087)	(0.197)	(0.091)	(0.210)	(0.002)	(0.001)	(0.002)	(0.104)
Log (real exchange rate)	0.137	16.541***	0.136	11.378*	0.112**	0.003	0.059	0.139*
	(0.127)	(4.407)	(0.121)	(5.840)	(0.050)	(0.003)	(0.051)	(0.078)
Household credit (% of GDP)	0.016*	0.074***	0.020*	0.238***	0.001**	0.000	0.003***	0.015**
	(0.009)	(0.028)	(0.011)	(0.059)	(0.000)	(0.000)	(0.001)	(0.007)
Log (GDP per capita)	0.180	11.718***	-0.032	7.879*	0.065*	0.001	0.066*	0.190
	(0.461)	(3.410)	(0.500)	(4.765)	(0.036)	(0.011)	(0.039)	(0.274)
MAPP	-0.304***	-0.708***	-0.304**	-0.475*	-0.009***	-0.003	-0.004*	-0.294***
	(0.099)	(0.170)	(0.146)	(0.250)	(0.003)	(0.002)	(0.003)	(0.089)
Constant	-7.160*		-9.999**		-0.694**	-0.099	-0.727**	-7.211***
	(3.719)		(4.354)		(0.311)	(0.117)	(0.332)	(2.486)
Country fixed effects	NO	YES	NO	YES	YES	NO	YES	NO
Year fixed effects	NO	NO	YES	YES	NO	YES	YES	NO
Observations	1990	1031	1276	1031	1990	1990	1990	1990
Credit booms	49	49	49	49	49	49	49	49
Countries	37	19	35	19	37	37	37	37
Pseudo R2 (LPM: R2)	0.0801	-	0.1487	-	-	0.0589	-	-
Chi-sq	24.47	-	498.43	-	-	-	-	36.49
Prob > chi-sq (LPM: F-test)	0.0019	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Robust standard errors in parentheses
*** 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 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.

Table 11. Aggregate macroprudential sub-indexes (MAPP_B_FI & MAPP_RR)

	Logit	Logit	LPM	Firth logit	Logit	Logit	LPM	Firth logit
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log (VIX)	-0.101	-0.106	0.003	0.039	-0.027	0.126	0.008	-0.006
	(0.600)	(0.525)	(0.011)	(0.474)	(0.643)	(0.522)	(0.011)	(0.471)
Real GDP growth	0.239***	0.462***	0.007***	0.263***	0.238***	0.492***	0.007***	0.233***
	(0.075)	(0.096)	(0.001)	(0.051)	(0.072)	(0.092)	(0.001)	(0.049)
Change CB policy rate	-0.001	-0.084	-0.000	0.005	-0.001	-0.028	-0.000	0.006
	(0.003)	(0.230)	(0.001)	(0.014)	(0.004)	(0.242)	(0.001)	(0.014)
Inflation	0.143	0.167	0.000	0.219**	0.139	0.162	0.000	0.193*
	(0.094)	(0.202)	(0.002)	(0.104)	(0.085)	(0.196)	(0.002)	(0.110)
Log (real exchange rate)	0.159	21.461***	0.136***	0.139*	0.088	10.523***	0.105**	0.090
	(0.120)	(4.883)	(0.050)	(0.078)	(0.103)	(3.546)	(0.051)	(0.073)
Household credit (% of GDP)	0.014	0.075**	0.001***	0.015**	0.012	0.062	0.001**	0.011*
	(0.009)	(0.030)	(0.000)	(0.007)	(0.009)	(0.026)	(0.000)	(0.007)
Log (GDP per capita)	0.244	15.828***	0.084**	0.190	0.110	6.523**	0.052	0.115
	(0.439)	(3.963)	(0.036)	(0.274)	(0.463)	(2.726)	(0.036)	(0.275)
MAPP_B_FI	-0.441***	-1.205***	-0.013***	-0.294***				
	(0.159)	(0.273)	(0.004)	(0.089)				
MAPP_RR					-0.245	-0.444*	-0.008*	-0.240*
					(0.158)	(0.236)	(0.004)	(0.131)
Constant	-6.890**		-0.852***	-7.211***	-6.208*		-0.594*	-6.232**
	(3.513)		(0.314)	(2.486)	(3.489)		(0.316)	(2.427)
Country fixed effects	NO	YES	YES	NO	NO	YES	YES	NO
Year fixed effects	NO	NO	NO	NO	NO	NO	NO	NO
Observations	1990	1031	1990	1990	1990	1031	1990	1990
Credit booms	49	49	49	49	49	49	49	49
Countries	37	19	37	37	37	19	37	37
Pseudo R2 (LPM: R2)	0.0794	-	-	-	0.0579	-	-	-
Chi-sq	16.37	75.68	-	36.42	22.79	52.02	-	28.78
Prob > chi-sq (LPM: F-test)	0.0373	0.0000	0.0000	0.0000	0.0036	0.0000	0.0000	0.0003

Robust standard errors in parentheses
*** 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 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 and LPM estimations without country fixed effects. All independent variables are lagged one quarter.

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 12 shows the average marginal effects for the macroprudential index MAPP (column 1 in Table 5, and columns 1 and 5 in Table 13) 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 frequency of credit booms with this threshold is only 2.81 percent. Moreover, the results in Table 12 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 and 2 standard deviations are shown in columns 1 and 3 in Table 12. An increase in the MAPP index by one standard deviation reduces the likelihood of smaller credit booms (threshold 1 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 threshold 1 and 1.75 standard deviations.

It could be of interest to examine whether the effectiveness of macroprudential policies differs 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 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 12. Average marginal effects for macroprudential indexes

	Bank credit			**Household credit**		
	Boom threshold			Boom threshold		
	1.5 s.d	1.75 s.d.	2 s.d.	1.5 s.d	1.75 s.d.	2 s.d.
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
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
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)	(0.005)	(0.004)	(0.003)
Observations	2171	2171	2171	1990	1990	1990
Countries	41	41	41	37	37	37
Booms	119	61	32	78	49	25
Std. Dev.	0.629	0.629	0.629	0.497	0.497	0.497

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

6. Robustness tests

To examine the robustness of the results it is essential to identify credit booms with different thresholds. Figure 9 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 11 show 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.

Table 13 show that the coefficient for the macroprudential policy index (MAPP) is negative and significant at the 1% level in all estimations with small credit booms (1.5 s.d.). For larger credit booms (2 s.d.) the MAPP index is negative and significant in all estimations except for LPM with both country and year fixed effects. To conclude, the findings suggest that macroprudential policies are effective to deal with both smaller and larger credit booms.

Figure 9. Distribution of credit booms with different thresholds between 2000Q1-2014Q4

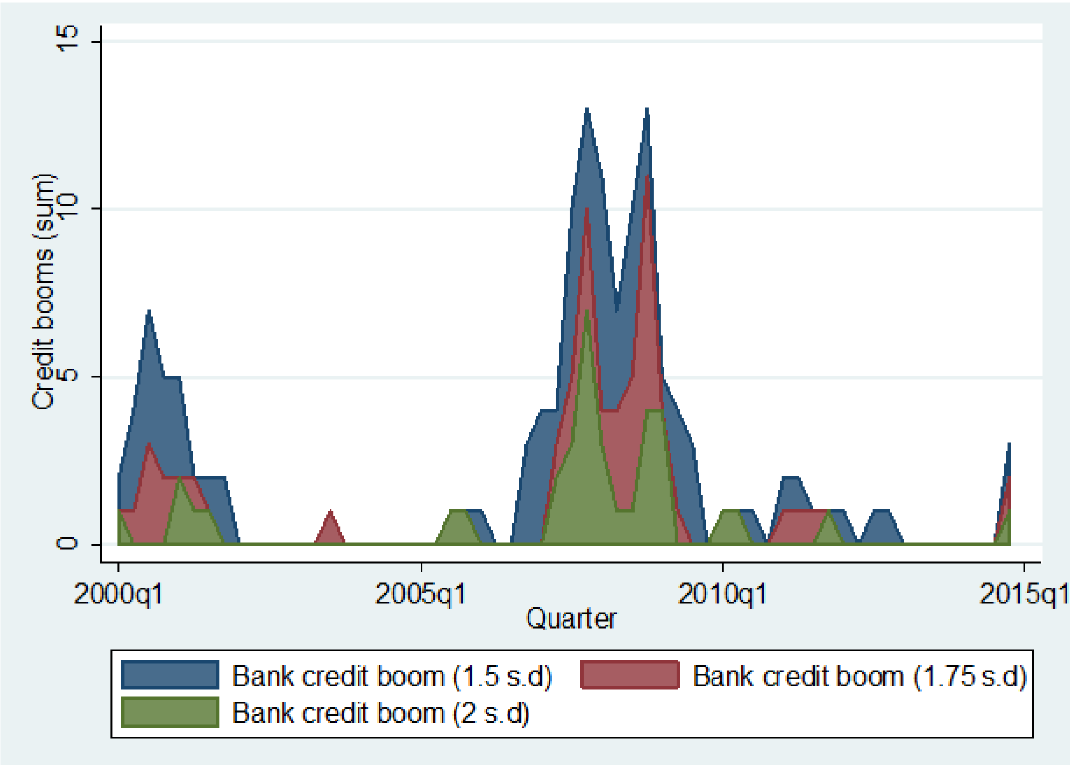


Table 13. MAPP index and credit booms with different thresholds

	Boom threshold 1.5 s.d.				Boom threshold 2 s.d.			
	Logit	LPM	LPM	Firth logit	Logit	LPM	LPM	Firth logit
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log (VIX)	1.632***	0.082***	0.085***	1.622***	1.789***	0.032***	0.077***	1.781***
	(0.393)	(0.015)	(0.027)	(0.304)	(0.644)	(0.008)	(0.015)	(0.511)
Real GDP growth	0.077*	0.011***	0.005***	0.076**	0.092	0.003***	0.001	0.090
	(0.045)	(0.002)	(0.002)	(0.033)	(0.056)	(0.001)	(0.001)	(0.063)
Change CB policy rate	0.712***	0.005***	0.005***	0.687***	0.005	0.000	0.000	0.018
	(0.187)	(0.001)	(0.001)	(0.172)	(0.006)	(0.001)	(0.001)	(0.018)
Inflation	0.250***	0.005	-0.003	0.255***	0.025	-0.002	-0.002	-0.022
	(0.079)	(0.004)	(0.004)	(0.084)	(0.084)	(0.002)	(0.003)	(0.188)
Log (real exchange rate)	-0.184*	0.370***	0.330***	-0.172**	0.013	0.072*	0.044	0.034
	(0.109)	(0.067)	(0.069)	(0.075)	(0.151)	(0.037)	(0.039)	(0.117)
Bank credit (% of GDP)	0.003	0.003***	0.004***	0.003	-0.010*	0.001***	0.001***	-0.010*
	(0.004)	(0.000)	(0.000)	(0.003)	(0.006)	(0.000)	(0.000)	(0.006)
Log (GDP per capita)	0.536	0.288***	0.267***	0.524***	1.113**	0.078***	0.050*	1.072***
	(0.345)	(0.046)	(0.048)	(0.176)	(0.482)	(0.025)	(0.027)	(0.332)
MAPP	-0.221***	-0.014***	-0.009***	-0.214***	-0.259***	-0.004**	-0.002	-0.242*
	(0.067)	(0.003)	(0.003)	(0.063)	(0.095)	(0.002)	(0.002)	(0.125)
Constant	-10.873***	-2.994***	-2.703***	-11.921***	-16.961***	-0.778***	-0.692***	-16.496***
	(2.352)	(0.411)	(0.421)	(1.742)	(3.214)	(0.225)	(0.237)	(3.144)
Country fixed effects	NO	YES	YES	NO	NO	YES	YES	NO
Year fixed effects	NO	NO	YES	NO	NO	NO	YES	NO
Observations	2171	2171	2171	2171	2171	2171	2171	2171
Credit booms	119	119	119	119	32	32	32	32
Countries	41	41	41	41	41	41	41	41
Pseudo R2 (LPM: R2)	0.1149	-	-	-	0.0976	-	-	-
Chi-sq	74.59	-	-	69.03	42.94	-	-	29.24
Prob > chi-sq (LPM: F-test)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0003

Robust standard errors in parentheses
*** 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 14 shows results for borrower- and financial institution-targeted policies with boom threshold 1.5 standard deviations. The coefficient for concentration limits is negative and significant at the 1% level for LPM with country fixed effects and at the 5% level for Firth logit. Moreover, interbank exposure limits are negative and significant at the 10% level for logit and 5% level for Firth logit. However, the coefficient for Loan-to-Value caps remains insignificant. The number of credit booms is about twice as many compared to for boom threshold 1.75 standard deviations shown in Table 7. In addition, results for credit booms with threshold 1.25 standard deviations are shown in Table A2 in the appendix. The results show that the coefficient for Loan-to-Value caps is negative and significant at the 5% level for LPM with country fixed effects.

Table 14. Borrower- and financial institution-targeted policies (boom threshold 1.5 s.d.)

VARIABLES	Logit (1)	LPM (2)	Firth logit (3)	Logit (4)	LPM (5)	Firth logit (6)	Logit (7)	LPM (8)	Firth logit (9)
Log (VIX)	1.239**	0.059**	1.250**	2.037***	0.105***	1.980***	0.997**	0.055***	0.991**
	(0.512)	(0.025)	(0.493)	(0.565)	(0.030)	(0.602)	(0.473)	(0.019)	(0.399)
Real GDP growth	-0.037	0.002	-0.034	0.304***	0.016***	0.290***	0.150***	0.013***	0.147***
	(0.073)	(0.003)	(0.053)	(0.078)	(0.005)	(0.107)	(0.049)	(0.002)	(0.043)
Change CB policy rate	0.766**	0.028	0.806**	1.321*	0.046**	1.212*	0.695***	0.005***	0.639***
	(0.320)	(0.018)	(0.353)	(0.712)	(0.023)	(0.623)	(0.187)	(0.001)	(0.185)
Inflation	0.077	-0.002	-0.012	0.342	0.010	0.334	0.107	0.006	0.129
	(0.118)	(0.007)	(0.127)	(0.314)	(0.014)	(0.297)	(0.097)	(0.006)	(0.143)
Log (real exchange rate)	-0.196	0.241*	-0.159	-0.160	0.698***	-0.132	-0.221	0.229***	-0.199*
	(0.353)	(0.146)	(0.145)	(0.233)	(0.251)	(0.162)	(0.209)	(0.076)	(0.111)
Bank credit (% of GDP)	0.009	0.002***	0.008*	0.006	0.001	0.006	-0.001	0.002***	-0.001
	(0.009)	(0.001)	(0.004)	(0.007)	(0.001)	(0.007)	(0.006)	(0.001)	(0.004)
Log (GDP per capita)	0.945***	0.232**	0.885***	0.369	0.517***	0.279	0.877**	0.183***	0.844***
	(0.331)	(0.094)	(0.288)	(0.505)	(0.196)	(0.423)	(0.379)	(0.048)	(0.237)
LTV_CAP	-0.088	-0.013	-0.077						
	(0.132)	(0.008)	(0.113)						
IBEX				-0.872*	0.006	-0.794**			
				(0.493)	(0.021)	(0.327)			
CONCRAT							-0.663	-0.038***	-0.610**
							(0.432)	(0.014)	(0.244)
Constant	-14.173***	-2.348***	-13.559***	-12.593***	-4.622***	-11.659***	-12.080***	-1.883***	-11.821***
	(3.625)	(0.873)	(2.948)	(4.176)	(1.552)	(3.901)	(2.871)	(0.432)	(2.296)
Country fixed effects	NO	YES	NO	NO	YES	NO	NO	YES	NO
Year fixed effects	NO	NO	NO	NO	NO	NO	NO	NO	NO
Observations	807	807	807	645	645	645	1275	1275	1275
Credit booms	41	41	41	36	36	36	68	68	68
Countries	25	25	25	14	14	14	25	25	25
Pseudo R2 (LPM: R2)	0.1342	-	-	0.1339	-	-	0.1336	-	-
Chi-sq	40.96	-	25.91	75.92	-	27.08	43.06	-	42.40
Prob > chi-sq (LPM: F-test)	0.0000	0.0000	0.0011	0.0000	0.0000	0.0007	0.0000	0.0000	0.0000

Robust standard errors in parentheses
*** 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. 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 1.5 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.

