Information sharing, credit booms, and financial stability[1]

Samuel Guérineau, Université d'Auvergne – CERDI*

Florian Léon, University of Luxembourg – CREA[#]

First version: November 2015

This version: June 2016 (article version)

Abstract

This paper analyzes the impact of credit information sharing on financial stability, drawing special attention to its interactions with credit booms. A probit estimation of financial vulnerability episodes – identified by jumps of the ratio of non-performing loans to total loans, is run for a sample of 159 countries dividing in two sub-samples according to their level of development: 80 advanced or emerging economies and 79 less developed countries. The results show that: i) credit information sharing reduces financial fragility for both groups of countries; ii) for less developed countries, the main effect is the direct effect (reduction of NPL ratio once credit boom is controlled), suggesting a portfolio quality effect; iii) for advanced and emerging countries, credit information sharing (IS) also mitigates the detrimental impact of credit boom on financial fragility, iv) the depth of IS has an negative impact on the likelihood of credit booms (but not the coverage of IS).

Keywords: Information sharing, financial stability, credit booms

JEL Classification: G21; G28

[1]This paper benefited from the financial support from the DFID-ESRC Growth Research Program, under Grant No. ES/L012022/1. The authors are grateful to P.R Agénor (Principal investigator), K. Neanidis (scientific advisor), Sylviane Guillaumont Jeanneney and other participants of the FERDI Workshop on financial stability and macroprudential policies in low-income countries (Clermont-Ferrand, November 2015, April 2016) for their useful comments.

* Université d'Auvergne, 65 Boulevard F. Mitterrand, 63000 Clermont-Fd. Email : samuel.guerineau@udamail.fr

[#] University of Luxembourg, 162 Avenue de la Faiencerie, L-1511 Luxembourg. Email: florian.leon@uni.lu

1. Introduction

Global financial crisis has shown the vulnerability of financial systems. It has consequently stressed the need for improving the management of financial vulnerability. A large literature has investigated this issue, mainly in the case of advanced and emerging countries. Several factors have been advanced as tools to reduce financial fragility. For instance, since the onset of the financial crisis, we observe a rapid expansion of macroprudential policies to complement existing tools to reduce both risk-taking of individual financial institution and interdependence between them (Cerutti et al., 2016). Early empirical studies indicate that these measures had a relatively good efficiency in curbing housing price growths, bank leverage and credit growth (Claessens, 2014). However it is not clear that this new set of tools is appropriate to manage financial fragility in all countries, particularly in less advanced countries. Other tools can be more effective in these countries.

In this paper, we concentrate on credit information sharing. Credit information sharing has been not developed to stabilize banking systems but rather to favor credit access for opaque firms and households through the provision of information on borrowers that reduce information asymmetries. Such mechanisms tend to be particularly effective in low-income countries (Djankov et al., 2007). Recent works have highlighted that the development of credit information sharing strengthens financial systems. The theoretical literature has explored three channels by which credit information sharing reduces banking fragility. First, information sharing can reduce moral hazard and enhance the borrowers' incentives to repay. Borrowers repay their loans because they know that defaulters will be blacklisted, reducing external finance in future (Klein, 1992; Vercammen, 1995; Padilla and Pagano, 2000). Furthermore, mitigation of the hold-up problem allowed by information sharing reduces interest rates, increasing entrepreneurs' incentives to exert effort and therefore reducing moral hazard (Padilla and Pagano, 1997). Second, credit information sharing reduces adverse selection by improving bank's information on credit applicants (Pagano and Jappelli, 1993). Third, credit information sharing reduces the risk of over-borrowing as individual lenders can access information on the overall indebtedness of borrowers from all lending sources (Bennardo et al., 2014). Empirical papers show that credit information sharing is beneficial for stability at the microeconomic level. Information sharing reduces credit risk (Jappelli and Pagano, 2002) and default rates (Powell et al. 2004; Houston et al., 2010). While credit information sharing reduces individual risks of defaults, it has ambiguous effects at the macro-level due to composition effect (Brown et al., 2009). Credit information sharing may lead to greater access to credit for riskier borrowers and banks' portfolio quality can be reduced. Recent empirical evidence, Houston et al. (2010) and Büyükkarabacak and Valev (2012) document that greater information sharing leads to a reduced likelihood of financial crisis.

In this paper, we revisit the relationship between credit information sharing and financial stability by investigating the complex interaction between credit information sharing, credit boom and financial fragility. A large literature has shown that excessive credit booms are one of the main drivers of financial crises. Many empirical works have shown that credit growth increases the probability of banking crises (Demirgüç-Kunt and Detragiache, 1998; Kaminsky et al., 1998; Kaminsky and Reinhart, 1999; Mendoza and Terrones, 2008; Gourinchas and Ostfeld, 2012). Recent studies have confirmed this fact using long-run data (Reinhart and Rogoff, 2009; Schularick and Taylor, 2012; Aikman et al., 2015). However, a credit boom does not necessarily induce a financial crisis. A credit boom may reflect an improvement in investment opportunities (Aghion et al., 1999) and some episodes of strong credit growth correspond to a catch-up phenomenon (Gourinchas et al., 2001). Dell'Ariccia et al. (2016), using data for 170 countries over the period 1970-2010, show that only one in three credit boom episodes are followed by a crisis. They also point out that larger and longer is a boom, the more likely that it ends up badly. Recent discussions in academic and policy circles focus on the causes and consequences of credit booms.

While credit information sharing may directly affect financial stability through its impact on portfolio quality, it can also attenuate the negative effect of credit booms and/or limit the occurrence of such booms (cf. dash lines in Figure 1). First, credit information sharing can mitigate the negative effect of credit booms. A rapid growth of credits can weaken the quality of credit screening. During credit booms, credit officers cannot devote sufficient time to correctly screen new projects and bad projects have a higher probability to be financed. The presence of efficient credit information sharing institutions could attenuate the negative effect of credit booms on screening. In addition, credit booms often fuel a rapid rise in asset prices (real estate and equity bubbles). Since assets may be used as collateral, the price rise will itself help an acceleration of credit growth ("financial accelerator") and reinforcing the deterioration of screening. The presence of information sharing mechanisms may allow banks to diversify their portfolio. This diversification can limit the increase of assets prices induced by rapid credit growth, and therefore limit the detrimental impact of such episodes. Second, credit information sharing might affect the occurrence of credit booms, even if its effect is theoretically unknown. On the one hand, information sharing may curb credit growth by avoiding that some customers borrow from several banks. On the other hand, Dell'Ariccia and Marquez (2006) show that a reduction in the information asymmetries across banks may lead to an easing of lending standards and, in turn, an increase in the volume of lending (lending boom).

The goal of this paper is threefold: i) to evaluate the impact of credit information sharing (IS) on financial fragility considering a large range of countries; ii) to identify channels through which IS, if so, impacts financial fragility; and, iii) to distinguish whether less developed countries differ from other countries (advanced and emerging). Banks in less developed countries operate in a context of institutional failures and high degree of opacity. Sharing information about borrowers could help them to cherry pick the best clients and avoid extending loans to bad borrowers. Djankov et al. (2007) have highlighted that credit information sharing is a strong determinant of private credit to GDP in low-income countries; we may expect that credit information sharing is also crucial for financial stability in these countries. In addition, we could expect that channels by which credit information sharing act differ across countries.

To doing so, we combine bank-level and country-level databases to build our dataset. The sample used covers 159 countries including 79 developing countries and 80 emerging and developed countries over the period 2008-2014. We identify all episodes of financial fragility (every time non-performing loans ratio jumps) even if the episode is not ending as a banking crisis and study the determinants of such episodes using a random-effect probit model. The development of IS is assessed by the depth index and the coverage of PCRs and PCBs. In a second step, we analyze the impact of credit information sharing (IS) on credit booms to disentangle indirect effects. The main results are the following: i) IS reduces financial fragility in both developed and developing countries, ii) for developing countries, the main effect is the direct effect (reduction of NPL ratio once credit boom is controlled); iii) for developed and emerging countries, IS also mitigates the positive effect of credit boom on financial fragility, iv) the depth of IS has an negative impact on the likelihood of credit booms (but not the coverage of IS).

This paper provides three main contributions on the literature on the impact of credit information sharing on financial stability. First, our paper includes a large number of countries. Secondly, we analyze the direct and indirect potential effects of information sharing institutions. Finally, we document that credit information sharing is beneficial for both less developed and advanced economies. However, we show that channels slightly differ between both groups of countries. We highlight that credit information sharing mitigates the detrimental effect of credit booms for advanced and emerging countries, while its effect is more direct for less developed countries.