The results for individual reserve requirement policies and credit booms with threshold 1.5 standard deviations are shown in Table 15. The coefficient for reserve requirements on accounts denominated in domestic currency (RR_D) is negative and significant at least at the 5% level in all estimations. However, reserve requirements on foreign currency accounts (RR_FX) are only negative and significant in the LPM estimation with country fixed effects.

Table 15. Reserve requirement policies (boom threshold 1.5 s.d.)

VARIABLES	Logit (1)	Logit (2)	LPM (3)	Firth logit (4)	Logit (5)	Logit (6)	LPM (7)	Firth logit (8)
Log (VIX)	1.660***	1.967***	0.087***	1.651***	1.589***	1.838***	0.082***	1.575***
	(0.396)	(0.337)	(0.015)	(0.301)	(0.391)	(0.328)	(0.015)	(0.300)
Real GDP growth	0.067	0.217***	0.010***	0.066**	0.049	0.201***	0.010***	0.048
	(0.043)	(0.051)	(0.002)	(0.033)	(0.042)	(0.049)	(0.002)	(0.032)
Change CB policy rate	0.691***	0.748***	0.005***	0.667***	0.752***	0.744***	0.005***	0.732***
	(0.153)	(0.236)	(0.001)	(0.158)	(0.224)	(0.244)	(0.001)	(0.179)
Inflation	0.246***	0.174	0.007	0.250***	0.221***	0.152	0.006	0.225***
	(0.073)	(0.141)	(0.004)	(0.084)	(0.079)	(0.139)	(0.005)	(0.084)
Log (real exchange rate)	-0.192*	7.795***	0.352***	-0.180**	-0.218*	7.262***	0.270***	-0.203**
	(0.107)	(2.416)	(0.069)	(0.073)	(0.117)	(2.464)	(0.065)	(0.076)
Bank credit (% of GDP)	0.003	0.045***	0.003***	0.003	0.002	0.045***	0.003***	0.002
	(0.004)	(0.009)	(0.000)	(0.003)	(0.005)	(0.009)	(0.000)	(0.003)
Log (GDP per capita)	0.515	6.205***	0.260***	0.500***	0.492	5.766***	0.192**	0.483***
	(0.352)	(1.765)	(0.047)	(0.176)	(0.328)	(1.804)	(0.042)	(0.175)
RR_D	-0.253**	-0.508**	-0.020***	-0.248**				
	(0.109)	(0.245)	(0.006)	(0.108)				
RR_FX					-0.435	-0.837	-0.018**	-0.298
					(0.305)	(0.936)	(0.008)	(0.267)
Constant	-12.062***		-2.784***	-11.910***	-11.358***		-2.176***	-11.227***
	(2.890)		(0.420)	(1.731)	(2.743)		(0.377)	(1.695)
Country fixed effects	NO	YES	YES	NO	NO	YES	YES	NO
Year fixed effects	NO	NO	NO	NO	NO	NO	NO	NO
Observations	2171	1370	2171	2171	2171	1370	2171	2171
Credit booms	119	119	119	119	119	119	119	119
Countries	41	24	41	41	41	24	41	41
Pseudo R2 (LPM: R2)	0.1040	-	-	-	0.1017	-	-	-
Chi-sq	72.97	126.90	-	66.13	57.96	123.84	-	61.75
Prob > chi-sq (LPM: F-test)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Robust standard errors in parentheses
*** 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 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 1.5 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.

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 16. 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.

Table 16. Separate estimations for time periods 2000Q1-2006Q4 and 2007Q1-2014Q4

	2000Q1-2006Q4				2007Q1-2014Q4			
	Logit	LPM	LPM	Firth logit	Logit	LPM	LPM	Firth logit
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log (VIX)	1.968***	0.059**	0.007	1.832**	1.392***	0.073***	0.109***	1.392***
	(0.711)	(0.025)	(0.043)	(0.742)	(0.380)	(3.487)	(3.161)	(4.006)
Real GDP growth	0.332***	0.015***	0.009***	0.317***	0.054	0.008***	0.004	0.053
	(0.089)	(0.003)	(0.003)	(0.088)	(0.050)	(3.064)	(1.436)	(1.398)
Change CB policy rate	0.896**	0.005***	0.005***	0.744***	0.875***	0.036**	0.027*	0.863***
	(0.450)	(0.001)	(0.001)	(0.268)	(0.339)	(2.435)	(1.869)	(3.234)
Inflation	0.141	0.001	-0.004	0.181	0.344**	0.013	-0.003	0.343***
	(0.194)	(0.005)	(0.005)	(0.246)	(0.160)	(1.541)	(-0.400)	(2.495)
Log (real exchange rate)	-1.756***	0.489***	0.489***	-1.445***	-0.068	0.960***	0.556***	-0.059
	(0.580)	(0.084)	(0.087)	(0.553)	(0.124)	(5.427)	(3.049)	(-0.767)
Bank credit (% of GDP)	0.005	0.002*	0.002***	0.005	0.001	0.005***	0.007***	0.001
	(0.009)	(0.001)	(0.001)	(0.008)	(0.004)	(5.260)	(7.902)	(0.222)
Log (GDP per capita)	-1.051**	0.271***	0.330***	-0.909**	0.658*	0.831***	0.524***	0.635***
	(0.490)	(0.068)	(0.069)	(0.457)	(0.398)	(6.843)	(4.415)	(3.217)
MAPP	-0.966*	-0.016**	-0.010	-0.923***	-0.207***	-0.020***	-0.008	-0.198***
	(0.493)	(0.008)	(0.008)	(0.331)	(0.067)	(-3.438)	(-1.316)	(-3.532)
Constant	-3.748	-2.951***	-3.082***	-4.172	-11.732***	-7.709***	-5.133***	-11.530***
	(4.217)	(0.595)	(0.595)	(4.439)	(2.997)	(-7.204)	(-4.871)	(-5.926)
Country fixed effects	NO	YES	YES	NO	NO	YES	YES	NO
Year fixed effects	NO	NO	YES	NO	NO	NO	YES	NO
Observations	938	938	938	938	1233	1233	1233	1233
Credit booms	31	31	31	31	88	88	88	88
Countries	37	37	37	37	41	41	41	41
Pseudo R2 (LPM: R2)	0.3116	-	-	-	0.0976	-	-	-
Chi-sq	42.90	-	-	43.08	63.23	-	-	43.85
Prob > chi-sq (LPM: F-test)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Robust standard errors in parentheses
*** 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.

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 10 and 11 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 10 and 11. 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 17. Table A3 in the appendix shows that one-third of the 41 countries are classified as developing countries and two thirds as advanced economies. 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.

Furthermore, re-estimating the specifications in Table 17 for the macroprudential sub-indexes show 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, index MAPP_RR 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 10 and 11.

Figure 10. Macroprudential policy indexes (averages) in advanced countries

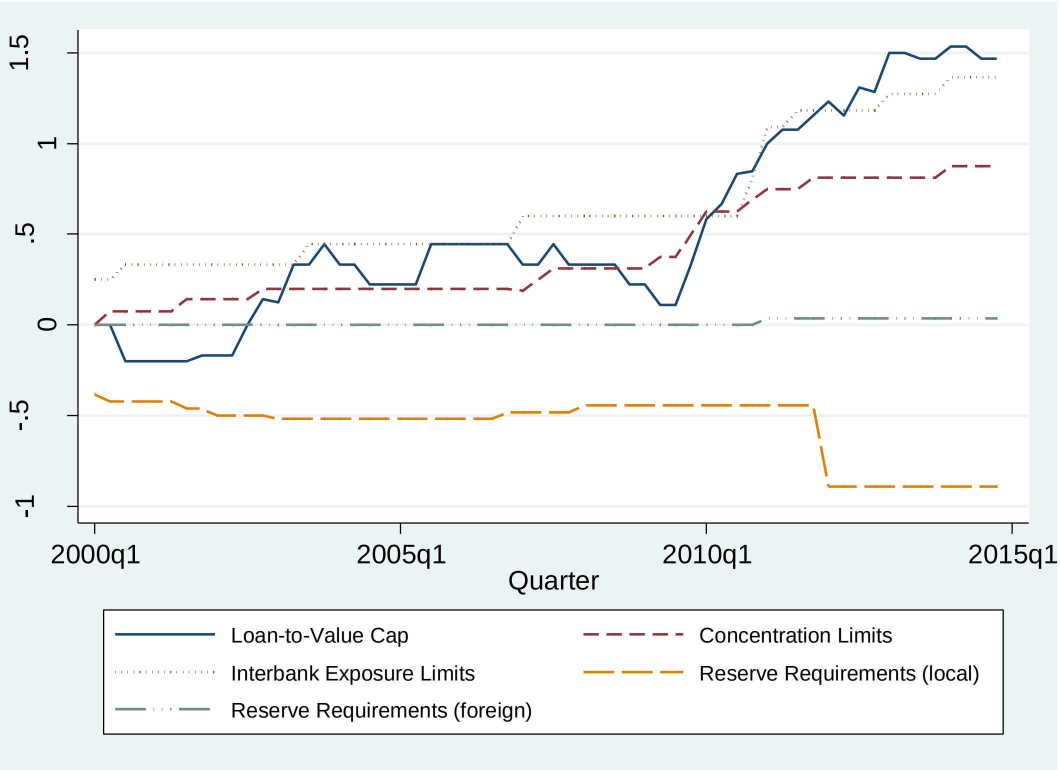


Figure 11. Macroprudential policy indexes (averages) in developing countries

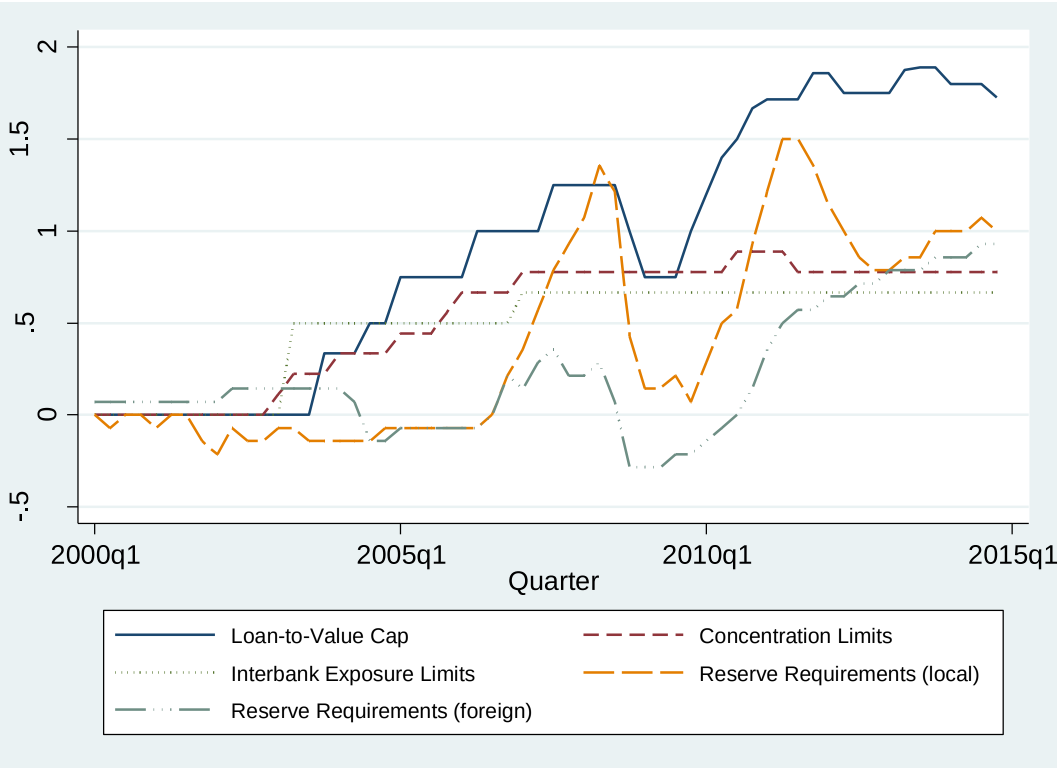


Table 17. Separate estimations for advanced and developing countries

	Advanced countries				Developing countries			
	Logit	LPM	LPM	Firth logit	Logit	LPM	LPM	Firth logit
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log (VIX)	1.779***	0.108***	0.100***	1.769***	1.535	0.064***	0.076*	1.591**
	(0.355)	(0.019)	(0.035)	(0.345)	(1.377)	(0.022)	(0.040)	(0.648)
Real GDP growth	0.052	0.008***	-0.000	0.051	0.153***	0.009***	0.008***	0.171**
	(0.053)	(0.003)	(0.003)	(0.040)	(0.030)	(0.002)	(0.003)	(0.067)
Change CB policy rate	0.931***	0.058***	0.037**	0.901***	0.560***	0.005***	0.005***	0.017
	(0.326)	(0.016)	(0.016)	(0.273)	(0.191)	(0.001)	(0.001)	(0.017)
Inflation	0.294**	0.003	-0.004	0.294*	0.235*	0.006	0.001	0.192**
	(0.128)	(0.007)	(0.007)	(0.157)	(0.138)	(0.005)	(0.005)	(0.082)
Log (real exchange rate)	-0.347*	0.561***	0.603***	-0.323**	-0.091	0.312***	0.378***	-0.053
	(0.189)	(0.118)	(0.134)	(0.126)	(0.160)	(0.080)	(0.096)	(0.120)
Bank credit (% of GDP)	0.005	0.003***	0.003***	0.005	0.008	0.004***	0.008***	0.008
	(0.005)	(0.000)	(0.001)	(0.003)	(0.012)	(0.001)	(0.001)	(0.008)
Log (GDP per capita)	1.094**	0.408***	0.502***	1.081***	0.771*	0.266***	0.296***	0.760*
	(0.491)	(0.085)	(0.116)	(0.258)	(0.432)	(0.049)	(0.047)	(0.442)
MAPP	-0.214**	-0.014**	-0.003	-0.211***	-0.237**	-0.015***	-0.015***	-0.196**
	(0.103)	(0.006)	(0.006)	(0.081)	(0.097)	(0.003)	(0.003)	(0.094)
Constant	-16.802***	-3.987***	-4.531***	-16.64***	-13.491**	-2.928***	-3.475***	-13.471***
	(3.602)	(0.714)	(0.942)	(2.406)	(5.310)	(0.523)	(0.547)	(3.881)
Country fixed effects	NO	YES	YES	NO	NO	YES	YES	NO
Year fixed effects	NO	NO	YES	NO	NO	NO	YES	NO
Observations	1563	1563	1563	1563	608	608	608	608
Credit booms	96	96	96	96	23	23	23	23
Countries	27	27	27	27	14	14	14	14
Pseudo R2 (LPM: R2)	0.1007	-	-	-	0.2216	-	-	-
Chi-sq	79.09	-	-	58.29	187.52	-	-	22.83
Prob > chi-sq (LPM: F-test)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0036

Robust standard errors in parentheses
*** 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.

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) suggest 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 18 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 (columns 5-9). In addition, the MAPP index is negative and significant at the 5% level for the Firth logit estimation with boom threshold 1.5 standard deviations (column 3).

Table 18. Credit booms identified with Hamilton filter

	Boom threshold 1.5 s.d.			Boom threshold 1.75 s.d.			Boom threshold 2 s.d.		
	Logit	LPM	Firth logit	Logit	LPM	Firth logit	Logit	LPM	Firth logit
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log (VIX)	0.007	0.058***	0.017	-0.080	0.055***	-0.058	0.123	0.016	0.165
	(0.466)	(0.021)	(0.259)	(0.570)	(0.016)	(0.362)	(0.686)	(0.012)	(0.556)
Real GDP growth	0.087*	0.003	0.086***	0.090**	0.002	0.088**	0.099**	0.001	0.096*
	(0.049)	(0.003)	(0.028)	(0.045)	(0.002)	(0.038)	(0.040)	(0.001)	(0.057)
Change CB policy rate	0.002	0.000	0.003	0.002	0.000	0.006	0.003	0.000	0.008
	(0.002)	(0.000)	(0.011)	(0.003)	(0.000)	(0.012)	(0.002)	(0.000)	(0.013)
Inflation	0.173*	0.009	0.181***	0.194**	0.007	0.210***	0.224**	0.006	0.240***
	(0.097)	(0.008)	(0.053)	(0.082)	(0.005)	(0.063)	(0.092)	(0.003)	(0.071)
Log (real exchange rate)	-0.321***	-0.013***	-0.312***	-0.303***	-0.007***	-0.287***	-0.453*	-0.004**	-0.400**
	(0.104)	(0.004)	(0.073)	(0.104)	(0.002)	(0.097)	(0.253)	(0.002)	(0.163)
Bank credit (% of GDP)	0.008	0.000	0.008***	0.010**	0.000*	0.010***	0.008	0.000	0.008*
	(0.005)	(0.000)	(0.002)	(0.004)	(0.000)	(0.003)	(0.008)	(0.000)	(0.005)
Log (GDP per capita)	-0.071	-0.009	-0.071	-0.214	-0.011	-0.212	-0.761**	-0.012	-0.724***
	(0.253)	(0.016)	(0.132)	(0.311)	(0.012)	(0.174)	(0.364)	(0.009)	(0.252)
MAPP	-0.081	-0.004	-0.076**	-0.111	-0.003*	-0.101*	-0.228*	-0.002*	-0.199*
	(0.070)	(0.003)	(0.035)	(0.075)	(0.002)	(0.052)	(0.130)	(0.001)	(0.108)
Constant	-2.797	-0.063	-2.811	-2.549	-0.079	-2.604	-0.097	0.048	-0.437
	(2.246)	(0.121)	(1.296)	(2.505)	(0.092)	(1.749)	(2.374)	(0.069)	(2.682)
Country fixed effects	NO	NO	NO	NO	NO	NO	NO	NO	NO
Year fixed effects	NO	YES	NO	NO	YES	NO	NO	YES	NO
Observations	2149	2149	2149	2149	2149	2149	2149	2149	2149
Credit booms	158	158	158	79	79	79	33	33	33
Countries	41	41	41	41	41	41	41	41	41
Pseudo R2 (LPM: R2)	0.0527	0.1008	-	0.0500	0.0752	-	0.0781	0.0400	-
Chi-sq	21.23	-	44.18	24.22	-	29.16	20.06	-	28.10
Prob > chi-sq (LPM: F-test)	0.0065	0.0006	0.0000	0.0021	0.0004	0.0003	0.0101	0.0000	0.0005

Robust standard errors in parentheses
*** 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 1.5, 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.

6.2. Additional control variables in the analysis

It is important to verify whether the results hold when controlling for other prudential policies. Table 19 report 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 take 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 19 show that the coefficient for the MAPP index is negative and significant at the 5% or 10% 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 highly significant both with and without country fixed effects for booms generated with the Hodrick-Prescott (HP) filter. However, the coefficient for the MAPP index is not significant for the LPM estimation with only year fixed effects for credit booms identified with the HP filter.

Table 19. Estimations including bank-capital-based prudential policies

	Hodrick-Prescott (HP) filter				Hamilton filter			
	Logit	LPM	LPM	Firth logit	Logit	LPM	LPM	Firth logit
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log (VIX)	1.178***	0.037***	0.095***	1.198***	0.208	0.010	0.062***	0.230
	(0.447)	(0.012)	(0.027)	(0.408)	(0.578)	(0.014)	(0.017)	(0.398)
Real GDP growth	0.080	0.005***	-0.001	0.077*	0.113**	0.008***	0.002	0.112***
	(0.053)	(0.001)	(0.001)	(0.045)	(0.045)	(0.002)	(0.002)	(0.039)
Change CB policy rate	0.004	0.000	0.001	0.005	0.002	-0.000	0.000	0.005
	(0.004)	(0.001)	(0.000)	(0.012)	(0.003)	(0.001)	(0.000)	(0.012)
Inflation	0.129**	-0.000	0.001	0.157**	0.202**	0.000	0.007	0.217***
	(0.058)	(0.003)	(0.002)	(0.073)	(0.083)	(0.004)	(0.005)	(0.063)
Log (real exchange rate)	-0.126	0.146***	-0.003*	-0.108	-0.308***	0.172***	-0.007**	-0.291***
	(0.116)	(0.051)	(0.002)	(0.094)	(0.101)	(0.058)	(0.003)	(0.098)
Bank credit (% of GDP)	-0.003	0.001***	-0.000	-0.002	0.009**	0.002***	0.000*	0.009***
	(0.005)	(0.000)	(0.000)	(0.004)	(0.004)	(0.000)	(0.000)	(0.003)
Log (GDP per capita)	0.568	0.143***	0.004	0.556**	-0.229	0.109***	-0.012	-0.228
	(0.384)	(0.035)	(0.007)	(0.245)	(0.321)	(0.040)	(0.013)	(0.178)
CAP_REQ	-0.748	-0.016**	-0.001	-0.591	0.414	0.001	0.036*	0.432**
	(0.576)	(0.007)	(0.008)	(0.439)	(0.451)	(0.008)	(0.020)	(0.206)
SSCB	-0.461	-0.006	-0.006	-0.430	-0.033	-0.002	-0.001	-0.025
	(0.470)	(0.006)	(0.004)	(0.282)	(0.186)	(0.006)	(0.007)	(0.132)
MAPP	-0.238**	-0.007***	-0.001	-0.219**	-0.129**	-0.003	-0.003*	-0.119**
	(0.097)	(0.002)	(0.001)	(0.101)	(0.065)	(0.002)	(0.002)	(0.052)
Constant	-10.922***	-1.406***	-0.239**	-10.873***	-3.426	-1.212***	-0.088	-3.466*
	(2.584)	(0.309)	(0.100)	(2.352)	(2.746)	(0.352)	(0.097)	(1.864)
Country fixed effects	NO	YES	NO	NO	NO	YES	NO	NO
Year fixed effects	NO	NO	YES	NO	NO	NO	YES	NO
Observations	2156	2156	2156	2156	2134	2134	2134	2134
Credit booms	61	61	61	61	79	79	79	79
Countries	40	40	40	40	40	40	40	40
Pseudo R2 (LPM: R2)	0.0843	-	0.0757	-	0.0549	-	0.0773	-
Chi-sq	57.17	-	-	32.38	28.93	-	-	32.58
Prob > chi-sq (LPM: F-test)	0.0000	0.0000	0.0002	0.0003	0.0013	0.0000	0.0002	0.0003

Robust standard errors in parentheses

*** 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 and LPM 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).

7. Conclusion

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. Moreover, individual macroprudential policy instruments are also found to reduce the occurrence of bank credit booms. 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. Moreover, this effect seems to be greater for larger booms in bank credit. In addition, the results show that borrower- and financial institution-targeted macroprudential policies are more effective to address household credit booms compared to booms in bank credit.

Finally, 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.

Acknowledgements

I am greatly indebted to Gabriella Chiesa and Paolo Manasse for their guidance. Moreover, I’m grateful for the comments of Guglielmo Barone, Valentina Bruno, Julián Caballero, Eugenio Cerutti, Nicola Gennaioli, Roberto Golinelli, James Hamilton, Marcus Ingholt, Salvatore Morelli, Sergio Pastorello, Sven Schreiber, Moritz Schularick and Andrea Teglio. Finally, I would also like to thank participants at First Behavioral Macroeconomics Workshop (University of Bamberg), 32nd Annual Irish Economic Association Conference 2018 (Central Bank of Ireland), International Days of Macroeconomics and Finance 2018 (Bank Al-Maghrib), BoMoPaV Economics Meetings 2018 (University of Padova), and the 4th International Conference on Applied Theory, Macro and Empirical Finance (University of Macedonia).

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Appendix

Table A1. GMM estimations with aggregate macroprudential indexes

VARIABLES	1	2	3	4	5	6	7	8	9
Real bank credit growth	0.1813*	0.1769*	0.1121	0.1433	0.1970	0.1429	0.1176	0.1577	0.1218
	(0.0933)	(0.0947)	(0.1058)	(0.0920)	(0.1512)	(0.0928)	(0.0948)	(0.1015)	(0.0925)
Real GDP growth	0.0012**	0.0012**	0.0013**	0.0012**	0.0016***	0.0011**	0.0011**	0.0013**	0.0012**
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0006)	(0.0005)	(0.0005)	(0.0005)	(0.0006)
Change CB policy rate	0.0003*	0.0003	0.0002	0.0003*	-0.0025**	0.0003*	0.0002	0.0003**	0.0003*
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0012)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Log (VIX)	-0.0006	-0.0006	-0.0004	-0.0003	-0.0006	-0.0013	-0.0004	-0.0008	-0.0011
	(0.0021)	(0.0024)	(0.0022)	(0.0023)	(0.0024)	(0.0023)	(0.0023)	(0.0022)	(0.0023)
MAPP	0.0010**	0.0016**	0.0012	0.0005	0.0008				
	(0.0004)	(0.0008)	(0.0011)	(0.0005)	(0.0007)				
MAPP x top 25% credit growth (dummy)	-0.0014***				-0.0016**				
	(0.0003)				(0.0008)				
MAPP x top 50% credit growth (dummy)		-0.0018*							
		(0.0009)							
MAPP x bottom 50% credit growth (dummy)			-0.0017						
			(0.0027)						
MAPP x bottom 25% credit growth (dummy)				0.0014	0.0003				
				(0.0026)	(0.0031)				
MAPP_B_FI						0.0002	-0.0002		
						(0.0008)	(0.0010)		
MAPP_B_FI x top 25% credit growth (dummy)						-0.0042*			
						(0.0022)			
MAPP_B_FI x bottom 25% credit growth (dummy)							-0.0011		
							(0.0025)		
MAPP_RR								0.0022***	0.0011
								(0.0007)	(0.0012)
MAPP_RR x top 25% credit growth (dummy)								-0.0017***	
								(0.0006)	
MAPP_RR x bottom 25% credit growth (dummy)									0.0040
									(0.0080)
Constant	0.0084	0.0090	0.0087	0.0083	0.0073	0.0123*	0.0100	0.0100	0.0118
	(0.0021)	(0.0069)	(0.0066)	(0.0067)	(0.0076)	(0.0065)	(0.0064)	(0.0068)	(0.0071)
Observations	2123	2123	2123	2123	2123	2123	2123	2123	2123
Number of countries	40	40	40	40	40	40	40	40	40
Number of instruments	37	37	37	37	38	37	37	37	37
AR(1)	0.000	0.000	0.000	0.000	0.045	0.000	0.000	0.000	0.000
AR(2)	0.164	0.152	0.375	0.274	0.221	0.364	0.328	0.222	0.383
Hansen J-test	0.275	0.232	0.311	0.201	0.184	0.240	0.281	0.181	0.171

Robust standard errors in parentheses
*** 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 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 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.

Table A2. Borrower- and financial institution-targeted policies (boom threshold 1.25 s.d.)

VARIABLES	Logit (1)	LPM (2)	Firth logit (3)	Logit (4)	LPM (5)	Firth logit (6)	Logit (7)	LPM (8)	Firth logit (9)
Log (VIX)	1.633***	0.109***	1.638***	2.548***	0.197***	2.488***	1.110***	0.092***	0.915***
	(0.421)	(0.029)	(0.414)	(0.508)	(0.036)	(0.500)	(0.417)	(0.023)	(0.302)
Real GDP growth	-0.022	0.004	-0.019	0.323***	0.026***	0.312***	0.117***	0.017***	0.128***
	(0.045)	(0.003)	(0.042)	(0.081)	(0.006)	(0.085)	(0.040)	(0.003)	(0.031)
Change CB policy rate	0.546**	0.033	0.550*	0.930*	0.061**	0.852*	0.571***	0.005***	0.021
	(0.245)	(0.022)	(0.289)	(0.563)	(0.028)	(0.441)	(0.172)	(0.002)	(0.018)
Inflation	0.198	0.002	0.188	0.160	0.005	0.157	0.077	0.007	0.116
	(0.122)	(0.009)	(0.170)	(0.232)	(0.017)	(0.236)	(0.078)	(0.007)	(0.072)
Log (real exchange rate)	0.042	0.409**	0.048	-0.008	0.936***	-0.005	-0.067	0.237**	-0.066
	(0.156)	(0.174)	(0.082)	(0.205)	(0.302)	(0.126)	(0.144)	(0.093)	(0.068)
Bank credit (% of GDP)	0.007	0.003***	0.007**	0.006	0.001	0.006	-0.001	0.002***	-0.001
	(0.006)	(0.001)	(0.003)	(0.007)	(0.001)	(0.006)	(0.004)	(0.001)	(0.003)
Log (GDP per capita)	0.715***	0.349***	0.682***	0.501	0.782***	0.438	0.623***	0.202***	0.600***
	(0.196)	(0.112)	(0.214)	(0.473)	(0.236)	(0.369)	(0.231)	(0.059)	(0.168)
LTV_CAP	-0.103	-0.023**	-0.099						
	(0.115)	(0.009)	(0.085)						
IBEX				-1.121**	0.004	-1.051***			
				(0.518)	(0.025)	(0.296)			
CONCRAT							-0.303	-0.047***	-0.299*
							(0.326)	(0.017)	(0.156)
Constant	-13.247***	-3.691***	-12.949***	-14.515***	-6.890***	-13.802***	-10.198***	-2.148***	-9.494***
	(1.861)	(1.042)	(2.263)	(3.830)	(1.868)	(3.368)	(1.720)	(0.528)	(1.640)
Country fixed effects	NO	YES	NO	NO	YES	NO	NO	YES	NO
Year fixed effects	NO	NO	NO	NO	NO	NO	NO	NO	NO
Observations	807	807	807	645	645	645	1275	1275	1275
Credit booms	62	62	62	57	57	57	106	106	106
Countries	25	25	25	14	14	14	25	25	25
Pseudo R2 (LPM: R2)	0.1038	-	-	0.1554	-	-	0.0837	-	-
Chi-sq	76.06	-	35.91	146.98	-	42.99	64.36	-	35.26
Prob > chi-sq (LPM: F-test)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Robust standard errors in parentheses
*** 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. 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 1.25 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 A3. Country list