This paper also adds to the literature on the determinants of financial (in)stability. On the one hand, this work integrates most low-income countries. The financial stability issue in low-income countries has received less attention in the recent years, insofar as they have been less impacted by the global financial crisis than emerging and advanced economies. The question of whether less developed economies are more vulnerable to financial crises than emerging and high income economies is ambiguous. Financial vulnerability depends on the balance between risk exposure and the capacity to deal with these risks. However, a better understanding of financial fragility mechanisms in LICs is crucial. First, financial vulnerability does exist. The experience of low-income countries shows that they could suffer sharp increases in non-performing loans and banking crises (see Leaven and Valencia, 2013). Second, the cost of banking crises is high in LICs (both in terms of fiscal cost and output cost, see Laeven and Valencia, 2013), even if the banking sector is small. Third, the current dynamics of financial development in many LICs will, in parallel with its beneficial effects on access to financial services, increase the risk of financial instability, unless financial regulation is progressively adapted to this evolution. New risks arise from the increase in the relative size of the financial sector, from the diversification of financial products and from the deepening of domestic and international financial integration. On the other hand, we propose a new measure of financial instability that identifies all episodes of financial fragility even if the episode is not ending as a banking crisis. The end of the NPL episode may be either a banking crisis (including bankruptcies and/or a restructuration of the banking system, or "only" a phase of write off of bad loans and a recapitalization of banks having suffered significant losses. In both cases, is frequently observed a credit fall after the NPL cycle.

The remainder of the paper is organized as follows. Section 2 presents data and variables and Section 3 develops the empirical methodology. Section 4 displays the results of our estimations and the final section concludes.

2. Data and variables

2.1. Data

To identify the effect of IS on financial fragility and its transmission channels; we combine bank-level and country-level databases. Bank-level data are used to compute the measure of financial fragility and were retrieved from the Bankscope database. Other variables are extracted from diverse country-level databases including the World Development Indicators, the International Financial Statistics and Doing Business. Our dataset restricts to the period 2008-2014 because data on information sharing is not available before 2006 and all explanatory variables are lagged. We consider all countries for which variables are available. To study whether developing countries differ from other countries, we distinguish two groups of countries: countries whose GNI per capita is below US$ 4,125 in 2014 (79, called developing countries)[2] and countries whose GNI per capita exceeds US$ 4,125 (80, called developed and emerging countries). The Table A1 presents the list of countries.

2.2. Financial fragility

A critical step consists on selecting a good measure of financial fragility. In this work, we focus on country-level analysis. Overall banking system instability is often measured by systemic banking distress, defined as periods where the banking system is not capable of fulfilling its functions. We do not adopt the same perspective in our paper for two major reasons. On the one hand, banking crises in developing countries are rare events in recent years.[3] On the other hand, a banking crisis is an extreme situation. Our aim is to have an indicator reflecting the fragility of financial system before the occurrence of a crisis rather than detecting crisis episodes. Indeed, the dynamics of NPLs has significant effects on the dynamics of credit even when a banking crisis is avoided, since it will dampen both credit supply (credit channel) and demand (Pool et al., 2015). We therefore refer to assets quality by using information on non-performing loans (NPLs) as a warning indicator of banking system fragility.[4]

We detect episodes of financial fragility by scrutinizing annual changes of the ratio of NPLs to gross loans. The experience of developing countries shows that financial systems are able to withstand for a long time moderate levels of NPLs without undergoing crisis if bank capital structure (larger interest margins, higher equity ratios) is consistent with this level of NPLs (Brock and Suarez, 2000, Beck and Hesse, 2009). However, financial stability is threatened by a rapid increase in NPLs, which does not allow the financial structure to adapt, since the latter can only evolve slowly. For instance, the peak of the ratio of NPLs to loans in 2009 was a signal of the banking crisis in Nigeria, albeit the level of NPLs was moderate in previous years. The recent global financial crisis provides another evidence of this difference between the level and difference of NPLs to signal fragility in banking systems.

---

[2] According to World Bank's classification, this cutoff separates countries into two groups: (i) low-income and lower-middle income countries and (ii) upper-middle income and high income countries.

[3] According to Laeven and Valencia's (2013) database, only three countries with a GDP per capita below US$ 4,125 have experienced a banking crisis since 2005 (Mongolia, Ukraine and Nigeria). A limited occurrence of such events does not allow us to apply robust econometric model.

[4] There are different bank-level indicators of financial stability used in the literature including Z-score, capital ratio, assets quality, or bank defaults. These indicators are less relevant than a NPL based indicator to give policy recommendations, since they are either less transparent and/or less linked to the lending policy (equity ratios).

We therefore create a dummy (called Banking Sector Distress, BSD henceforth) equals to one if the annual change of this ratio exceeds 3 points:

$$BSD_{it} = \begin{cases} 1, & if\ \Delta \left({}^{NPLs_{it}}/_{Loans_{it}} \right) \geq 3 \\ 0, & otherwise \end{cases}$$

Our calculations are based on individual bank data drawn from the commercially available BankScope database. An advantage of the Bankscope database consists on its coverage of low-income countries.[5] Insofar as we focus our attention on banking system, we keep commercial, savings and cooperative banks. In addition, we use unconsolidated data when available and consolidated data if unconsolidated data are not available, in order not to double count subsidiaries of international banks. The share of NPLs to loans is computed as the sum of NPLs divided by the sum of total loans (thus is a weighted average of bank NPL ratio).

2.3. Credit information sharing

The existing literature has studied the effect of credit information sharing (IS) on financial stability. To study the impact of credit information sharing, a first measure often employed is a dummy indicating whether a private bureau or a credit registry operates in a country. While the dummy variable approach tests whether the existence of credit information sharing matters, it does not distinguish between the different information provided by and the coverage of information sharing mechanisms. To circumvent this limit, an index capturing the depth of information provided is computed by Doing Business. The index ranges from 0 to 6, with higher values indicating the availability of more credit information.[6] Doing Business also provides the coverage of credit information sharing mechanisms. Credit bureau (respectively credit registry) coverage reports the number of individuals and firms listed in a credit bureau's (respectively registry's) database relative to the number of adults. We add credit bureau coverage and credit registry coverage to get the total coverage of information sharing. In this paper, we use both the depth and the coverage to proxy the development of information sharing mechanisms.

[5] Until recently, the coverage of banks in low-income countries by the Bankscope was limited but many improvements have been made during the past decade. There is one alternative database, namely the Financial Soundness Indicators database from the IMF. The IMF's database considers the period from 2005 to 2014. However, the coverage of low-income countries is limited in this database due to filters rules applied. However, for remaining countries, the correlation coefficient of the ratio of NPLs to loans equals 0.75.

[6] Since 2013, Doing Business provides an index ranging from 0 to 8 (see the Doing Business website: http://www.doingbusiness.org/). However, to allow comparison over time, we use the former index ranging from 0 to 6. Precise description of the index can be found in Djankov et al. (2007) or in Büyükkarabacak and Valev (2012).

2.4. Credit booms

In the literature different methods have been employed to detect credit booms ranging from credit growth to econometric filter methods (see Dell'Ariccia et al., 2016). In this work, we employ a simple measure following the approach adopted by Gorton and Ordoñez (2016). We define a credit boom as starting whenever a country experiences at least three consecutive years of positive growth in credit over GDP that averages more than 5%. In the robustness check, we consider an alternative measure of credit boom. Data about credit to GDP is obtained from the WDI.

2.5. Control variables

We follow the existing literature to select control variables (Demirgüç-Kunt and Detragiache, 1998, 2002; Beck et al., 2006; Büyükkarabacak et Valev, 2010, 2012). Variables are grouped in two categories: financial system and macroeconomic factors.

Financial fragility also depends on the risk-taking by banks in their credit operations. The magnitude of credit risk depends on the rate of credit growth, the quality of credit screening and the diversification of the credit portfolio. Unlike credit growth, the quality of the credit selection and portfolio diversification are not readily observable. Therefore, it is useful to include in the analysis the characteristics of the banking system that affect the incentives for banks to take risks. We include a measure of the structure of banking systems. A large literature has studied the impact of bank competition on financial stability. The degree of bank competition has ambiguous impact on financial fragility. The majority of papers using country-level data and banking crisis dummy are in line with the competition-stability view (Demirgüç-Kunt and Detragiache, 1998; Laeven and Valencia, 2013) with the notable exception of Beck et al. (2006). Studies using bank-level data are more ambiguous. Some studies considering a large sample of countries support the competition-stability view (Amidu and Wolfe, 2013), while other papers find the opposite (Turk-Ariss, 2010; Beck et al., 2013). We therefore include an indicator of concentration, namely the Hirschman-Herfindahl index, as a control variable. Controlling for banking system concentration also allows us to partially capture changes in terms of regulations (entry rules, capital regulation).[7]

[7] A large empirical literature has investigated the effect of capital regulation, restrictions on bank entry, restrictions on nonlending activities (Barth, Caprio and Levine, 2004) or deposit insurance scheme (Demirgüç-Kunt and Detragiache, 2002; Anginer et al., 2014) on bank risk taking or financial stability. These papers use updated data on regulation from Barth, Caprio and Levine (2004) and/or deposit insurance database provided by Demirgüç-Kunt,

We also control for capital inflows due to their importance in financial crises in Asia or Latin America in the 1990s (Kaminsky and Reinhart, 1999). We therefore control by adding the net total inflows to GDP as a control variable. We build this variable by adding portfolio, FDI and aid flows relative to GDP. In addition, we control for changes of nominal exchange rate.[8] A rapid exchange rate depreciation raises repayment costs for foreign currency loans and could induce less repayment (Gourinchas and Obstfeld, 2012). At the opposite, a rapid appreciation of the real exchange rate might render exporters less competitive and affect their ability to repay their loans. Exchange rate variation is computed as the percentage change of value of one dollar in local currency.

Several features of the macroeconomic situation may affect borrowers' capacity to service their debt. GDP growth increases borrowers' repayment capacity and should reduce the financial fragility. The theoretical effect of inflation is ambiguous since inflation reduces the real value of debt service but can also reduce the borrowers' income. Empirical literature identifies a negative impact of GDP growth on the likelihood of a banking crisis (Demirguc-Kunt and Detragiache, 1998; Kaminsky and Reinhart, 1999) and on NPL ratio (Glen and Mondragon-Vélez, 2011; Klein, 2013; Beck et al. 2015). Conversely, these studies find a positive impact of inflation and unemployment on financial vulnerability (bank crisis likelihood and NPL ratio). We use as control variables the rate of growth of real GDP and the rate of inflation. The rate of inflation is obtained by computing the annual change of Consumer Price Index (CPI). We expect that financial distresses are more likely in period of slow growth and high inflation.

3. Econometric specification

3.1. Baseline model

Our first specification considers the net effect of information sharing on financial fragility. More formally, we estimate the following equation:

$$Pr(BSD_{it} = 1) = \alpha + \beta IS_{it-1} + \Gamma \boldsymbol{X}_{it-1} + \varepsilon_{it} \qquad (1)$$

where subscripts *i* and *i* refer to country and year respectively. *BSD* is a dummy variable equal to one if a country experienced a situation of financial distress (see 3.1.2) and 0 otherwise. *IS* is a measure of

Kane and Laeven (2015). The use of this variable would significantly redue the sample of developing countries, on which we focus.

[8] Considering real exchange rate should be better but including real exchange rates sharply reduces our sample due to the lack of data. Using the nominal effective exchange rate instead of the us dollar bilateral would be a useful extension.

the development of credit information sharing mechanisms (depth index and coverage) and $\boldsymbol{X}$ is a matrix of control variables. We expect that $\beta < 0$; in other words, we expect that the likelihood to experience a financial distress decreases with the depth and coverage of information sharing.

3.2. Transmission channels

In a second step of analysis, we investigate the transmission channels through which information sharing affects financial fragility. As expressed above, we dedicated special attention to credit booms (Figure 1). First, we study whether information sharing exerts an impact on financial fragility through an additional channel than credit booms (blue arrow in Figure 1). We therefore estimate the following equation:

$$Pr(BSD_{it} = 1) = \alpha + \beta IS_{it-1} + \delta CB_{it-1} + \Gamma \boldsymbol{X}_{it-1} + \varepsilon_{it} \tag{2}$$

We expect that $\delta > 0$, indicating that a situation of financial distress is more likely after a credit boom; and $\beta < 0$.

Secondly, the development of information sharing can mitigate the detrimental impact of credit growth. We therefore extend Eq. 2 by adding an interaction between IS and CB as follows:

$$Pr(BSD_{it} = 1) = \alpha + \beta IS_{it-1} + \delta CB_{it-1} + \gamma IS_{it-1} * CB_{it-1} + \Gamma \boldsymbol{X}_{it-1} + \varepsilon_{it} \tag{3}$$

Finally, we test the impact of information sharing on credit booms. Formally, we estimate the following equation:

$$Pr(CB_{it} = 1) = \alpha' + \beta' IS_{it-1} + \Gamma' \boldsymbol{X}_{it-1} + \varepsilon_{it} \tag{4}$$

where *CB* is a dummy equals to one if a country i experienced a credit boom in year t. The sign of β' is theoretically unknown. The development of credit information sharing may limit the likelihood to observe a credit boom by avoiding that some borrowers borrow from different banks ($\beta' < 0$). However, credit information sharing may increase the occurrence of credit booms by facilitating access to credit ($\beta' > 0$).

In all models, we add time dummy variables to control for common shocks (such as 2008 Global Financial Crisis). The specifications employ independent variables lagged by one-year to reduce endogeneity. At the exception of Eq. 3, we use a random-effect probit due to the binary nature of dependent variable and to control for unobserved country heterogeneity. For Eq. 3, we employ a linear random-effect model.[9] Indeed, the interpretation of interaction poses some challenges in non-linear, especially for random-effect probit model (Greene, 2010).

Finally insofar as we are particularly concerned by developing countries, all equations are estimated not only for the sample of all countries but also separately for advanced/emerging countries (80, whose GNI per capita is above US$ 4,125 in 2014) and for less developed countries (79, whose GNI per capita is below US$ 4,125 in 2014).

4. Results

4.1. Descriptive statistics

Table 1 provides some summary statistics. These statistics document that episodes of rapid degradation of loan quality are frequent. As documented in Figure 2, such events affect both groups of countries. In addition, we clearly observe the effect of the recent 2008 global financial crisis that induces an increase of NPLs in subsequent years. Table 1 points out that correlation coefficient between BSD and a (one-lagged) credit boom seems moderate; however, such correlation is not always informative due to the nature of variables (dummies). We scrutinize in more details this relationship. Among 133 episodes of rapid loan quality degradation, one third (43) are preceded by a credit boom in the previous year. It should be noted that similar figures are obtained by Dell'Ariccia et al. (2016). This ratio reaches almost 50% in the case of developed and emerging countries (30 out of 66 episodes) that can be explained by the recent financial crises. For developing countries, 20% of financial distresses were preceded by a credit boom (13 out of 67).

Scrutinizing credit information sharing data, we observe that both depth and coverage of credit information sharing is higher in high-income countries. However, developing economies – especially middle-income countries - have experienced a rapid expansion of information sharing institutions during the last ten years. The rate of coverage of public and private institutions as well as the quality of information increased in middle-income countries during the last decade (see Figure A1). For instance, the depth index has increased from 1.4 to 3.8 in lower middle income countries and from 2.4 to 4.3 for upper-middle income countries. The trend is similar for the coverage of IS that has almost tripled for both groups of countries during the past decade. After a long period of stagnation, low-income countries

[9] Our robustness checks presented in the Appendix document that linear and non-linear models provide close results, both in terms of statistical significance and economic amplitude.

have experienced some improvements in recent years. The depth of IS has therefore increased from 0.3 to 0.8 in three years (from 2012 to 2014) and the coverage has doubled during the same period.

4.2. The net effect of credit information sharing on financial fragility

4.2.1. Baseline results

We start by testing whether credit information sharing development affects the occurrence of financial fragility episodes. Econometric results are reported in Table 2. The two first columns consider all countries, while columns [3] and [4] concentrate on countries whose GNI per capita exceeds US$ 4,125 in 2014 and columns [5] and [6] on countries whose GNI per capita exceeds US$ 4,125 in 2014 (called "developing countries"). We consider two measures of credit information sharing: the depth of information provided by and the coverage of credit bureaus and credit registries. The bottom of the Table reports the usual tests of model validity. The LR test valid our choice to take into account unobserved country heterogeneity.

The baseline model provides two main messages. First, the development of credit information sharing (IS) mechanisms is negatively related to financial fragility. Both the index of depth and the coverage of information sharing mechanisms are negatively, and statistical significant so, associated with the likelihood to experience a period of rapid loan quality degradation. The impact of credit information sharing development is not only statistical significant but the effect is also economically significant. The results indicate that a one-standard deviation of credit depth index reduces the likelihood to observe a financial crisis episode by 3.5 percentage points and a one-standard deviation of the coverage of information sharing by 4 percentage points. Second, credit information sharing mechanisms exert a role on both developed and developing countries. As documented in columns [3] to [6], the depth and the coverage of credit information sharing mechanisms are negatively associated with financial fragility for both sub-samples of countries.