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	

Figure A1. Average growth rate of real domestic bank credit around boom episodes

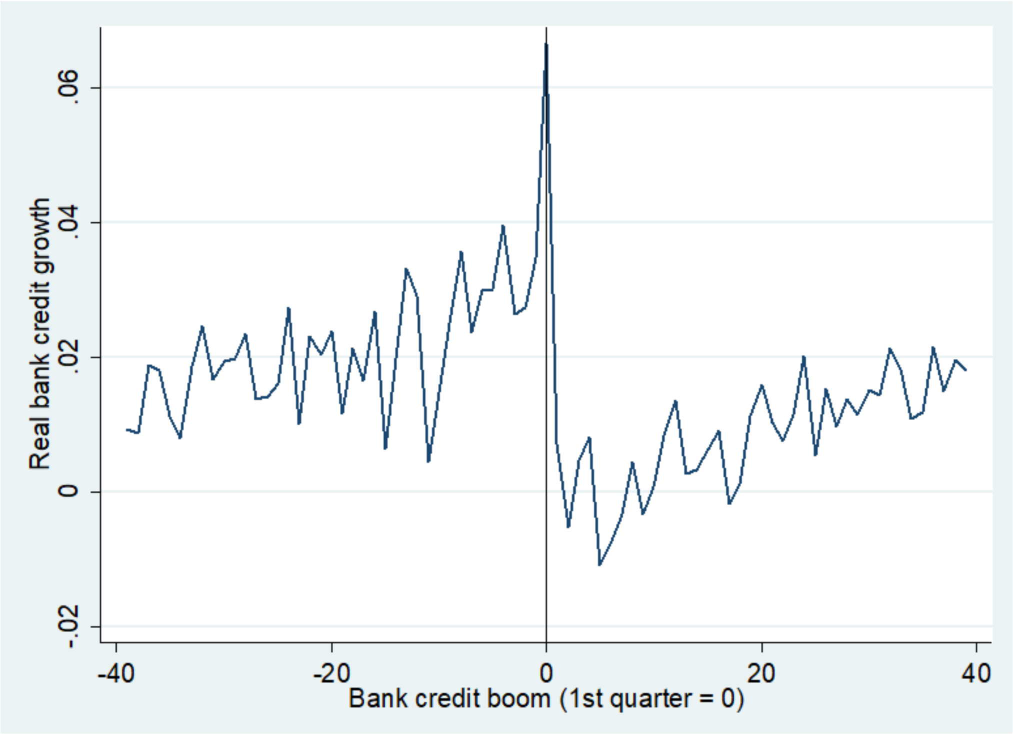
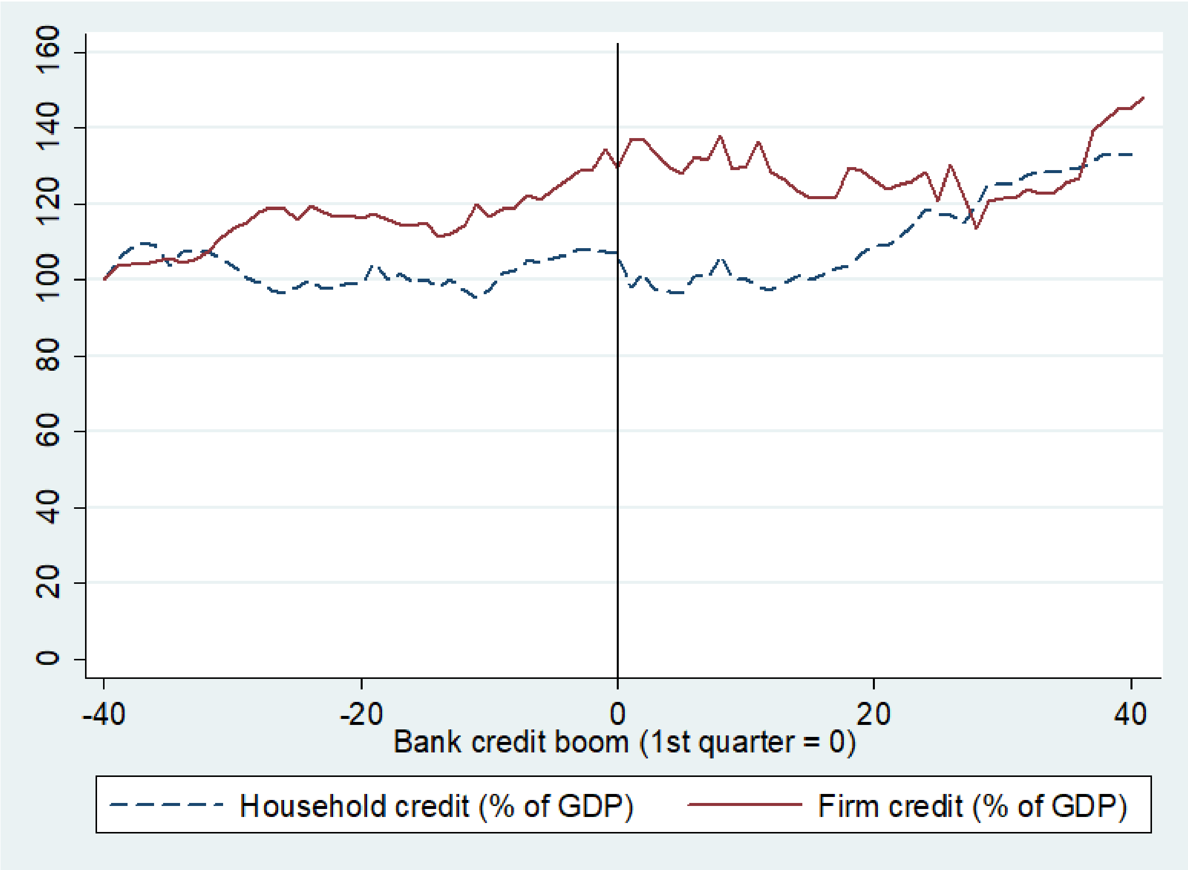
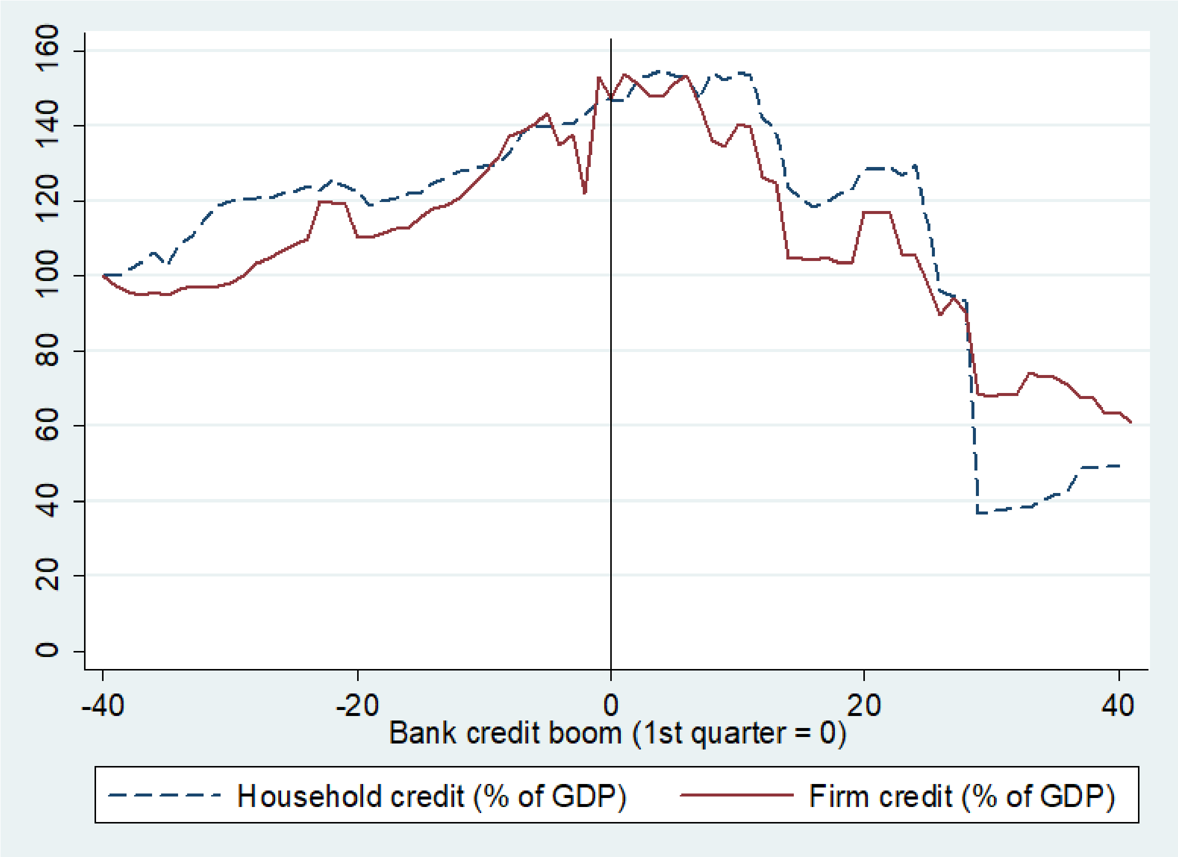


Figure A2. Median ratio of household and firm credit (% of GDP) around good credit booms



Note: The Figure shows the median ratio of household and firm credit (% of GDP) around good credit booms (32 episodes). A good credit boom is defined as a bank credit boom (1.75 s.d.) not followed by a systemic banking crisis. Both the ratio of household credit and firm credit (% of GDP) have been scaled to value 100 forty quarters (-40) before the first quarter of the credit boom.

Figure A3. Median ratio of household and firm credit (% of GDP) around bad credit booms



Note: The Figure shows the median ratio of household and firm credit (% of GDP) around bad credit booms (20 episodes). A credit boom is defined as "bad" if a systemic banking crisis occurs during the bank credit boom (1.75 s.d.) or within three years after the end of the boom. Both the ratio of household credit and firm credit (% of GDP) have been scaled to value 100 forty quarters (-40) before the first quarter of the credit boom.

Banks’ Systemic Risk and Macroprudential Policy

Peter Karlström*

October 2018

Abstract

The ultimate objective of macroprudential regulation is to avoid the build-up of systemic risk in the financial system according to De Nicólo et al. (2012). This study examines the impact of macroprudential policies on banks’ systemic risk in advanced and developing countries during the period 2000-2015. The main finding suggests that a tighter macroprudential policy stance in a country is negatively and significantly associated with the level of systemic risk for banks. Moreover, tighter conditions for concentration limits seem to reduce the growth rate of systemic risk. Finally, the results also show that tightenings of macroprudential policies were negatively associated with the growth rate of systemic risk for banks prior to the Global Financial Crisis.

JEL codes: E58, G18, G28, H12

Keywords: macroprudential policy, systemic risk, financial institutions, capital shortfall

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1. Introduction

The former President of the European Central Bank Jean-Claude Trichet described systemic risk as financial instability "so widespread that it impairs the functioning of the financial system to the point where economic growth and welfare suffer materially (Trichet, 2010)". Consequently, it is necessary to identify and mitigate the build-up of systemic risk to ensure financial stability (Arnold et al., 2012).

Allen and Carletti (2013) propose that systemic risk can be divided into four different areas: (i) panics, (ii) asset price falls, (iii) contagion and (iv) foreign exchange mismatches. First, systemic risk can be a consequence of panics which can create multiple equilibria and lead to a banking crisis. For example, Diamond and Dybvig (1983) showed that panics can be described as self-fulfilling events. In addition, guarantees were used frequently at the beginning of the Global Financial Crisis which suggests that many policymakers believed the rise in systemic risk was due to a panic.

Second, asset price falls are considered as important determinants of systemic risk. Several theories suggest that banking crises are linked to the downturn of the business cycle. A worsening of economic performance reduces banks' asset value which implies that they are not able to fulfill their commitments (Allen and Carletti, 2013). News about a large fall in economic activity will induce depositors to withdraw their funds prematurely as they anticipate financial instability in the banking sector (Gorton, 1988). Reinhart and Rogoff (2009) emphasize that booms followed by busts in real estate prices and credit are considered as major causes of banking crises. Moreover, mispricing of assets driven by inefficient provision of liquidity and sovereign debt defaults are likely to also be important sources of systemic risk. Finally, a sharp increase in interest rates can lead to a collapse in security prices which implies solvency problems for banks (Allen & Carletti, 2012).

Third, contagion has been found to be one of the most important sources of systemic risk. Contagion can be described as the distress a financial institution contribute to the entire financial system. The "too-big-to-fail" paradigm emphasizes that the size of a financial institution is a key driver of contagion and the build-up of systemic risk. Moreover, according to the "too-interconnected-to-fail" paradigm contagion is not only influenced by a company's size but also how the firm is interconnected with other actors in the financial system. In addition, systemic risk can be caused by common asset exposures and short-term debt. Contagion has often been used as an argument to intervene and provide support to financial institutions such as when the Federal Reserve let JP Morgan take over Bear Stearns in 2008 (Allen & Carletti, 2012).

Finally, currency mismatches can lead to higher systemic risk and potentially a banking crisis. The foreign exchange reserves held by central banks during the Asian Crisis in 1998 were not sufficient. Consequently, several central banks were unable to borrow and had to ask for support from the IMF. In contrast to the Asian Crisis, all major central banks made agreements on foreign exchange swaps during the Global Financial Crisis which was essential to reduce financial instability (Allen & Carletti, 2012).

The risk in a financial system has traditionally been viewed as the sum of the individual risks of all financial institutions (Allen & Carletti, 2012). The rationale of microprudential regulation is to maintain the stability of the financial system by ensuring the solvency of all individual financial institutions. Basel I and II capital accords are typically viewed as examples of microprudential regulation. However, the main critique against microprudential regulation is the "fallacy of composition" which implies that ensuring the solvency of individual institutions is not sufficient to safeguard the financial system (Brunnermeier et al., 2009). There are two main reasons why safeguarding the solvency of financial institutions is not sufficient to ensure stability for the entire system: (i) to focus on the individual risk of financial institutions instead of the entire financial system neglect correlation risk (Acharya, 2009), (ii) to stabilize an individual financial institution from a microprudential perspective can lead to a destabilization of the entire system. An example of (ii) is if a regulator requires a troubled bank to restore the capital ratio in a situation where many banks are in difficulty. If the bank chooses to restore the capital ratio by reducing lending then this could cause a system-wide credit crunch (Hanson et al., 2011). Finally, 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)".

The purpose of this study is to investigate the impact of macroprudential policy on banks' systemic risk. To the best of the author's knowledge, this is the first study that examines the link between macroprudential regulation and systemic risk at the bank-level in both advanced and developing countries.

The structure of this paper is as follows. Section 2 reviews the recent literature related to macroprudential policy and systemic risk. Section 3 describes the measure of systemic risk, macroprudential policies and control variables used in this study. Section 4 discusses the empirical approach used to assess the impact of macroprudential policy on systemic risk. The results are highlighted in section 5 followed by a discussion about robustness checks and potential extensions in section 6. Finally, concluding remarks are summarized in section 7.