Regarding control variables, the likelihood to experience an episode of financial distress is reduced in countries with a higher GDP per capita, a limited size of financial system, with high growth and in competitive banking markets. It should be noted that some of these results hold for developed countries but tend to vanish when we consider only developing countries.[10]

[10] In an alternative model, we consider macroprudential policies as control variables (in all specifications). Data are extracted from Cerutti et al. (2016) and we employ the three alternative variables developed by the authors (Global index, borrowers' targeted instruments index and financial institutions' targeted instruments index). The sample of

4.2.2. *Sensitivity tests*

We have established that IS development reduces financial fragility. In the next section we will explore transmission channels in this relationship. Before doing so, we run sensitivity analysis to be ascertaining that our results are not driven by misspecification. Results are reported in the Appendix (Tables A3 and A4). First, we exclude all control variables (columns [1]). Second, we change the econometric method. The baseline model uses a random-effect probit model to control for country heterogeneity. An alternative method is population-averaged probit model. An advantage of the population-averaged method is that it allows us to reduce the influence of outliers (columns [2]). Third, we also consider a probability linear model (random-effect model) (columns [3]). Fourth, we change our measure of financial distress by considering a shock of 5 percentage points instead of 3 percentage points (columns [4]). Two final tests of sensitivity focus on the sample considered. On the one hand, we exclude the year following the start of the banking system distress (columns [5]). On the other hand, we select country-year observations where the number of banks exceeds five banks. Indeed, in some low-income countries, only a handful of banks operate. As a result, variation of NPLs might only capture the difficulties faced by one bank. We re-estimate our model on these sub-samples (columns [6]). Our findings are unchanged - both statistically and economically. Finally, the development of IS may be influenced by the fragility of the banking sector and the assumption of exogeneity could be no longer valid. To limit this issue, all explanatory variables are lagged. However, we also use an instrumental variable approach. We follow instrumental strategy proposed by Büyükkarabacak and Valev (2012) considering the total population and urbanization rate.[11] For sake of brevity, we do not report the results but our results confirm the negative effect of IS. Coefficients associated with IS remain negative and statistically significant in all specifications (all countries and both sub-samples; depth and coverage). In addition, our instrumentation strategy seems valid: the F-stat of the first stage estimation exceeds 10 and instruments are exogenous according to over-identification tests (applied to linear IV estimations). In addition, the Wald tests of exogeneity tend to reject the presence of endogeneity. For the remainder of our paper, we therefore assume that IS development is exogenous.

---

countries is largely reduced from 159 to 96 countries due to the lack of information. Our results can be summarized as follows: (i) the introduction of macroprudential policies does not alter our results regarding credit information sharing; (ii) coefficients associated with macroprudential policies are never statistically significant and/or robust. Results are available upon request.

[11] We also test another instrument, namely the share of informal economy. The idea is that development of IS is lower in economies with a large share of informal activity. However, our results are not improved. It should be noted that our instrumentation strategy provide less clear-cut results when we consider sub-samples, even if coefficients associated with IS remain negative and statistically significant. Our regressions suffer from weak instruments and/or difficulties to converge.

4.3. Transmission channels

The baseline model points out that information sharing mechanisms limit the risk to experience an episode of financial distress for a country. In addition, results do not differ between developing and developed countries. In a second step of analysis, we shed lights on transmission channels. As documented in Figure 1, IS might exert a role on financial fragility through at least three channels. We test each channel in separate models.

4.3.1. Direct effects of credit information sharing after controlling for credit booms

While we expect that IS affects financial fragility through credit booms, it can also have independent effect. To test this hypothesis, we run Eq. 2 that consists on the baseline model with an additional variable, namely credit boom (CB). Results are reported in Table 3. First, we document that a credit boom in previous years induces a higher probability to observe a financial distress, in line with previous studies. A credit boom increases by almost 5 percentage points the likelihood to observe a situation of banking distress. Interestingly, the economic impact of credit boom is higher for developing countries. Moreover, we document that, after controlling for credit booms, neither the sign nor the amplitude of marginal effects associated with the depth and coverage of IS has been dramatically affected. In other words, IS exerts an impact on financial fragility through other channels than credit booms. When we focus on sub-samples of developed and developing countries, our results are largely unchanged. We run the same battery of sensitivity analysis than those presented in section 4.2. In addition, we consider an alternative definition of credit booms (an average of 3% instead of 5%). Our main results are not altered by these different changes. These findings document that IS act directly on financial fragility by improving the portfolio quality

4.3.2. Interaction between credit information sharing and credit booms

Information sharing may also reduce financial fragility by mitigating the detrimental effect of credit booms. To test this channel, we add an interaction between IS and credit booms as expressed in Eq. 3. Contrary to previous specifications, we run a probability linear model because the signs of interactions cannot be easily computed in a non-linear model, especially for random-effect probit models (Greene, 2010). A linear model allows us to directly get the impact of interaction by observing the sign and significance of coefficient. Results are reported in Table 4. The two first columns report econometric results for the sample of all countries. We observe that not only variables related to the development of IS enter significantly and negatively, but their interactions with credit booms also enter negatively and are statistically different from zero. The impact of credit information sharing is not only statistically significant but also economically meaningful. A credit boom increases the likelihood of experiencing an episode of banking distress by 30 percentage points in a country without information sharing. However the effect of a credit boom is reduced by 10 percentage points in a country having a moderately developed credit information sharing mechanisms (i.e. IS whose level of development equals the average, namely the depth index of 3 and coverage of 32%). Put differently, information sharing exerts a direct impact on financial fragility but also mitigates the detrimental effect of credit booms.

In a second step, we divide our sample between advanced/emerging and developing countries. Information provided are instructive. For countries whose GNI exceeds US$ 4,125, the positive effect of IS on financial stability tend to be related to their role during credit booms. Indeed, we observe that variables of IS in levels do not remain statistically significant, albeit interactions are. On the contrary, for developing countries, variables in level remain negative and statistically significant, but interactions between credit booms and IS are not different from zero. Even if we ignore statistical significance, the economic size of interaction is reduced for developing countries. To sum up, the development of IS seems to mitigate the negative impact of credit booms; however, this mitigation effect is driven by developed and emerging economies.

4.3.3. Determinants of credit booms

The previous sub-section has documented that IS play a different role in developed and developing countries. While IS seems to mitigate credit booms in developed and emerging countries, its effects pass through another channel in developing countries. To complete our analysis, we shed lights on the impact of IS on the likelihood to observe a credit boom. We test this potential hypothesis by investigating the determinants of a credit boom (Eq. 4). Table 5 reports the determinants of credit booms. The results are interesting: the depth of credit information sharing tends to reduce the likelihood to observe a credit boom. This result occurs in the different specifications (all countries, developed and developing sub-samples). The results indicate that a one-standard deviation of credit depth index reduces the likelihood to observe a credit boom by 1.5 percentage points. This result is far from anecdotal insofar as the likelihood to observe a credit boom equals 20%. As previously, the impact of the quality of credit information sharing is higher for developed countries (reduction by 3.5 pp.). At the opposite, the coverage of credit information sharing has not statistical impact on the occurrence of credit booms.

5. Conclusion

In this paper, we analyze the effect of credit information sharing on financial vulnerability on a large sample of countries. Instead of banking crisis dummy, we consider an alternative measure of financial fragility based on changes in the ratio of NPLs to loans to capture all episodes of financial distress and not only the extreme ones. Our first result confirms findings from other papers by highlighting the stabilizing impact of credit information sharing. We also document that this result hold for both less developed countries (whose GNI per capita is below US$ 4,125) and other countries (advanced and emerging). In a second step, we study the complex relationships between credit information sharing, credit booms and financial fragility. Our econometric results point out several important results: (i) information sharing development has a direct effect, after controlling for credit booms; (ii) higher the scope of information collected, lower the likelihood to observe a credit boom is (but the coverage of credit information sharing information does not matter); (iii) credit information sharing mitigates the detrimental effect of credit boom but this result holds only for advanced and emerging countries; and (iv) credit booms are strong predictors of financial vulnerability, especially in advanced and emerging countries.

Our results, although preliminary, have several policy implications. First, the credit growth is a key variable to conduct macroprudential policies in low and middle-income countries. Second, current efforts to develop credit information sharing schemes should be strengthened, since the latter allow a credit expansion without excessive increase in the overall credit risk. Our results also document that credit information sharing has little.impact on credit booms in developing countries, which justifies the extension of other tools – such as macroprudential policies - to prevent excessive credit growth. At last, extending the coverage of information sharing systems is not enough, since depth of information sharing is more efficient to avoid credit booms.

References

Aghion, P., P., Bachetta, and A., Banerjee, (1999), “Capital markets and the instability of open economies”, *Studienzentrum Gerzense Working papers*, 99.01

Aikman, D., Haldane, A. G. and Nelson, B. D. (2015), “Curbing the Credit Cycle”. The Economic Journal, 125: 1072–1109.

Amidu, M. and Wolfe, S. (2013) “Bank competition, diversification, and financial stability”, Review of Development Finance, Vol. 3, No. 3, p. 152-166.

Anginer, D., Demirgüç-Kunt, A. and Zhu, M. (2014) “How does deposit insurance affect bank risk? Evidence from the recent crisis”, *Journal of Banking & Finance*, 48, p.312-321.

Barth, J.R. Caprio, G. and Levine, R. (2004) “Bank regulation and supervision: What works best?” *Journal of Financial Intermediation*, 13, p.205-248.

Beck, R., Jakubik, P. and A. Piloiu (2015), “Key determinants of non-performing loans: New evidence from a global sample”, *Open Economic Review*, 26, p.525-550.

Beck, T., and H. Hesse, (2009), “Why are interest spreads so high in Uganda?”, *Journal of Development Economics*, 88, p.192-204.

Beck, T., De Jonghe, O. and G. Schepens, (2013), “Bank competition and stability: Cross-country heterogeneity”, *Journal of Financial Intermediation*, 22, p.218-244.

Beck, T., Demirgüç-Kunt, A. and R. Levine, (2006), “Bank concentration, competition, and crises: First results”, *Journal of Banking & Finance*, 30, p.1581-1603.

Bennardo, A., Pagano, M. and S., Piccolo (2014) “Multiple-bank lending, creditor rights, and information sharing”, *Review of Finance*, 19(2), p.519-570.

Brock, P. L., and L. Rojas-Suarez, (2000), “Understanding the Behaviour of Bank Spreads in Latin America,” *Journal of Development Economics,* Vol. 63, No. 1, p.113–34.

Brown, M., Jappelli, T. and M. Pagano, (2009) “Information sharing and credit: Firm level evidence from transition countries”, *Journal of Financial Intermediation*, 18, p.151-172.

Büyükkarabacak, B. and N. T. Valev, (2010), “The role of household and business credit in banking crises”, *Journal of Banking & Finance*, 34, p.1247-1256.

Büyükkarabacak, B. and N. T., Valev, (2012), “Credit information sharing and banking crises: An empirical investigation”, *Journal of Macroeconomics*, 34, p.1247-1256.

Cerutti, E., Claessens, S. and Laeven, L. (2016), “The use and effectiveness of macroprudential policies: New evidence”, Journal of Financial Stability, in press.

Claessens, S., (2014), “An Overview of Macroprudential Policy Tools”, International Monetary Fund, *IMF Working Paper*, WP/14/214.

Dell’Ariccia, G., and R., Marquez, (2006), “Lending Booms and Lending Standards.”, *The Journal of Finance*, 51(5), p.2511-2546.

Dell’Ariccia, G., Igan, D., Laeaven, L. and Tong, H. (2016) “Credit booms and macrofinancial stability”, *Economic Policy*, p. 299-357.

Demirgüç-Kunt, A. and E. Detragiache, (1998), “The determinants of banking crises in developing and developed countries”, International Monetary Fund, *IMF Staff Papers*, 45(1), p.81-109.

Demirgüç-Kunt, A. and E. Detragiache, (2002), “Does deposit insurance increase banking system stability? An empirical investigation”, *Journal of Monetary Economics*, 49(7), p.1373-1406.

Demirgüç-Kunt, A., Kane, E.J. and L. Laeven, (2015), “Deposit insurance around the World: A comprehensive analysis and database”, *Journal of Financial Stability*, forthcoming.

Djankov, S., C. McLiesh and A. Shleifer (2007) “Private credit in 129 countries”, *Journal of Financial Economics*, Vol. 12, No. 2, p. 77-99.

Glen, J. and C. Mondragon-Vélez, (2011), “Business cycle effects on commercial bank loan portfolio performance in developing countries”, *Review of Development Finance*, 1, p.150-165.

Gorton, G. and Ordoñez, G. (2016) “Good booms, bad booms”, NBER Working Paper, 22008.

Gourinchas, P., Valdes, R., and O., Landerretche, (2001), “Lending booms: Latin America and the world”, *Economia,* p. 47–99

Gourinchas, P-O. and Obstfeld, R. (2012), “Stories of the twentieth century for the twenty-first”, American Economic Journal: Macroeconomics, Vol. 4, p. 226-265.

Greene, W. (2010), “Testing hypotheses about interaction terms in non-linear models”, Economics Letters, Vol. 107, No. 2, p. 291-296.

Houston, J. F., C. Lin, P. Lin, and Y. Ma, (2010), “Creditor rights, information sharing, and bank risk taking”, *Journal of Financial Economics*, 96, p.485–512.

Jappelli, T. and Pagano, M., (2002), “Information sharing, lending and defaults: Cross-country evidence”, *Journal of Banking & Finance*, 26, p.2017-2045.

Kaminsky, G. L., and C. M., Reinhart, (1999), “The twin crises: the causes of banking and balance of payments problems”, *American Economic Review,* 89 (3), June, p.473–500.

Kaminsky, G., Lizondo, S. and C. Reinhart, (1998), “Leading indicators of currency crises”, International Monetary Fund, *IMF Staff Papers*, 45, p.

Klein, D.B. (1992), “Promise keeping in the great society: A modle of credit information sharing”, *Economics Politics*, 4, p. 117-139.

Klein, N., (2013), “Non-Performing Loans in CESEE: Determinants and Macroeconomic Performance”, International Monetary Fund, *IMF Working paper*, WP/13/72.

Laeven, L. and F. Valencia, (2013), “Systemic banking crises database”, International Monetary Fund, *IMF Economic Review*, 61, p.225-270.

Mendoza, E.G., and M.E., Terrones, (2008), “An Anatomy of Credit Booms: Evidence from Macro Aggregates and Micro Data”, International Monetary Fund, *IMF Working Paper*, n°08/226.

Padilla, A. J. and M. Pagano, (1997), “Endogenous communication among lenders and entrepreneurial incentives,” *Review of Financial Studies*, 10, p.205-236.

Padilla, A. J. and M. Pagano, (2000), “Sharing Default Information as a Borrower Discipline Device,” *European Economic Review*, 44(10), p.1951-1980.

Pagano, M. and T., Jappelli (1993), “Information sharing in credit markets”, *Journal of Finance*, 43, p. 1693-1718.

Pool, S., L. de Haan, and J. Jacobs (2015), “Loan loss provisioning, bank credit and the real economy”, *Journal of Macroeconomics,*Vol. 45, p. 124-136.

Powell, A., N. Mylenko, M. Miller, and G. Majnoni, (2004), “Improving Credit Information, Bank Regulation and Supervision: On the Role and Design of Public Credit Registries”, World Bank, *World Bank Policy Research Working Paper* 3443, November.

Reinhart, C.M. and Rogoff, K.S. (2009). “This Time is Different: Eight Centuries of Financial Folly”, Princeton, NJ: Princeton University Press.

Schularick, M. and Taylor, A., (2012),. “Credit booms gone bust: monetary policy, leverage cycles and financial crises, 1870–2008”, *American Economic Review*, 102(2), pp. 1029–61.

Turk-Ariss, R. (2010), “On the implications of market power in banking: Evidence from developing countries”, Journal of Banking & Finance, Vol. 34, No. 4, p. 765-775.

Vercammen, J. A., (1995), “Credit Bureau Policy and Sustainable Reputation Effects in Credit Markets”**,** *Economica*, 62(248), p. 461-478.