2. Literature review

Acharya (2009) provide a theoretical framework emphasizing that it is essential for prudential regulation to address both each bank's individual risk as well as the correlated risk with other banks. Regulation that only target individual bank risk, such as capital requirements and bank closure policy, could unintentionally increase systemic risk in the financial system. Consequently, a macroprudential approach that accounts for general equilibrium effects is necessary to ensure financial stability (Hanson et al., 2011). The former Chairman of the Federal Reserve Ben Bernanke emphasized the importance of macroprudential regulation as an alternative approach to microprudential policies for dealing with systemic risk:

"Going forward, a critical question for regulators and supervisors is what their appropriate "field of vision" should be. Under our current system of safety-and-soundness regulation, supervisors often focus on the financial conditions of individual institutions in isolation. An alternative approach, which has been called systemwide or macroprudential oversight, would broaden the mandate of regulators and supervisors to encompass consideration of potential systemic risks and weaknesses as well (Bernanke, 2008)."

Several empirical studies show that macroprudential regulation is effective to address credit and house price growth. Cerutti et al. (2017a) investigate the effectiveness of macroprudential policies to deal with credit growth. Their study which comprises twelve macroprudential policies in more than one hundred countries between 2000-2013 shows that macroprudential regulation reduces credit growth. Moreover, several recent studies confirm the effectiveness of macroprudential regulation (see for example studies by Akinci and Olmstead-Rumsey, 2018; Bruno et al., 2017; and Fendoğlu, 2017). In addition, Cerutti et al. (2017a) emphasize the importance of investigating the effects of macroprudential policy on systemic risk or the probability of financial crises. However, only a few studies examine the impact of prudential policy on bank risk or systemic risk.

Altunbas et al. (2018) examine the impact of macroprudential policies on bank risk for 61 advanced and developing countries between 1990 and 2012. The measures of bank risk used in the study are the Z-Score and the expected default frequency (EDF). Importantly, the authors emphasize that the aim of the study should ideally be to assess the effectiveness of macroprudential policy to address systemic risk and not only bank risk. Moreover, to assess the influence of macroprudential policies on bank risk S-GMM regressions are conducted with the yearly growth rate of bank risk as dependent variables. The macroprudential policy indexes measure the net sum of tightenings (+1) and easings (-1) for each year. The results found suggest that: (i) macroprudential policies are effective to mitigate the build-up of bank risk, (ii) the effects differ depending on the characteristics of the balance sheets and (iii) the effect of a tightening of macroprudential instruments is larger than an easing. Finally, Altunbas et al. (2018) emphasize that advanced and developing countries had different experiences concerning the frequency of policy tightenings and easing since 2000. Consequently, pooling data from both advanced and developing countries significantly reduces the concern for omitted variable bias (Demirgüç-Kunt et al., 2013).

Furthermore, Gauthier et al. (2012) employ a network-based structural model to measure systemic risk for a sample of Canadian banks. The study shows that macroprudential capital requirements can potentially reduce default probabilities for individual institutions and the likelihood of a systemic crisis by approximately 25 percent. The authors conclude that a systemic perspective on bank regulation can substantially increase financial stability.

A recent study by Gehrig and Iannino (2018) investigate the impact of Basel capital regulation on systemic risk for European banks. First, the authors show that systemic risk as measured by SRISK has increased steadily during the past three decades. Importantly, most of the increase in systemic risk has occurred in those banks that belong to the highest quintile of the size distribution. Furthermore, evidence provided in the study highlight that the Basel process of capital regulation has not been effective in reducing systemic risk for the largest institutions. In addition, not even for smaller banks did the Basel process significantly decrease systemic risk.

Finally, several recent empirical studies investigate which factors that may contribute to higher systemic risk. Anginer et al. (2014) find that greater competition induces banks to diversify more which reduce systemic risk. Moreover, Laeven et al. (2016) show that bank size increases systemic risk while bank capital has the opposite effect. In addition, Karolyi et al. (2018) provide evidence suggesting that cross-border bank inflows decrease systemic risk for larger and more interconnected banks.

3. Data and descriptive statistics

The dataset encompasses yearly data for 460 banks in 55 advanced and developing countries between 2000-2015. Variable definitions and sources are shown in Tables A1 and A2 (Appendix 1). The countries included in this study and the number of banks in each country are listed in Table A3 in Appendix 1.

3.1 Systemic risk measure

The measure of systemic risk employed in this study is SRISK[1] developed by Brownlees and Engle (2017). SRISK measures the capital shortfall of a bank conditional on a severe market decline (Engle et al., 2015). 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 an aggregate measure of a bank's exposure to systemic risk and is informative when assessing the resiliency of a bank (Gehrig and Iannino, 2018).

Benoit et al. (2017) provide empirical results showing a strong link between a firm's Marginal Expected Shortfall (MES) and the systematic risk of the firm measured by beta. As has been shown by Benoit et al. (2017, pp. 134-135), SRISK include both MES 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). Moreover, Table 1 shows that both beta (systematic risk) and market capitalization (size) are positively and significantly correlated with SRISK as expected. In addition, the evolution of the average positive SRISK between 2000 and 2015 is shown in Figure 1.

Table 1. Correlation between banks' SRISK, beta and market capitalization

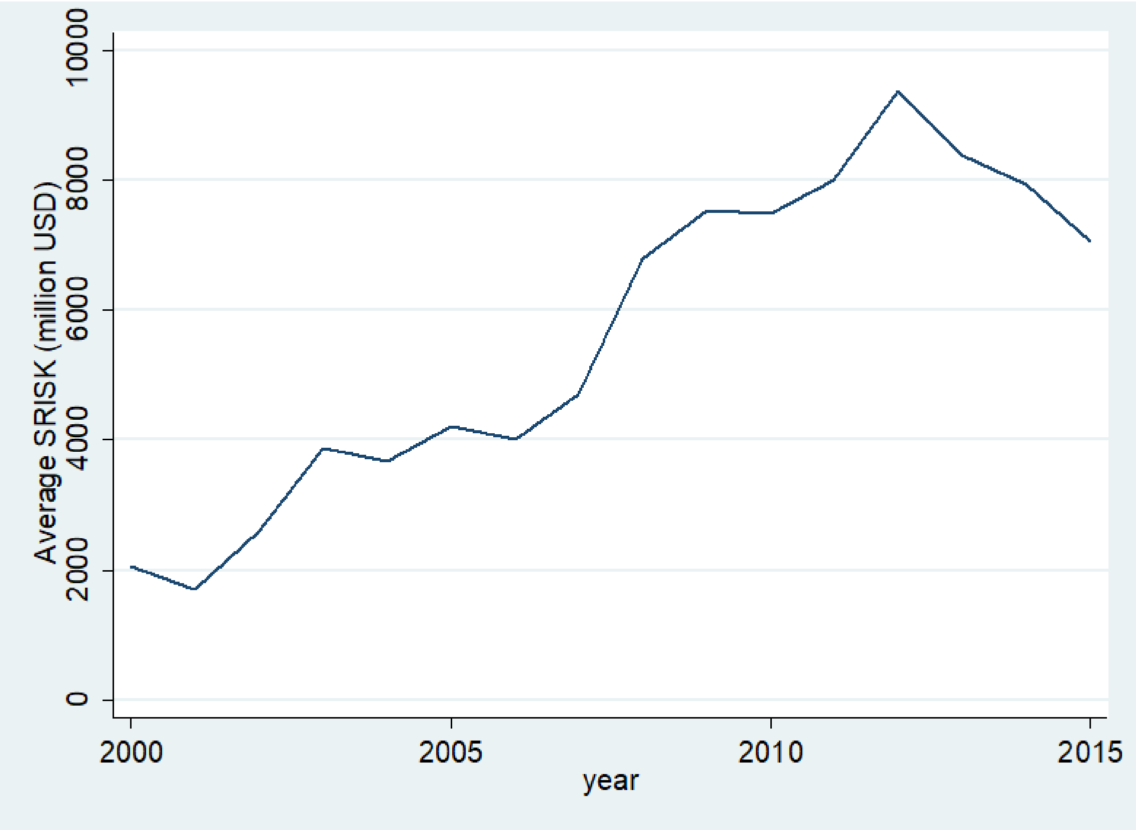
	SRISK	Beta	Market Cap.
SRISK	1.000		
Beta	0.315*	1.000	
Market Cap.	0.545*	0.187*	1.000

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

[1] The definition of SRISK and its components is described in the paper by Benoit et al. (2017, pp. 134-135).

Finally, 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.

Figure 1. Evolution of SRISK between 2000-2015



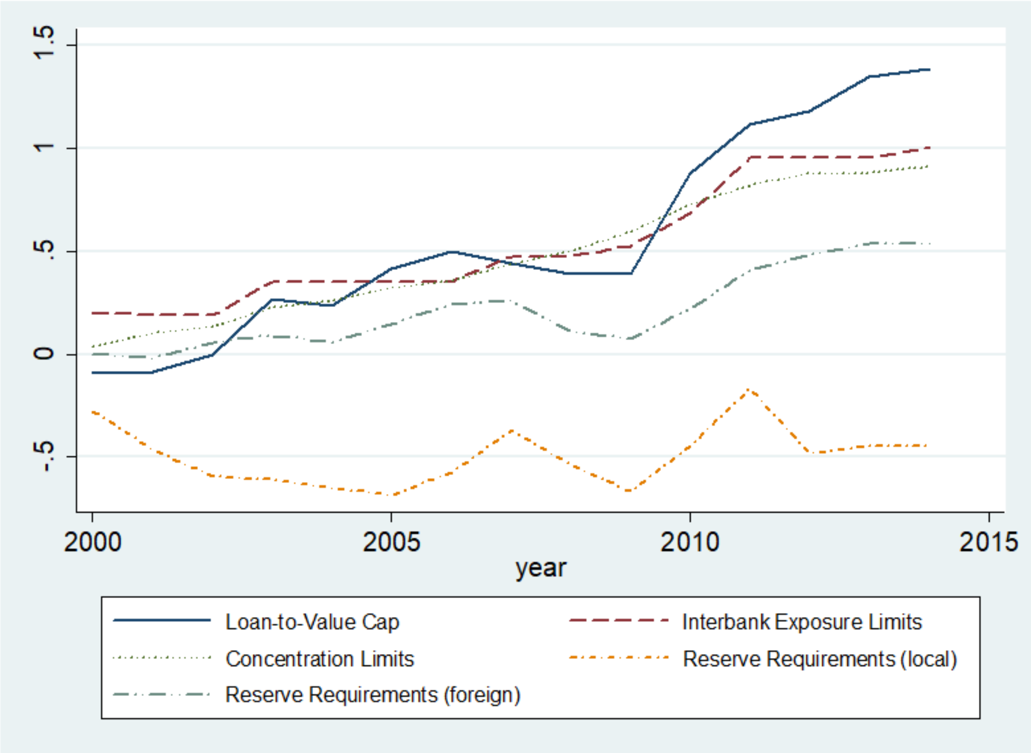
3.2 Macroprudential policy indexes

Quarterly data for macroprudential instruments are compiled from the IBRN Prudential Instruments Database for the period 2000-2014 (Cerutti et al., 2017b). To assess the effect of macroprudential policies on systemic risk the indexes are included both in levels and as yearly changes. Moreover, similar to Altunbas et al. (2018) the indexes are aggregated to yearly time series since the control variables are not available in quarterly frequency. Table A2 in Appendix 1 show variable description for the macroprudential policies.

The macroprudential instruments included in this study are loan-to-value caps, interbank exposure limits, concentration limits and reserve requirements on accounts denominated in local or foreign currency. Moreover, an aggregate index MAPP (ΔMAPP) is constructed including all instruments to better measure the overall impact of the macroprudential policies. In addition, since reserve requirements are mainly used in developing countries a sub-index MAPP_RR (ΔMAPP_RR) is created only including reserve requirements policies. Loan-to-value caps, interbank exposure limits and concentration limits are included in the sub-index MAPP_B_FI (ΔMAPP_B_FI). Table 2 show descriptive statistics for all indexes with macroprudential policies.

The level of macroprudential instruments can be viewed as a measure of the "macroprudential policy stance" in a country. Following the approach used by Akinci and Olmstead-Rumsey (2018) the cumulative sum of tightenings (+1) net of easings (-1) since the first quarter of 2000 is used as a proxy for macroprudential instruments' tightness. However, for reserve requirements RR_D and RR_FX, a tightening (easing) can take a value higher (lower) than +1 (-1) which better captures the intensity of the changes. Consequently, for the aggregate indexes MAPP and MAPP_RR where reserve requirements are included the instruments are constrained to take a maximum (minimum) value of +1 (-1) in each quarter. The cumulative sum of tightenings net of easings in the fourth quarter is used when aggregating the data to yearly frequency. Figure 2 illustrates the evolution of the macroprudential instruments (in levels) between 2000 and 2015.

Figure 2. Evolution of macroprudential instruments (averages) between 2000-2015



Furthermore, following the approach in the study by Altunbas et al. (2018) indexes measuring changes in macroprudential policies are constructed. A tightening action of a policy takes value +1 and an easing action -1 as for the cumulative indexes. However, the change in a macroprudential instrument is measured as the sum of tightenings net of easings for each year separately. Consequently, this index can take values 0, -1 or 1, …, -4 or 4 for those instruments (i.e. ΔLTV_CAP, ΔIBEX, and ΔCONCRAT) where a tightening (easing) has a maximum (minimum) value of 1 (-1) in each quarter. Consequently, the value for reserve requirements instruments ΔRR_D and ΔRR_FX can be lower or higher than -4 and 4. The reserve requirements instruments are constrained to take a maximum (minimum) value 1 (-1) in each quarter when included the aggregate indexes ΔMAPP and ΔMAPP_RR. Figure 3 illustrates the sum of all tightening and easing actions between 2000-2015.