Figures

Figure 1: Information sharing, credit booms and financial fragility

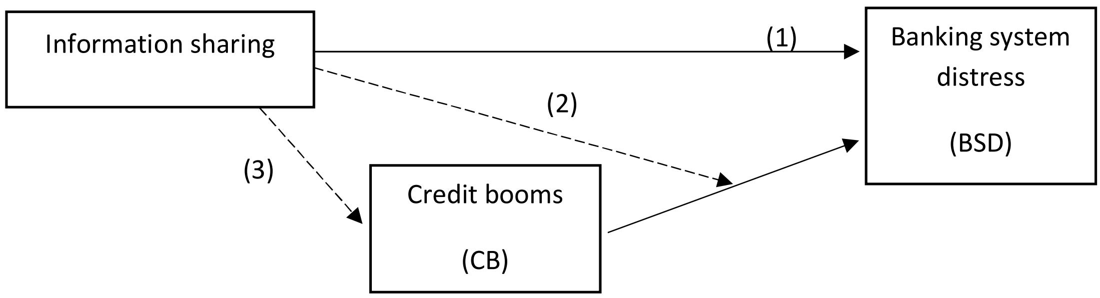
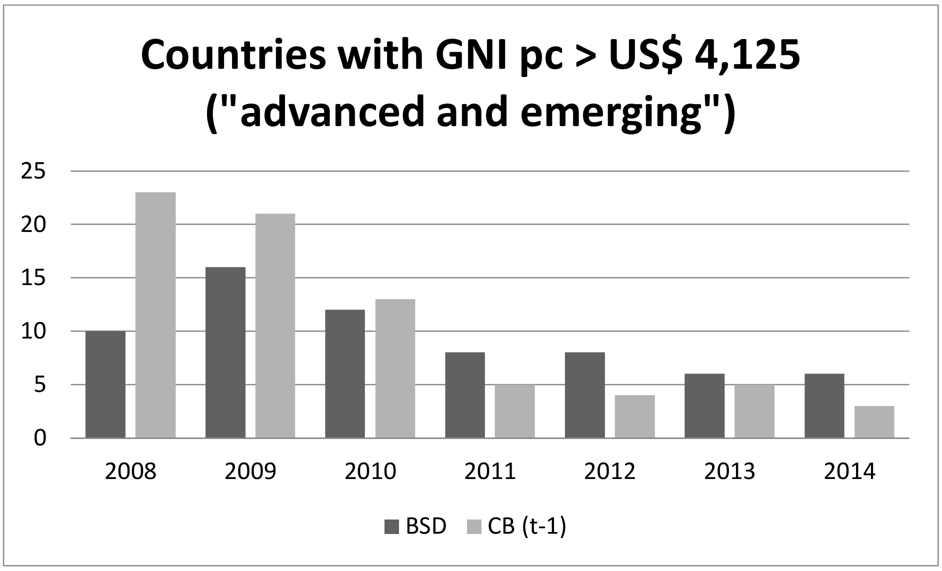
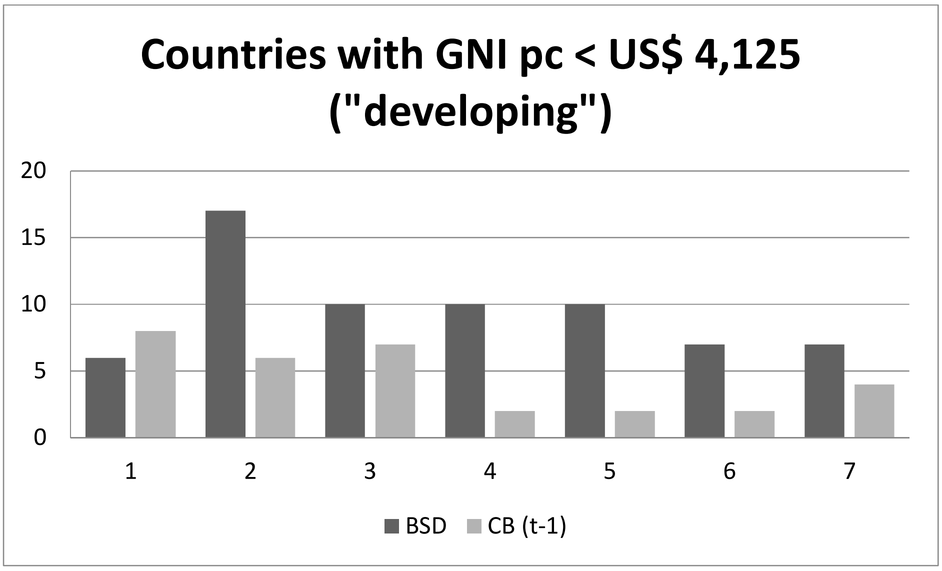


Figure 2: Banking system distress and (lagged) credit booms, by year and group of countries





Table

Table 1: Summary statistics

	Bank distress	Credit booms	Info Depth	Info Cover.	ln(GDPpc)	PC/GDP	inflation	Growth	Capital flows	Exchange rate (var.)	HHI
Obs	977	977	977	977	977	977	977	977	977	977	977
Mean	0.14	0.20	2.89	32.708	8.25	54.003	6.3448	3.6773	0.1093	0.0171	973.52
Std. Dev	0.34	0.31	2.47	36.873	1.58	44.720	8.3941	4.3482	0.3506	0.0904	2041.04
Min	0	0	0	0	4.9980	0.2959	-30.613	-15.088	-2.2683	-0.1847	0.7242
Max	1	1	6	100	11.363	253.45	103.82	25.049	4.9607	0.6759	10000
Correlations											
BSD	1.00										
Credit boom	0.20	1.00									
Info depth	-0.16	0.03	1								
Info coverage	-0.15	0.03	0.76	1.00							
ln(GDPpc)	-0.06	0.17	0.54	0.55	1.00						
PC/GDP	0.00	0.29	0.39	0.41	0.69	1.00					
inflation	0.06	-0.05	-0.16	-0.18	-0.29	-0.29	1.00				
Growth	-0.09	-0.06	-0.20	-0.23	-0.33	-0.31	0.23	1.00			
Capital flows	0.00	0.04	-0.14	-0.10	0.06	0.04	-0.03	0.03	1.00		
Exch. Rate	0.04	-0.02	-0.05	-0.03	-0.14	-0.10	0.30	-0.19	-0.02	1.00	
HHI	0.17	-0.07	-0.38	-0.29	-0.18	-0.19	0.01	0.02	0.06	-0.03	1.00

Table 2: Baseline model

	All countries		GNI per capita > US$ 4,125		GNI per capita ≤ US$ 4,125	
	[1]	[2]	[3]	[4]	[5]	[6]
Depth of IS	-0.0149***		-0.0094**		-0.0225**	
	(-2.75)		(-2.07)		(-2.43)	
Coverage of IS		-0.0011***		-0.0006**		-0.0020**
		(-2.70)		(-2.07)		(-2.04)
Ln(GDPpc)	-0.0219*	-0.0229**	-0.0498***	-0.0476***	0.0265	0.0200
	(-1.89)	(-2.00)	(-3.01)	(-2.95)	(0.97)	(0.74)
PC/GDP	0.0008**	0.0009**	0.0007**	0.0007***	0.0006	0.0004
	(2.32)	(2.49)	(2.57)	(2.69)	(0.64)	(0.43)
Inflation	-0.0000	-0.0001	-0.0025**	-0.0024**	0.0025	0.0025
	(-0.01)	(-0.05)	(-1.99)	(-1.99)	(1.53)	(1.52)
Growth	-0.0052**	-0.0051**	-0.0032	-0.0028	-0.0061	-0.0065
	(-2.23)	(-2.19)	(-1.58)	(-1.44)	(-1.47)	(-1.54)
Capital	-0.0073	-0.0048	-0.0024	-0.0011	0.0103	0.0039
	(-0.21)	(-0.14)	(-0.09)	(-0.04)	(0.08)	(0.03)
Exch. Rate	0.0623	0.0659	0.0122	0.0177	0.2452	0.2478
	(0.61)	(0.65)	(0.14)	(0.21)	(1.31)	(1.32)
HHI	0.0000**	0.0000***	0.0000	0.0000	0.0000***	0.0000***
	(2.23)	(2.62)	(0.35)	(0.70)	(2.59)	(2.73)
# Obs.	977	977	499	499	478	478
# countries	159	159	80	80	79	79
Pseudo R^2	0.08	0.08	0.12	0.12	0.09	0.08
LR test (rho=0)	38.42***	37.17***	34.97***	35.59***	1.84*	1.74*
Wald test	50.16***	49.83***	29.56***	29.20***	32.96***	31.81***

The dependent variable is a dummy equals to one if a country experienced a financial distress in year t. All explanatory variables are includes with one-year lag. Year dummies are included but not reported. Random effect probit model is used. LR statistic test the relevance of random effects (rho). Under the null hypothesis, random-effect probit model and pooled probit model provide similar results. Wald test tests the significance of all explanatory variables. Marginal effects are reported instead of coefficients and z-stats are in brackets. *, **, and *** indicates significance level of 10, 5 and 1% respectively.