Figure 3. Number of macroprudential policy actions between 2000-2015

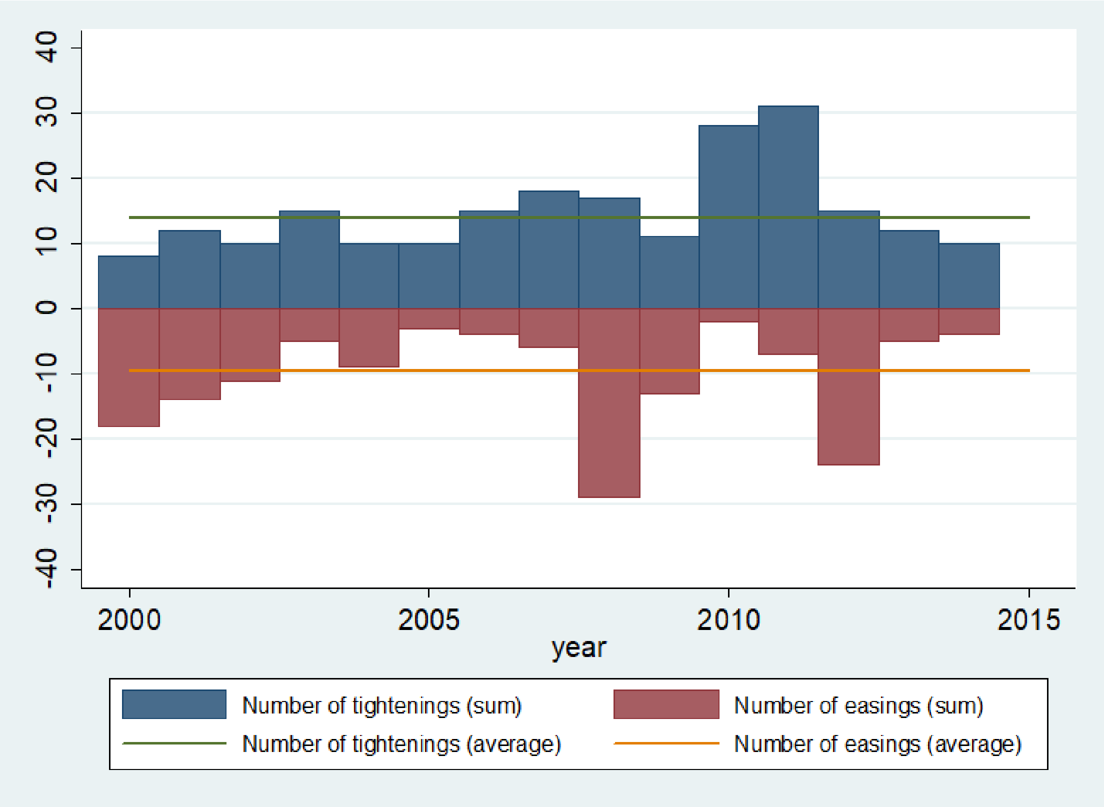


Table 2. Descriptive statistics for macroprudential indexes

	Mean	Median	Min	Max	Std. Dev.	Obs
Macroprudential indexes (levels)						
LTV_CAP	1.338	1	-3	8	2.400	1954
IBEX	0.440	0	-1	4	0.738	2957
CONCRAT	0.367	0	0	4	0.735	5027
RR_D	0.116	0	-7	12	2.172	6900
RR_FX	0.214	0	-6	11	1.207	6900
MAPP	1.221	0	-15	24	4.143	7360
MAPP_B_FI	0.782	0	-2	9	1.682	7360
MAPP_RR	0.439	0	-16	17	3.024	7360
Macroprudential indexes (changes)						
ΔLTV_CAP	0.261	0	-1	3	0.681	1954
ΔIBEX	0.063	0	-1	2	0.252	2957
ΔCONCRAT	0.044	0	0	1	0.205	5027
ΔRR_D	0.023	0	-4	7	0.792	6900
ΔRR_FX	0.040	0	-5	4	0.426	6900
ΔMAPP	0.125	0	-2	3	0.680	7360
ΔMAPP_B_FI	0.112	0	-1	2	0.386	7360
ΔMAPP_RR	0.013	0	-2	2	0.560	7360

3.3 Control variables

Several control variables which have been found to influence systemic risk are included in the estimations (see Table A1 in Appendix 1). 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, several 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 account for the development of the stock market. Finally, the variable log (GDP per capita) is included to control for the level of development.

4. Empirical Approach

To begin with, this study aims to investigate whether a tighter macroprudential policy stance in a country is associated with a lower ratio of SRISK-to-GDP for banks. The macroprudential policy stance is measured by the cumulative sum of tightenings (+1) net of easings (-1) since 2000 following the approach in Akinci and Olmstead-Rumsey (2018) and Epure et al. (2017). Figure 2 illustrates the average cumulative measure for the macroprudential instruments included in this study. Moreover, since this is a cross-country study SRISK has been scaled by real GDP in all estimations following the approach in Karolyi et al. (2018) and Engle et al. (2015). OLS regressions with only year fixed effects or both 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.

Moreover, Gehrig and Iannino (2018) 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 (2018). 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-Chamberlein device is applied which include time averages of all time-varying regressors (Wooldridge, 2010; Chamberlin & Ricker-Gilbert, 2016).

In addition, the global financial crisis began in the middle of the period which is likely to have a substantial influence on the results. Figure 1 illustrates that SRISK increased rapidly from 2007 at the same time as macroprudential policies were tightened more frequently shown in Figure 3. Consequently, it is likely that the results for the period 2000-2006 are different from the period 2007-2015. Following the approach by Bruno et al. (2017) dummies are constructed for the period 2000-2006 (pre 2007) and 2007-2015 (post 2007). Interaction variables are constructed with the period dummies and aggregate macroprudential indexes as well as individual macroprudential instruments.

Furthermore, the next step is to investigate whether the macroprudential policy stance influences the growth rate of banks' SRISK. Regressions with the same cumulative macroprudential policy indexes as before are estimated but this time with the log percentage change in SRISK scaled by real GDP as the dependent variable. This approach has been employed by Akinci and Olmstead-Rumsey (2018) when assessing the effectiveness of macroprudential policies to address credit growth.

Finally, regressions with yearly changes in macroprudential policies are conducted following the approach in the study by Altunbas et al. (2018). Macroprudential policy changes are defined as the sum of tightenings net of easings within one year. Consequently, in contrast to the cumulative index, this measure does not account for all previous tightenings and easings since 2000. However, using indexes with the yearly change instead of the cumulative sum may be a more precise way to examine if macroprudential policies influence the growth rate of systemic risk. Period dummies are included in all estimations since endogeneity between macroprudential policies and SRISK after 2007 is likely to be stronger for indexes with yearly changes. In addition, dynamic system GMM regressions are conducted following the approach in the study by Altunbas et al. (2018) as a robustness check.

5. Results

Estimations with aggregate macroprudential indexes (in levels) and SRISK scaled by real GDP are shown in Table 3. The coefficient for the aggregate index MAPP which includes all five macroprudential instruments has a negative and highly significant coefficient in estimations with only year or 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 with two reserve requirements instruments is negative and significant in all estimations.

Results for 0.25, 0.50 and 0.75 quantile regressions are shown in Table A4 in Appendix 2. 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.

Furthermore, estimations with macroprudential policy indexes interacted with period dummies are shown in Table A5 in Appendix 2. The MAPP index is negative and highly significant in all estimations without bank fixed effects. Moreover, the coefficient for the MAPP_B_FI index is negative and significant at the 10% level in the estimation with year and country fixed effects contrary to the results in Table 3. In addition, MAPP_B_FI is highly significant for the period 2000-2006 in the estimation with both year and bank fixed effects. Finally, the coefficient for the index MAPP_RR is negative and significant except for the pre-2007 period in the estimation with both year and bank fixed effects.

Several control variables are found to be significant in the estimations with SRISK scaled by GDP as the dependent variable. The bank-specific variables size and leverage have coefficients with different signs depending on the type of fixed effects included in the specification. The coefficient for the size of the company is positive and highly significant for estimations with only year or year and country fixed effects. However, in the estimations with year and bank fixed effects the coefficient is negative and highly significant. Similarly, the coefficient for leverage is negative and significant in estimations with only year fixed effect but turns positive and significant with bank fixed effects. Moreover, the coefficients for real GDP growth and market return are negative and highly significant in estimations with year and country fixed effects but not when bank controls are included. In addition, the coefficients for volatility and concentration are both positive and significant in estimations with only year dummies but insignificant with bank fixed effects.

Table 4 shows the results for the log annual percentage change of SRISK scaled by real GDP and cumulative macroprudential indexes. The aggregate index MAPP is found to be positive and significant for the post-2007 period as expected. In addition, loan-to-value caps (LTV_CAP) and reserve requirements on accounts denominated in local or foreign currency (RR_D and RR_FX) also have positive and significant coefficients for the post-2007 period. However, the coefficients for loan-to-value caps and concentration limits are negative and significant for estimations with year and country fixed effects for the pre-2007 period. The coefficient for concentration limits is also negative and significant for the post-2007 period in all estimations. It should be emphasized that none of the coefficients are positive and significant for the pre-2007 period.

Table 5 shows the results for the yearly change in aggregate macroprudential indexes with the log annual percentage change in SRISK scaled by real GDP as the dependent variable. The coefficient for the ΔMAPP index is negative and significant at the 10% level for the pre-2007 period in all estimations. Moreover, the coefficients for ΔMAPP_B_FI and ΔMAPP_RR are negative but typically insignificant for the pre-2007 period. One exception is the coefficient for ΔMAPP_RR during the pre-2007 period in the estimation with only year fixed effects. For the period after the start of the global financial crisis (post 2007), the coefficients for all three macroprudential indexes are positive and highly significant.

Finally, Table 6 shows the results for the yearly change in individual macroprudential instruments and the log percentage change in the SRISK-to-GDP ratio. All coefficients for the macroprudential instruments are negative for the period 2000-2006. However, only the coefficients for the change in loan-to-value caps (ΔLTV_CAP) and reserve requirements on accounts denominated in local currency (ΔRR_D) are negative and significant. In addition, the coefficients for changes in loan-to-value caps (ΔLTV_CAP) and reserve requirements on accounts denominated in foreign currency (ΔRR_FX) are positive and significant for the post-2007 period.

Table 3. Estimations with macroprudential indexes (in levels) and SRISK-to-GDP

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Size	1.830***	2.207***	-2.072***	1.725***	2.140***	-2.213***	1.831***	2.209***	-2.036***
	(0.300)	(0.297)	(0.563)	(0.288)	(0.291)	(0.543)	(0.303)	(0.300)	(0.543)
Leverage	-0.003***	0.001	0.002**	-0.004***	0.001	0.002**	-0.002**	0.001	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Real GDP growth	0.015	-0.302***	-0.172***	-0.131*	-0.329***	-0.176***	0.000	-0.302***	-0.171***
	(0.077)	(0.068)	(0.062)	(0.070)	(0.071)	(0.062)	(0.083)	(0.069)	(0.063)
Market return	-0.029**	-0.012**	-0.000	-0.020	-0.006	0.003	-0.027**	-0.010*	0.000
	(0.013)	(0.006)	(0.006)	(0.013)	(0.006)	(0.007)	(0.012)	(0.006)	(0.006)
Volatility	0.081**	0.106***	-0.02	0.074**	0.116***	-0.018	0.078**	0.111***	-0.018
	(0.036)	(0.025)	(0.032)	(0.035)	(0.025)	(0.031)	(0.036)	(0.026)	(0.032)
Non-interest income	-0.016	0.005	-0.027	0.004	0.006	-0.028	-0.021	0.004	-0.027
	(0.035)	(0.044)	(0.06)	(0.034)	(0.044)	(0.06)	(0.035)	(0.043)	(0.060)
Concentration	0.112***	0.010	-0.021	0.115***	0.022	-0.017	0.108***	0.010	-0.021
	(0.027)	(0.022)	(0.027)	(0.027)	(0.022)	(0.027)	(0.026)	(0.022)	(0.026)
MAPP	-0.273***	-0.368***	-0.102						
	(0.083)	(0.080)	(0.085)						
MAPP_B_FI				-0.257	-0.296	0.073			
				(0.225)	(0.183)	(0.258)			
MAPP_RR							-0.377***	-0.465***	-0.164*
							(0.106)	(0.101)	(0.090)
Constant	-18.718***	-20.933***	23.273***	-18.237***	-21.005***	24.599***	-18.266***	-20.851***	22.902***
	(3.713)	(3.568)	(5.838)	(3.591)	(3.585)	(5.658)	(3.724)	(3.568)	(5.678)
Year fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country fixed effects	NO	YES	NO	NO	YES	NO	NO	YES	NO
Bank fixed effects	NO	NO	YES	NO	NO	YES	NO	NO	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	0.1828	0.5425	0.8148	0.1769	0.5393	0.8146	0.1836	0.5428	0.8150

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Table showing 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, and 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, 2018). The time period is 2000-2015 and all independent variables are lagged one period. The standard errors are clustered for banks.

Table 4. Estimations with macroprudential indexes (in levels) and growth of SRISK

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Size	0.009	0.183***	0.011	0.400***	0.012	0.177***	0.012	0.202***	0.016*	0.205***
	(0.008)	(0.040)	(0.017)	(0.098)	(0.009)	(0.043)	(0.009)	(0.040)	(0.008)	(0.038)
Leverage	-0.001***	-0.002***	-3.159**	2.344	-0.001***	-0.002***	-0.001***	-0.002***	-0.001***	-0.002***
	(0.008)	(0.040)	(0.017)	(0.098)	(0.009)	(0.043)	(0.009)	(0.040)	(0.008)	(0.038)
Real GDP growth	0.004	0.000	0.054*	0.040	0.003	-0.005	0.006	0.001	0.006	-0.001
	(0.010)	(0.011)	(0.030)	(0.038)	(0.013)	(0.015)	(0.010)	(0.012)	(0.010)	(0.011)
Market return	0.001	0.000	-0.001	-0.001	-0.000	-0.000	0.000	-0.000	0.000	0.000
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Volatility	-0.014***	-0.013***	-0.012	-0.002	-0.022***	-0.020***	-0.016***	-0.012***	-0.014***	-0.012***
	(0.004)	(0.004)	(0.010)	(0.012)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
Non-interest income	-0.004	-0.002	-0.004	-0.003	-0.002	-0.000	-0.005*	-0.003	-0.004	-0.002
	(0.003)	(0.003)	(0.004)	(0.005)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
Concentration	0.004	0.005	-0.004	-0.003	0.008***	0.011***	0.003	0.004	0.003	0.005
	(0.003)	(0.003)	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
MAPP * pre 2007	0.028	0.017								
	(0.023)	(0.025)								
MAPP * post 2007	0.037***	0.019*								
	(0.008)	(0.010)								
LTV_CAP * pre 2007			-0.226*	-0.212						
			(0.132)	(0.136)						
LTV_CAP * post 2007			0.057**	0.037						
			(0.027)	(0.034)						
CONCRAT * pre 2007					-0.430***	-0.347**				
					(0.153)	(0.160)				
CONCRAT * post 2007					-0.135***	-0.119**				
					(0.046)	(0.051)				
RR_D * pre 2007							0.002	-0.020		
							(0.024)	(0.027)		
RR_D * post 2007							0.044***	0.011		
							(0.015)	(0.018)		
RR_FX * pre 2007									-0.041	0.002
									(0.125)	(0.137)
RR_FX * post 2007									0.046*	0.049
									(0.027)	(0.032)
Constant	0.222	-1.255***	0.830	-2.933***	-0.011	-1.371**	0.264	-1.428***	0.177	-1.491***
	(0.197)	(0.470)	(0.584)	(1.036)	(0.221)	(0.529)	(0.198)	(0.481)	(0.204)	(0.452)
Year fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country fixed effects	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO
Bank fixed effects	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES
# Observations	2648	2648	773	773	2020	2020	2648	2648	2648	2648
# Countries	51	51	28	28	32	32	51	51	51	51
# Banks	362	362	166	166	276	276	362	362	362	362
R-squared	0.2500	0.3464	0.2582	0.3750	0.2685	0.3668	0.2465	0.3455	0.2456	0.3463

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Table showing regressions with log percentage change of 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). Macroprudential indexes measure the cumulative sum of tightenings net of easings since 2000 (Akinci & Olmstead-Rumsey, 2018). The dummy variables "pre 2007" ("post 2007") takes value 1 for the years 2000-2006 (2007-2015) and zero otherwise. The time period is 2000-2015 and all independent variables are lagged one period. The standard errors are clustered for banks.