Table 3: Extended model (including credit booms)

	All countries		GNI per capita > US$ 4,125		GNI per capita $\leq$ US$ 4,125	
	[1]	[2]	[3]	[4]	[5]	[6]
Depth of IS	-0.0132**		-0.0096*		-0.0197**	
	(-2.47)		(-1.95)		(-2.19)	
Coverage of IS		-0.0009**		-0.0005*		-0.0018*
		(-2.29)		(-1.83)		(-1.88)
CB	0.1073***	0.1054***	0.0468**	0.0442**	0.1721***	0.1719***
	(-4.16)	(-4.08)	(-2.49)	(-2.37)	(-3.04)	(-3.12)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
# Obs.	977	977	499	499	478	478
# countries	159	159	80	80	79	79
Pseudo R^2	0.09	0.09	0.12	0.12	0.10	0.09
LR test (rho=0)	29.73***	28.91***	28.15***	28.03***	1.36	1.41
Wald test	65.43***	64.93***	35.56***	35.40***	40.14***	39.41***

The dependent variable is a dummy equals to one if a country experienced a financial distress in year t. All explanatory variables are includes with one-year lag. Control variable and year dummies are included but not reported. Random effect probit model is used. LR statistic test the relevance of random effect. Under the null hypothesis, random-effect probit model and pooled probit model provide similar results. Wald test tests the significance of all explanatory variables. Marginal effects are reported instead of coefficients and z-stats are in brackets. *, **, and *** indicates significance level of 10, 5 and 1% respectively.

Table 4: Interactions between information sharing and credit booms

	All countries		GNI per capita > US$ 4,125		GNI per capita ≤ US$ 4,125	
	[1]	[2]	[3]	[4]	[5]	[6]
Depth of IS	-0.0114*		-0.0149		-0.0183**	
	(-1.86)		(-1.42)		(-2.40)	
Depth of IS*CB	-0.0374*		-0.0528*		-0.0111	
	(-1.64)		(-1.80)		(-0.35)	
Coverage of IS		-0.0006*		-0.0067		-0.00128*
		(-1.76)		(-1.52)		(-1.95)
Coverage of IS*CB		-0.0034***		-0.0035***		-0.0036
		(-2.79)		(-2.58)		(-1.06)
CB	0.307***	0.310***	0.345***	0.307***	0.249*	0.305**
	(3.30)	(4.37)	(2.90)	(3.45)	(1.82)	(2.30)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
# Obs.	977	977	499	499	478	478
# countries	159	159	80	80	79	79
R^2 (overall)	0.11	0.12	0.17	0.17	0.11	0.11
Wald test	74.71***	74.69***	66.11***	64.62***	82.64***	85.14***

The dependent variable is a dummy equals to one if a country experienced a financial distress in year t. All explanatory variables are includes with one-year lag. Year dummies are included but not reported. Linear random effect model is used. Wald test tests the significance of all explanatory variables. *, **, and *** indicates significance level of 10, 5 and 1% respectively.

Table 5: Determinants of credit booms

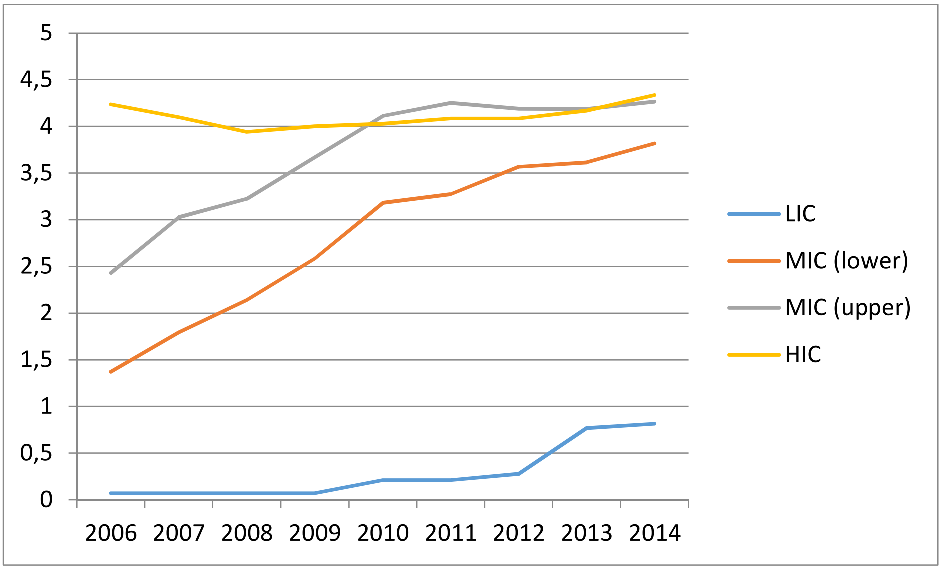
	All countries		GNI per capita > US$ 4,125		GNI per capita ≤ US$ 4,125	
	[1]	[2]	[3]	[4]	[5]	[6]
Depth of IS	-0.0051*		-0.0146***		-0.0019*	
	(-1.88)		(-2.61)		(-1.75)	
Coverage of IS		-0.0002		-0.0005		0.0000
		(-1.09)		(-1.40)		(0.22)
Ln(GDPpc)	0.0054	0.0041	-0.0195	-0.192	0.0078*	0.0053
	(0.95)	(0.71)	(-1.21)	(-1.15)	(1.86)	(1.22)
PC/GDP	0.0007***	0.0007***	0.0012***	0.0012***	0.0003***	0.0003**
	(4.18)	(4.23)	(4.32)	(4.21)	(2.60)	(2.52)
Inflation	0.0000	0.0001	0.0010	0.0012	-0.0002	-0.0002
	(0.03)	(0.06)	(0.57)	(0.70)	(-0.66)	(-0.58)
Growth	0.0020	0.0022*	0.0032	0.0038	-0.0002	-0.0000
	(1.57)	(1.64)	(0.98)	(1.14)	(-0.36)	(-0.05)
Capital	-0.0032	-0.0019	-0.0022	0.0010	0.0220	0.0245
	(-0.27)	(-0.16)	(-0.11)	(0.05)	(0.95)	(1.00)
Exch. Rate	-0.0248	-0.0299	-0.0385	-0.0534	-0.0211	-0.0293
	(-0.35)	(-0.43)	(-0.27)	(-0.38)	(-0.68)	(-0.83)
HHI	-0.00001*	-0.00001	-0.00001*	-0.00001	-0.0000	-0.0000
	(-1.86)	(-1.43)	(-1.84)	(-1.41)	(-0.99)	(-0.82)
# Obs.	1083	1083	555	555	528	528
# countries	159	159	80	80	79	79
Pseudo R^2	0.12	0.12	0.18	0.18	0.07	0.06
LR test (rho=0)	29.51***	28.63***	5.57***	7.34***	18.06***	16.04***
Wald test	72.63***	70.72***	56.89***	52.35***	22.55***	20.73***

The dependent variable is a dummy equals to one if a country experienced a credit boom in year t. All explanatory variables are includes with one-year lag. Year dummies are included but not reported. Random effect probit model is used. LR statistic test the relevance of random effect. Under the null hypothesis, random-effect probit model and pooled probit model provide similar results. Wald test tests the significance of all explanatory variables. Marginal effects are reported instead of coefficients and z-stats are in brackets. *, **, and *** indicates significance level of 10, 5 and 1% respectively.