Table 5. Estimations with changes in macroprudential indexes and growth of SRISK

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Size	0.030***	0.015*	0.196***	0.033***	0.016*	0.199***	0.030***	0.017**	0.203***
	(0.008)	(0.008)	(0.037)	(0.008)	(0.008)	(0.038)	(0.008)	(0.008)	(0.037)
Leverage	-0.001***	-0.001***	-0.002***	-0.001***	-0.001***	-0.002***	-0.001***	-0.001***	-0.002***
	(0.008)	(0.008)	(0.037)	(0.008)	(0.008)	(0.038)	(0.008)	(0.008)	(0.037)
Real GDP growth	0.011**	0.005	-0.000	0.010**	0.006	-0.000	0.015***	0.007	0.001
	(0.005)	(0.010)	(0.012)	(0.005)	(0.010)	(0.012)	(0.005)	(0.010)	(0.012)
Market return	-0.002*	-0.000	-0.000	-0.002	0.000	0.000	-0.002*	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Volatility	-0.002	-0.015***	-0.012***	-0.003	-0.015***	-0.013***	-0.002	-0.015***	-0.012***
	(0.002)	(0.004)	(0.004)	(0.002)	(0.003)	(0.004)	(0.002)	(0.004)	(0.004)
Non-interest income	-0.002	-0.004	-0.002	-0.002	-0.004	-0.002	-0.001	-0.004*	-0.003
	(0.001)	(0.003)	(0.003)	(0.001)	(0.003)	(0.003)	(0.001)	(0.003)	(0.003)
Concentration	0.001*	0.003	0.005	0.001*	0.002	0.005	0.001**	0.002	0.005
	(0.001)	(0.003)	(0.003)	(0.001)	(0.003)	(0.003)	(0.001)	(0.003)	(0.003)
ΔMAPP * pre 2007	-0.101*	-0.107*	-0.105*						
	(0.052)	(0.056)	(0.055)						
ΔMAPP * post 2007	0.114***	0.111***	0.093***						
	(0.028)	(0.029)	(0.031)						
ΔMAPP_B_FI * pre 2007				-0.111	-0.246	-0.231			
				(0.154)	(0.157)	(0.151)			
ΔMAPP_B_FI * post 2007				0.144***	0.149***	0.126***			
				(0.037)	(0.040)	(0.042)			
ΔMAPP_RR * pre 2007							-0.107**	-0.083	-0.083
							(0.053)	(0.058)	(0.058)
ΔMAPP_RR * post 2007							0.090**	0.088**	0.074*
							(0.042)	(0.041)	(0.044)
Constant	-0.199	0.211	-1.390***	-0.195	0.247	-1.406***	-0.239	0.203	-1.455***
	(0.150)	(0.196)	(0.447)	(0.150)	(0.197)	(0.450)	(0.149)	(0.196)	(0.453)
Year fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country fixed effects	NO	YES	NO	NO	YES	NO	NO	YES	NO
Bank fixed effects	NO	NO	YES	NO	NO	YES	NO	NO	YES
# Observations	2648	2648	2648	2648	2648	2648	2648	2648	2648
# Countries	51	51	51	51	51	51	51	51	51
# Banks	362	362	362	362	362	362	362	362	362
R-squared	0.2068	0.2506	0.3500	0.2042	0.2494	0.3490	0.2026	0.2464	0.3470

Robust standard errors in parentheses

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

Notes: Table showing regressions with log percentage change of SRISK scaled by real GDP as the dependent variable. The ΔMAPP index includes all five macroprudential instruments (ΔLTV_CAP, ΔIBEX, ΔCONCRAT, ΔRR_D, and ΔRR_FX). Moreover, the sub-index ΔMAPP_B_FI is the sum of ΔLTV_CAP, ΔIBEX, and ΔCONCRAT. In addition, ΔMAPP_RR include both reserve requirement instruments (ΔRR_D and ΔRR_FX). Macroprudential indexes measure the sum of tightenings net of easings for each year separately (Altunbas et al., 2018). The dummy variables "pre 2007" ("post 2007") takes value 1 for the years 2000-2006 (2007-2015) and zero otherwise. The time period is 2000-2015 and all independent variables are lagged one period. The standard errors are clustered for banks.

Table 6. Estimations with changes in macroprudential policies and growth of SRISK

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Size	0.007	0.403***	0.015*	0.186***	0.018**	0.212***	0.017**	0.203***	0.017**	0.209***
	(0.018)	(0.101)	(0.009)	(0.046)	(0.009)	(0.038)	(0.008)	(0.037)	(0.008)	(0.038)
Leverage	-2.526*	3.049*	-0.001***	-0.002***	-0.001***	-0.002***	-0.001***	-0.002***	-0.001***	-0.002***
	(0.018)	(0.101)	(0.009)	(0.046)	(0.009)	(0.038)	(0.008)	(0.037)	(0.008)	(0.038)
Real GDP growth	0.042	0.023	-0.002	-0.008	0.007	0.001	0.007	0.001	0.007	0.000
	(0.031)	(0.039)	(0.013)	(0.016)	(0.010)	(0.012)	(0.010)	(0.012)	(0.010)	(0.012)
Market return	-0.002	-0.002	0.000	0.000	0.000	0.000	0.000	-0.000	0.000	-0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Volatility	-0.022**	-0.009	-0.023***	-0.020***	-0.015***	-0.011***	-0.014***	-0.012***	-0.013***	-0.011**
	(0.009)	(0.011)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Non-interest income	-0.003	-0.002	-0.003	-0.001	-0.004*	-0.002	-0.004	-0.002	-0.004	-0.002
	(0.004)	(0.005)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Concentration	-0.005	-0.003	0.008***	0.011***	0.002	0.004	0.002	0.005	0.002	0.004
	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
ΔLTV_CAP * pre 2007	-0.635***	-0.350								
	(0.222)	(0.217)								
ΔLTV_CAP * post 2007	0.201***	0.230***								
	(0.052)	(0.057)								
ΔCONCRAT * pre 2007			-0.271	-0.297						
			(0.202)	(0.183)						
ΔCONCRAT * post 2007			-0.091	-0.114						
			(0.097)	(0.103)						
ΔRR_D * pre 2007					-0.069**	-0.080**			-0.064*	-0.078**
					(0.033)	(0.033)			(0.033)	(0.034)
ΔRR_D * post 2007					-0.002	-0.000			-0.014	-0.010
					(0.022)	(0.023)			(0.022)	(0.023)
ΔRR_FX * pre 2007							-0.101	-0.060	-0.074	-0.024
							(0.098)	(0.098)	(0.101)	(0.102)
ΔRR_FX * post 2007							0.116**	0.110**	0.122**	0.113**
							(0.047)	(0.054)	(0.048)	(0.055)
Constant	1.322**	-2.657**	0.051	-1.415**	0.202	-1.558***	0.176	-1.468***	0.155	-1.551***
	(0.542)	(1.043)	(0.226)	(0.552)	(0.198)	(0.457)	(0.199)	(0.446)	(0.201)	(0.452)
Year fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country fixed effects	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO
Bank fixed effects	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES
# Observations	773	773	2020	2020	2648	2648	2648	2648	2648	2648
# Countries	28	28	32	32	51	51	51	51	51	51
# Banks	166	166	276	276	362	362	362	362	362	362
R-squared	0.2696	0.3873	0.2657	0.3657	0.2451	0.3466	0.2465	0.3470	0.2475	0.3483

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Table showing regressions with log percentage change of SRISK scaled by real GDP as the dependent variable. Macroprudential indexes measure the sum of tightenings net of easings for each year separately (Altunbas et al., 2018). The dummy variables "pre 2007" ("post 2007") takes value 1 for the years 2000-2006 (2007-2015) and zero otherwise. The time period is 2000-2015 and all independent variables are lagged one period. The standard errors are clustered for banks.

6. Robustness analysis

The results discussed in the previous section showed that tighter macroprudential policy conditions are negatively associated with the ratio of SRISK-to-GDP for banks. However, if developing countries both have a tighter macroprudential policy stance and a lower ratio of SRISK-to-GDP for banks then it is essential to control for the income level between countries in pooled estimations.

Consequently, Table A6 (Appendix 2) show similar estimations as in Table 3 but this time also including the log of GDP per capita or dummies for advanced and EU countries. The coefficient for the MAPP index is negative and significant at the 5 percent level in estimations with year fixed effects including GDP per capita or dummies for advanced and EU countries. However, the MAPP index is not significant in estimations with both year and country or bank fixed effects with GDP per capita. Moreover, similar results are found for the MAPP_RR index but the MAPP_B_FI index is not significant in any of the estimations. Finally, the results for quantile regressions shown in Table A4 (Appendix 2) generally hold also when including GDP per capita but the coefficients have lower significance (MAPP_B_FI is not significant). In addition, the coefficients for MAPP, MAPP_B_FI and MAPP_RR are negative and highly significant for the 0.50 and 0.75 quantiles when including advanced and EU country dummies.

Table A7 (Appendix 2) show results for estimations with the change in macroprudential indexes and GDP per capita or dummies for advanced and EU countries. The coefficient for the ΔMAPP index is negative and significant at the 10% level in all estimations for the pre-2007 period. Moreover, the sub-index MAPP_RR is negative and significant at the 5% level prior to the Global Financial Crisis when only including year controls and at the 10% level with country or bank fixed effects. However, the coefficient for the sub-index with borrower- and financial institutions-targeted instruments MAPP_B_FI is negative but not significant in any of the estimations. As expected, all the aggregate indexes have positive and significant coefficients for the post-2007 period.

Furthermore, dynamic system GMM estimations are conducted to further try to address endogeneity between macroprudential policies and SRISK following the approach in Altunbas et al. (2018). Table 7 shows the results for GMM estimations with aggregate indexes and macroprudential instruments. The change in the aggregate index including all macroprudential instruments (ΔMAPP) is negative and significant at the 5% level for the pre-2007 period. Moreover, the coefficient for the sub-index MAPP_B_FI is negative and significant at the 1% level while the MAPP_RR coefficient is only significant at the 10% level for the period 2000-2006.

Table 7. Dynamic GMM estimations with changes in macroprudential indexes

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable (t-1)	0.040	-0.005	0.029	0.030	0.002	0.017
	(0.047)	(0.049)	(0.048)	(0.046)	(0.045)	(0.044)
Size	0.071***	0.089***	0.075***	0.082***	0.094***	0.094***
	(0.014)	(0.014)	(0.014)	(0.013)	(0.014)	(0.016)
Leverage	-0.002**	-0.001*	-0.002**	-0.002**	-0.002**	-0.002**
	(0.014)	(0.014)	(0.014)	(0.013)	(0.014)	(0.016)
Real GDP growth	0.037***	0.044***	0.044***	0.039***	0.044***	0.057***
	(0.007)	(0.009)	(0.007)	(0.007)	(0.007)	(0.009)
Market return	-0.002*	-0.003*	-0.003**	-0.003**	-0.002*	-0.004**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Volatility	-0.003	-0.003	-0.004	-0.005**	-0.001	-0.005**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Non-interest income	-0.005**	-0.006***	-0.004*	-0.004*	-0.004*	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Concentration	0.002	0.003*	0.002*	0.002	0.002	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
ΔMAPP * pre 2007	-0.198**					
	(0.079)					
ΔMAPP * post 2007	0.246***					
	(0.037)					
ΔMAPP_BI_FI * pre 2007		-0.748***				
		(0.218)				
ΔMAPP_B_FI * post 2007		0.171***				
		(0.054)				
ΔMAPP_RR * pre 2007			-0.156*			
			(0.084)			
ΔMAPP_RR * post 2007			0.292***			
			(0.043)			
ΔRR_D * pre 2007				-0.137***		
				(0.047)		
ΔRR_D * post 2007				0.152***		
				(0.017)		
ΔRR_FX * pre 2007					-0.186	
					(0.152)	
ΔRR_FX * post 2007					0.056	
					(0.056)	
ΔCONCRAT * pre 2007						-0.411
						(0.308)
ΔCONCRAT * post 2007						0.049
						(0.114)
Constant	-0.527***	-0.697***	-0.551***	-0.561***	-0.763***	-0.847***
	(0.161)	(0.149)	(0.162)	(0.162)	(0.158)	(0.182)
# Observations	2197	2197	2197	2197	2197	1669
# Countries	48	48	48	48	48	29
# Banks	334	334	334	334	334	252
AB AR(1) Test	0.000	0.000	0.000	0.000	0.000	0.000
AB AR(2) Test	0.619	0.407	0.428	0.522	0.216	0.791
Hansen J-test	0.371	0.368	0.424	0.428	0.417	0.172

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Table showing dynamic system GMM estimations with log percentage change of SRISK scaled by real GDP as the dependent variable. The ΔMAPP index includes all five macroprudential instruments (ΔLTV_CAP, ΔIBEX, ΔCONCRAT, ΔRR_D, and ΔRR_FX). Moreover, the sub-index ΔMAPP_B_FI is the sum of ΔLTV_CAP, ΔIBEX, and ΔCONCRAT. In addition, ΔMAPP_RR include both reserve requirement instruments (ΔRR_D and ΔRR_FX). Macroprudential indexes measure the sum of tightenings net of easings for each year separately (Altunbas et al., 2018). The dummy variables "pre 2007" ("post 2007") takes value 1 for the years 2000-2006 (2007-2015) and zero otherwise. The time period is 2000-2015 and all independent variables are lagged one period. The standard errors are clustered for banks.

Finally, among the individual macroprudential instruments, it is only reserve requirements on accounts denominated in local currency (ΔRR_D) that is negative and significant for the pre-2007 period. All aggregate indexes and ΔRR_D have positive and significant coefficients for the period 2007-2015. Finally, the Hansen J-test and Arellano Bond AR(2) test are important to verify that the system GMM estimator is consistent. Both tests fail to reject the null hypothesis in all estimations which suggest that the model specifications are suitable (Altunbas et al. 2018).

7. Conclusion

The ultimate objective of macroprudential regulation is to mitigate the build-up of systemic risk in the financial system according to De Nicólo et al. (2012). The purpose of this study is to investigate the impact of macroprudential policies on banks' systemic risk. The analysis includes yearly data on systemic risk (SRISK) for 460 banks in 55 advanced and developing countries between 2000-2015.

The results suggest that the macroprudential policy stance (i.e. the cumulative sum of tightenings net of easings since 2000) for the aggregate index including five instruments is negatively associated with the ratio of SRISK scaled by GDP. This result is generally robust also when controlling for the level of development. In addition, tighter conditions for concentration limits seem to reduce the future growth rate of systemic risk.

Furthermore, the empirical evidence shows that also yearly changes in macroprudential policies influence the growth rate of systemic risk. The findings suggest that a tightening of aggregate macroprudential indexes prior to the Global Financial Crisis was associated with a lower growth rate of systemic risk one year ahead. Moreover, this finding is stronger for S-GMM estimations which better can address potential endogeneity between macroprudential policies and systemic risk. In addition, the results further suggest that a tightening of loan-to-value-caps or reserve requirements on accounts denominated in local currency lowered the growth rate of systemic risk before 2007.

To sum up, this is one of the first studies examining the impact of macroprudential regulation on banks' systemic risk. The results suggest that macroprudential policies can be effective to mitigate the build-up of systemic risk.

Acknowledgments

I am greatly indebted to Gabriella Chiesa and Paolo Manasse for their guidance. I would also like to thank NYU's V-Lab for sharing firm-level systemic risk data.

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Appendix 1

Table A1. Variable definitions and sources

Variable	Definition	Source
Dependent variables		
SRISK-to-GDP	Positive SRISK scaled by real GDP.	NYU's V-Lab, World Bank Databank
Δ(SRISK-to-GDP)	Log annual change in positive SRISK scaled by real GDP.	NYU's V-Lab, World Bank Databank
Control variables		
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	The year-over-year change in GDP.	World Development Indicators
Volatility	The annual stock market volatility.	Global Financial Development Database.
Market return	The annual stock market return.	Global Financial Development Database.
Non-interest income	The annual value for aggregate non-interest income relative to the banking system's total income.	Global Financial Development Database.
Concentration	The assets of the three largest commercial banks as percent of total assets for the banking sector.	Global Financial Development Database.
GDP per capita	Log of GDP per capita	World Development Indicators

Table A2. Macroprudential variable definitions and sources

Variable	Definition	Source
Levels		
LTV_CAP	Cumulative change (sum of tightenings net of easings since 2000) in the Loan-to-Value Cap.	Cerutti et al. (2017b)
IBEX	Cumulative change in the interbank exposure limit. Limits banks exposures to other banks.	Cerutti et al. (2017b)
CONCRAT	Cumulative change in concentration limits. Limits banks' exposures to specific borrowers or sectors.	Cerutti 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.	Cerutti 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.	Cerutti 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.	Cerutti et al. (2017b)
MAPP_B_FI	Sum of LTV_CAP, IBEX, and CONCRAT.	Cerutti 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.	Cerutti et al. (2017b)
Changes		
ΔLTV_CAP	Yearly change (sum of tightenings net of easings for each year separately) in the Loan-to-Value Cap.	Cerutti et al. (2017b)
ΔIBEX	Yearly change in the instrument interbank exposure limits.	Cerutti et al. (2017b)
ΔCONCRAT	Yearly change in the instrument concentration limits.	Cerutti et al. (2017b)
ΔRR_D	Yearly change in the instrument reserve requirements on local currency-denominated accounts.	Cerutti et al. (2017b)
ΔRR_FX	Yearly change in the instrument reserve requirements on foreign currency-denominated accounts.	Cerutti et al. (2017b)
ΔMAPP	Sum of ΔLTV_CAP, ΔIBEX, ΔCONCRAT, ΔRR_D, and ΔRR_FX. All individual instruments are adjusted to have maximum and minimum changes of 1 and -1 in each year.	Cerutti et al. (2017b)
ΔMAPP_B_FI	Sum of ΔLTV_CAP, ΔIBEX, and ΔCONCRAT. All individual instruments are adjusted to have maximum and minimum changes of 1 and -1 in each year.	Cerutti et al. (2017b)
ΔMAPP_RR	Sum of ΔRR_D and ΔRR_FX. All individual instruments are adjusted to have maximum and minimum changes of 1 and -1 in each year.	Cerutti et al. (2017b)

Table A3. List of countries

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		

Appendix 2

Table A4. Quantile regressions with macroprudential indexes (in levels)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Q.0.25	Q.0.50	Q.0.75	Q.0.25	Q.0.50	Q.0.75	Q.0.25	Q.0.50	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)
Constant	-1.136**	-4.245***	-6.578*	-1.131**	-4.394***	-5.880	-0.911*	-3.466**	-6.622*
	(0.510)	(1.482)	(3.512)	(0.473)	(1.659)	(5.547)	(0.511)	(1.519)	(3.524)
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 parentheses
*** 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). Moreover, the sub-index MAPP_B_FI is the sum of LTV_CAP, IBEX, and CONCRAT. In addition, MAPP_RR include both reserve requirement instruments (RR_D and RR_FX). As an approximation to "fixed effects" the Mundlak-Chamberlein device is applied which include 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, 2018). 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).

Table A5. Estimations with macroprudential indexes (in levels) and different periods

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Size	1.833***	2.206***	-2.090***	1.729***	2.144***	-2.190***	1.829***	2.211***	-2.031***
	(0.300)	(0.297)	(0.564)	(0.292)	(0.293)	(0.531)	(0.302)	(0.301)	(0.541)
Leverage	-0.002*	0.001	0.002*	-0.004***	0.000	0.002*	-0.002	0.001	0.002
	(0.300)	(0.297)	(0.564)	(0.292)	(0.293)	(0.531)	(0.302)	(0.301)	(0.541)
Real GDP growth	0.008	-0.300***	-0.167***	-0.129*	-0.315***	-0.151**	-0.008	-0.303***	-0.172***
	(0.076)	(0.068)	(0.063)	(0.069)	(0.069)	(0.063)	(0.081)	(0.069)	(0.063)
Market return	-0.031**	-0.012**	-0.001	-0.020	-0.008	-0.001	-0.028**	-0.010*	-0.000
	(0.013)	(0.006)	(0.006)	(0.013)	(0.006)	(0.006)	(0.012)	(0.006)	(0.006)
Volatility	0.079**	0.106***	-0.020	0.075**	0.116***	-0.019	0.077**	0.111***	-0.018
	(0.036)	(0.025)	(0.032)	(0.036)	(0.025)	(0.031)	(0.037)	(0.026)	(0.032)
Non-interest income	-0.019	0.005	-0.029	0.005	0.007	-0.026	-0.023	0.005	-0.026
	(0.036)	(0.045)	(0.062)	(0.034)	(0.044)	(0.060)	(0.036)	(0.044)	(0.062)
Concentration	0.114***	0.010	-0.019	0.116***	0.026	-0.010	0.109***	0.010	-0.022
	(0.028)	(0.022)	(0.027)	(0.028)	(0.022)	(0.027)	(0.027)	(0.022)	(0.026)
MAPP * pre 2007	-0.544**	-0.417***	-0.259						
	(0.232)	(0.137)	(0.158)						
MAPP * post 2007	-0.255***	-0.366***	-0.090						
	(0.082)	(0.081)	(0.090)						
MAPP_B_FI * pre 2007				-0.646	-1.463*	-2.101***			
				(0.787)	(0.768)	(0.800)			
MAPP_B_FI * post 2007				-0.245	-0.343*	0.024			
				(0.230)	(0.184)	(0.253)			
MAPP_RR * pre 2007							-0.518**	-0.395***	-0.118
							(0.226)	(0.130)	(0.167)
MAPP_RR * post 2007							-0.358***	-0.469***	-0.168*
							(0.102)	(0.105)	(0.097)
Constant	-18.627***	-20.915***	23.496***	-18.302***	-21.130***	23.961***	-18.188***	-20.885***	22.825***
	(3.697)	(3.585)	(5.880)	(3.653)	(3.611)	(5.441)	(3.712)	(3.591)	(5.703)
Year fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country fixed effects	NO	YES	NO	NO	YES	NO	NO	YES	NO
Bank fixed effects	NO	NO	YES	NO	NO	YES	NO	NO	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	0.1836	0.5519	0.8150	0.1771	0.5401	0.8174	0.1839	0.5428	0.8150

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Table showing 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, and 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, 2018). The dummy variables "pre 2007" ("post 2007") takes value 1 for the years 2000-2006 (2007-2015) and zero otherwise. The time period is 2000-2015 and all independent variables are lagged one period. The standard errors are clustered for banks.

Table A6. Macroprudential indexes (in levels) and controls for level of development

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Size	1.941***	2.292***	-1.822***	1.806***	1.839***	2.311***	1.727***	1.938***	2.303***	1.781***
	(0.347)	(0.312)	(0.589)	(0.286)	(0.339)	(0.319)	(0.279)	(0.353)	(0.314)	(0.288)
Leverage	-0.002	0.001	0.002*	0.000	-0.004***	0.000	-0.001	-0.002	0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Real GDP growth	-0.107	-0.226***	-0.138**	0.235**	-0.249*	-0.197***	0.138	-0.124	-0.229***	0.196**
	(0.136)	(0.061)	(0.061)	(0.110)	(0.137)	(0.060)	(0.107)	(0.127)	(0.062)	(0.098)
Market return	-0.030**	-0.017***	-0.004	-0.013	-0.020	-0.018***	-0.006	-0.027**	-0.017***	-0.009
	(0.013)	(0.006)	(0.007)	(0.011)	(0.013)	(0.006)	(0.011)	(0.013)	(0.006)	(0.011)
Volatility	0.061*	0.058**	-0.039	0.057*	0.056	0.051**	0.055*	0.059	0.061**	0.056*
	(0.036)	(0.026)	(0.032)	(0.033)	(0.036)	(0.025)	(0.033)	(0.036)	(0.025)	(0.033)
Non-interest income	-0.012	0.001	-0.029	-0.069**	0.011	-0.001	-0.049	-0.016	0.002	-0.068**
	(0.035)	(0.044)	(0.062)	(0.034)	(0.033)	(0.043)	(0.032)	(0.035)	(0.044)	(0.034)
Concentration	0.121***	0.002	-0.022	0.054**	0.123***	0.006	0.057**	0.116***	-0.001	0.050*
	(0.031)	(0.022)	(0.027)	(0.027)	(0.031)	(0.021)	(0.026)	(0.030)	(0.022)	(0.027)
GDP per capita	-0.537	-11.805***	-5.928*	0.094	-0.549	-15.010***	0.059	-0.542	-10.805***	0.181
	(0.492)	(2.767)	(3.251)	(0.574)	(0.489)	(3.020)	(0.573)	(0.500)	(2.380)	(0.582)
Advanced country dummy				0.094			0.059			0.181
				(0.574)			(0.573)			(0.582)
EU country dummy				6.243***			6.479***			6.099***
				(1.655)			(1.737)			(1.639)
MAPP * pre 2007	-0.492**	-0.098	-0.120	-0.472**						
	(0.211)	(0.128)	(0.148)	(0.183)						
MAPP * post 2007	-0.264***	-0.054	0.038	-0.272***						
	(0.079)	(0.080)	(0.098)	(0.083)						
MAPP_B_FI * pre 2007					-0.553	-0.794	-1.282			
					(0.768)	(0.684)	(0.793)			
MAPP_B_FI * post 2007					-0.263	0.373	-0.407			
					(0.222)	(0.237)	(0.249)			
MAPP_RR * pre 2007								-0.471**	-0.087	-0.377**
								(0.203)	(0.131)	(0.153)
MAPP_RR * post 2007								-0.368***	-0.190**	-0.333***
								(0.102)	(0.075)	(0.090)
Constant	-13.859***	105.682***	84.534**	6.243***	-13.401***	139.971***	6.479***	-13.364***	94.930***	6.099***
	(4.502)	(27.566)	(33.294)	(1.655)	(4.530)	(30.173)	(1.737)	(4.446)	(23.529)	(1.639)
Year fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country fixed effects	NO	YES	NO	NO	NO	YES	NO	NO	YES	NO
Bank fixed effects	NO	NO	YES	NO	NO	NO	NO	NO	NO	NO
# Observations	2958	2958	2958	2958	2958	2958	2958	2958	2958	2958
# Countries	54	54	54	54	54	54	54	54	54	54
# Banks	387	387	387	387	387	387	387	387	387	387
R-squared	0.1855	0.5462	0.8157	0.2277	0.1791	0.5472	0.2238	0.1858	0.5467	0.2260

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Table showing 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, and 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, 2018). The dummy variables "pre 2007" ("post 2007") takes value 1 for the years 2000-2006 (2007-2015) and zero otherwise. The time period is 2000-2015 and all independent variables are lagged one period (except for advanced and EU country dummies). The standard errors are clustered for banks.

Table A7. Changes in macroprudential indexes and controls for level of development

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Size	0.029***	0.006	0.191***	0.030***	0.029***	0.008	0.032***	0.029***	0.006	0.030***
	(0.008)	(0.009)	(0.046)	(0.007)	(0.008)	(0.009)	(0.007)	(0.008)	(0.009)	(0.007)
Leverage	-0.001***	-0.001***	-0.002***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.008)	(0.009)	(0.046)	(0.007)	(0.008)	(0.009)	(0.007)	(0.008)	(0.009)	(0.000)
Real GDP growth	0.013*	-0.001	-0.001	0.014**	0.014**	0.001	0.016**	0.015**	-0.001	0.018***
	(0.007)	(0.010)	(0.012)	(0.006)	(0.007)	(0.011)	(0.006)	(0.007)	(0.010)	(0.006)
Market return	-0.002*	0.001	-0.000	-0.001	-0.002	0.001	-0.001	-0.002*	0.001	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Volatility	-0.002	-0.011***	-0.012***	-0.004	-0.002	-0.012***	-0.004	-0.002	-0.011***	-0.004
	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)
Non-interest income	-0.002	-0.004	-0.002	-0.003**	-0.002	-0.003	-0.004**	-0.001	-0.004	-0.003*
	(0.001)	(0.003)	(0.003)	(0.002)	(0.001)	(0.003)	(0.002)	(0.001)	(0.003)	(0.002)
Concentration	0.001*	0.004	0.005	-0.000	0.001	0.004	-0.000	0.001*	0.004	-0.000
	(0.001)	(0.003)	(0.003)	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)	(0.003)	(0.001)
GDP per capita	0.007	0.704***	0.063		0.017	0.579***		0.003	0.812***	
	(0.016)	(0.155)	(0.237)		(0.016)	(0.160)		(0.016)	(0.162)	
Advanced country dummy				-0.045	-0.342	-5.974***	-0.021			-0.051
				(0.042)	(0.209)	(1.751)	(0.042)			(0.043)
EU country dummy				0.216***			0.211***			0.218***
				(0.037)			(0.037)			(0.038)
ΔMAPP * pre 2007	-0.102*	-0.104**	-0.105*	-0.092*						
	(0.052)	(0.052)	(0.055)	(0.053)						
ΔMAPP * post 2007	0.113***	0.109***	0.093***	0.119***						
	(0.028)	(0.029)	(0.031)	(0.028)						
ΔMAPP_B_FI * pre 2007					-0.113	-0.201	-0.131			
					(0.155)	(0.153)	(0.160)			
ΔMAPP_B_FI * post 2007					0.148***	0.129***	0.138***			
					(0.037)	(0.040)	(0.036)			
ΔMAPP_RR * pre 2007								-0.108**	-0.092*	-0.091*
								(0.053)	(0.056)	(0.054)
ΔMAPP_RR * post 2007								0.088**	0.107**	0.107**
								(0.042)	(0.042)	(0.042)
Constant	-0.264	-7.352***	-2.022	-0.033	-0.342	-5.974***	-0.055	-0.268	-8.514***	-0.061
	(0.211)	(1.702)	(2.310)	(0.158)	(0.209)	(1.751)	(0.156)	(0.210)	(1.770)	(0.156)
Year fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country fixed effects	NO	YES	NO	NO	NO	YES	NO	NO	YES	NO
Bank fixed effects	NO	NO	YES	NO	NO	NO	NO	NO	NO	NO
# Observations	2648	2648	2648	2648	2648	2648	2648	2648	2648	2648
# Countries	51	51	51	51	51	51	51	51	51	51
# Banks	362	362	362	362	362	362	362	362	362	362
R-squared	0.2069	0.2543	0.3500	0.2151	0.2045	0.2518	0.2120	0.2026	0.2513	0.2109

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Table showing regressions with log percentage change of SRISK scaled by real GDP as the dependent variable. The ΔMAPP index includes all five macroprudential instruments (ΔLTV_CAP, ΔIBEX, ΔCONCRAT, ΔRR_D, and ΔRR_FX). Moreover, the sub-index ΔMAPP_B_FI is the sum of ΔLTV_CAP, ΔIBEX, and ΔCONCRAT. In addition, ΔMAPP_RR include both reserve requirement instruments (ΔRR_D and ΔRR_FX). Macroprudential indexes measure the sum of tightenings net of easings for each year separately (Altunbas et al., 2018). The time period is 2000-2015 and all independent variables are lagged one period (except for advanced and EU country dummies). The standard errors are clustered for banks.