Appendix (only for referee)

Figure A1: Evolution of depth and coverage of information sharing, by groups of countries

(a) Depth



(b) Coverage

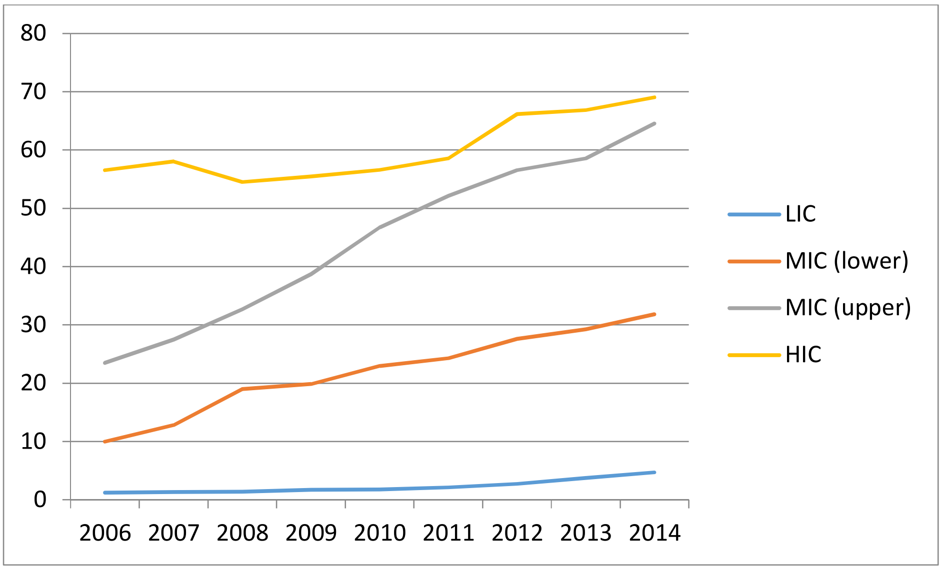


Table A1: List of countries

Countries whose GNI exceeds US$ 4,125		*Countries whose GNI is below US$ 4,125*	
Antigua and Barbuda	Latvia	Afghanistan	Jordan
Argentina	Lebanon	Albania	Kenya
Australia	Libya	Algeria	Kosovo
Austria	Lithuania	Angola	Kyrgyz Republic
Bahamas	Luxembourg	Armenia	Lao PDR
Bahrain	Malaysia	Azerbaijan	Lesotho
Belarus	Maldives	Bangladesh	Liberia
Belgium	Malta	Benin	Macedonia, FYR
Botswana	Mauritius	Bolivia	Madagascar
Brazil	Mexico	Bosnia and Herz.	Malawi
Brunei Darussalam	Montenegro	Burkina Faso	Mali
Bulgaria	Namibia	Burundi	Mauritania
Canada	Netherlands	Cabo Verde	Moldova
Chile	New Zealand	Cambodia	Mongolia
Colombia	Oman	Cameroon	Morocco
Costa Rica	Panama	Central African Rep.	Mozambique
Croatia	Papua New Guinea	Chad	Nepal
Cyprus	Poland	China	Nicaragua
Czech Republic	Portugal	Comoros	Niger
Denmark	Qatar	Congo, Dem. Rep.	Nigeria
Dominica	Romania	Congo, Rep.	Pakistan
Dominican Republic	Russia	Cote d'Ivoire	Paraguay
Equatorial Guinea	Saudi Arabia	Djibouti	Peru
Estonia	Serbia	Ecuador	Philippines
Finland	Seychelles	Egypt, Arab Rep.	Senegal
France	Singapore	El Salvador	Sierra Leone
Gabon	Slovak Republic	Ethiopia	Sri Lanka
Germany	Slovenia	Gambia, The	Sudan
Greece	South Africa	Georgia	Swaziland
Grenada	Spain	Ghana	Tajikistan
Hong Kong SAR, China	Sweden	Guatemala	Tanzania
Hungary	Switzerland	Guinea	Thailand
Iceland	Syria	Guinea-Bissau	Togo
Ireland	Tunisia	Guyana	Tonga
Israel	Turkey	Haiti	Uganda
Italy	United Arab Emirates	Honduras	Ukraine
Japan	United Kingdom	India	Vietnam
Kazakhstan	United States	Indonesia	Yemen, Rep.
Korea, Rep.	Uruguay	Iran, Islamic Rep.	Zambia
Kuwait	Venezuela, RB	Iraq	

Table A2: Variables – Definitions and sources

Variable	Definition	Source
BSD	Dummy equals to 1 if the ratio of NPLs to loans increases by more than 5 points in one year	Bankscope
Credit boom	Dummy equals to one if a country experienced a credit boom (see Section 3.1.4 for complete definition)	WDI
Info_coverage	Coverage of information sharing mechanisms	Doing Business
Info_depth	Depth of information provided by the credit information sharing mechanism (ranging from 0 to 6)	Doing Business
PC/GDP	Credit to the private sector / GDP	WDI
Growth	Rate of growth of real GDP	WDI
Inflation	Percentage change in the CPI	WDI
Capital inflows	(Equity inflows+FDI inflows + Bilateral aid inflows)/GDP	WDI
Δ(Exchange rate)	Annual variation of exchange rate (in percent)	IFS
GDPpc	Real GDP per capita	WDI
HHI	Herfindahl-Hirschmann index of concentration in banking sector	Bankscope

WDI: World Development Indicators; IFS: International Financial Statistics

Table A3: Robustness checks (Depth of information sharing)

Panel A: All countries						
	[1]	[2]	[3]	[4]	[5]	[6]
Depth of IS	-0.0180***	-0.0180***	-0.0195***	-0.0084**	-0.0130***	-0.0063**
	(-3.99)	(-2.67)	(-2.58)	(-2.51)	(-2.59)	(-2.09)
Control variables	No	Yes	Yes	Yes	Yes	Yes
# Obs.	1,000	977	977	977	852	705
# Countries	161	159	159	159	159	114

Lecture des colonnes

Panel B: Countries whose GNI exceeds US$ 4,125 in 2014						
	[1]	[2]	[3]	[4]	[5]	[6]
Depth of IS	-0.0148***	-0.0203**	-0.0292**	-0.0054*	-0.0100**	-0.0050**
	(-2.73)	(-2.21)	(-1.99)	(-1.74)	(-2.33)	(2.26)
Control variables	No	Yes	Yes	Yes	Yes	Yes
# Obs.	515	499	499	499	439	421
# Countries	91	80	80	80	80	67

Panel C: Countries whose GNI is below US$ 4,125 in 2014						
	[1]	[2]	[3]	[4]	[5]	[6]
Depth of IS	-0.0219***	-0.0230**	-0.0221***	-0.0117**	-0.0224**	-0.0158**
	(-2.74)	(-2.46)	(-2.71)	(-2.30)	(-2.48)	(-2.23)
Control variables	No	Yes	Yes	Yes	Yes	Yes
# Obs.	485	478	478	478	413	284
# Countries	80	79	79	79	79	47

The dependent variable is a dummy equals to one if a country experienced a financial distress in year t. All explanatory variables are includes with one-year lag and year dummies are included but not reported. Random effect probit model is used at the exception of columns [2] (population-averaged probit model) and [3] linear model. In column [4], the dependent variable is an alternative measure of financial distress. In columns [5] and [6], sub-samples are considered. Marginal effects are reported and z-stat are in brackets. For more details, see Section 4.1.2. *, **, and *** indicates significance level of 10, 5 and 1% respectively.

Table A4: Robustness checks (Coverage of information sharing)

Panel A: All countries						
	[1]	[2]	[3]	[4]	[5]	[6]
Coverage of IS	-0.0012***	-0.0013***	-0.0012***	-0.0005**	-0.0010***	-0.0005**
	(-3.52)	(2.59)	(-2.60)	(-1.96)	(-2.73)	(-2.30)
Control variables	No	Yes	Yes	Yes	Yes	Yes
# Obs.	1,000	977	977	977	852	705
# Countries	161	159	159	159	159	114

Panel B: Countries whose GNI exceeds US$ 4,125 in 2014						
	[1]	[2]	[3]	[4]	[5]	[6]
Coverage of IS	-0.0009**	-0.0011**	-0.0013**	-0.0003	-0.0006**	-0.0003**
	(-2.51)	(-2.01)	(-2.32)	(-1.36)	(-2.25)	(-2.52)
Control variables	No	Yes	Yes	Yes	Yes	Yes
# Obs.	515	499	499	499	439	421
# Countries	91	80	80	80	80	67

Panel C: Countries whose GNI is below US$ 4,125 in 2014						
	[1]	[2]	[3]	[4]	[5]	[6]
Coverage of IS	-0.0021**	-0.0021**	-0.0017**	-0.0009*	-0.0021**	-0.0013*
	(-2.24)	(-2.06)	(-2.17)	(-1.66)	(-2.11)	(-1.77)
	No	Yes	Yes	Yes	Yes	Yes
	485	478	478	478	413	284
	80	79	79	79	79	47

The dependent variable is a dummy equals to one if a country experienced a financial distress in year t. All explanatory variables are includes with one-year lag and year dummies are included but not reported. Random effect probit model is used at the exception of columns [2] (population-averaged probit model) and [3] linear model. In column [4], the dependent variable is an alternative measure of financial distress. In columns [5] and [6], sub-samples are considered. Marginal effects are reported and z-stat are in brackets. For more details, see Section 4.1.2. *, **, and *** indicates significance level of 10, 5 and 1% respectively.