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Information sharing, credit booms and financial stability: Do developing economies differ from advanced countries?☆

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ABSTRACT

This paper analyses 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 in the ratio of non-performing loans to total loans—is run for a sample of 159 countries divided into 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) credit information sharing also mitigates the detrimental impact of a credit boom on financial fragility but this result holds only for advanced and emerging countries and for household credit booms; and iv) the depth of information sharing has a negative impact on the likelihood of credit booms (but not the coverage of IS).

1. Introduction

Global financial crisis has shown the vulnerability of financial systems. It has consequently stressed the need to improve the management of financial vulnerability. A large volume of 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 the risk-taking of individual financial institutions and their interdependence (Cerutti et al., 2017). Early empirical studies indicate that these measures have been relatively efficient in curbing housing price growth, bank leverage and credit growth (Claessens, 2014). However, the implementation of these macroprudential policies requires monitoring financial fragilities and a good understanding of their dynamics. More generally, the effectiveness of financial stability policy relies heavily on the complementarities between the different tools.

In this paper, we concentrate on credit information sharing. Credit information sharing has not been developed to stabilize banking systems, but rather to favour credit access for opaque firms and households through the provision of information on borrowers that reduces information asymmetries. These 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 may reduce banking fragility. Firstly, credit information sharing reduces adverse selection by improving banks' information on credit applicants (Pagano and Jappelli, 1993). Secondly, information sharing can reduce moral hazard and enhance 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 thereby reducing moral hazard (Padilla and Pagano, 1997). Thirdly, credit

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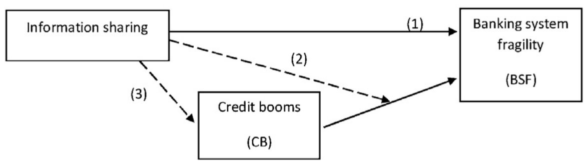

Fig. 1. Information sharing, credit booms and financial fragility.

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 default risks, it has ambiguous effects at the macro-level due to the 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. The introduction of credit sharing mechanisms allows banks to extend grant loans to clients from other banks by obtaining their credit history with other banks. But, this strategy may induce possible adverse consequences. Banks may rely too much on previous credit history without efficiencly screen loan demand. As a result, borrowers with risky project but good credit history may obtain a loan from a bank, if their usual lender refuses to extend their credit line. Meanwhile, banks may offer too much credit if they receive demand from many clients. Recent empirical evidence (Houston et al., 2010; Büyükkarabacak and Valev, 2012) documents that greater information sharing leads to a reduced likelihood of financial crisis.

In this paper, we deepen the analysis of 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 body of literature has shown that excessive credit booms are one of the main drivers of financial crises. Many empirical works have documented 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 Obstfeld, 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 is followed by a crisis. They also point out that the larger and longer the boom, the more likely that it ends 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. dashed lines in Fig. 1). Firstly, credit information sharing can mitigate the negative effect of credit booms. A rapid growth of credit can weaken the quality of credit screening. During credit booms, credit officers cannot devote sufficient time to screen correctly new projects, and bad projects have a higher probability of being 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 reinforce the deterioration of screening. The presence of information sharing mechanisms may allow banks to diversify their portfolios. This diversification can limit the increase of asset prices induced by rapid credit growth, and therefore limit the detrimental impact of such episodes. Secondly, 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 some customers borrowing from several banks. On the other hand, Dell'Ariccia and Marquez (2006) show that a reduction in information asymmetries across banks may lead to an easing of lending standards and, in turn, to 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 wide range of countries; ii) to identify channels through which IS impacts financial fragility, if it does so; and iii) to distinguish whether less developed countries differ in this respect from other countries (advanced and emerging). Banks in less developed countries operate in a context of institutional failure and a 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 the channels through which credit information sharing acts to differ across countries.

To do 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 loan ratios jump), even if the episode does not end 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 analyse 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) and is stronger for small shocks on financial stability than for large ones; iii) IS also mitigates the positive effect of credit boom on financial fragility but this result holds only for advanced and emerging countries and for household credit booms; and iv) the depth of IS (but not the coverage of IS) has an negative impact on the likelihood of a credit boom.

This paper provides three main contributions to the literature on the impact of credit information sharing on financial stability. Firstly, our paper includes a large number of countries, providing better coverage of developing countries than previous studies. Secondly, we analyse the direct and indirect potential effects of information sharing institutions. Finally, we document that credit information sharing is beneficial for both developing (as defined above) and emerging and advanced economies. However, we show that channels differ slightly between the two 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 and stronger for small shocks for less developed countries.

This paper also adds to the literature on the determinants of financial (in)stability. First, this work integrates most low-income countries. The financial stability issue in low-income countries (LICs) has received less attention in 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. Firstly, 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 Laeven and Valencia, 2013). Secondly, 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. Thirdly, 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. Second, we propose a new measure of financial instability that identifies all episodes of financial fragility, even if the episode does not end 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, a credit fall after the NPL cycle is frequently observed.

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 information sharing (IS henceforth) 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 are retrieved from the Bankscope database. Other variables are extracted from diverse country-level databases, including World Development Indicators, International Financial Statistics and Doing Business. Our dataset is restricted to the period 2008–2014 for two reasons: firstly, data on information sharing is not available before 2006[1]; secondly, the coverage of the Bankscope database is rather limited in low-income countries before the mid-2000s. 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 was below US$ 4,125 in 2014 (79, called developing countries)[2] and countries whose GNI per capita exceeded US$ 4,125 (80, called developed and emerging countries). Table A1 presents the list of countries.

2.2. Financial fragility

A critical step consists of 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. Firstly, banking crises in developing countries are rare events in recent years.[3] Secondly, a banking crisis is an extreme situation. Our aim is to have an indicator reflecting the fragility of a financial system before the occurrence of a crisis rather than detecting crisis episodes. Indeed, the dynamics of non-performing loans (NPLs) have significant effects on the dynamics of credit even when a banking crisis is avoided, since they will dampen both credit supply (credit channel) and demand (Pool et al., 2015). We therefore refer to assets quality by using information on NPLs as a warning indicator of banking system fragility.[4]

We detect episodes of financial fragility by scrutinizing annual changes in the ratio of NPLs to gross loans. The experience of developing countries shows that financial systems are able to withstand moderate levels of NPLs for a long time without undergoing crisis if the bank capital structure (larger interest margins, higher equity ratios) is consistent with this level of NPLs (Brock and Rojas-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 evolve only 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 had been moderate in previous years. The recent global financial crisis provides further evidence of this difference between the level and difference of NPLs signalling fragility in banking systems.The relationship between NPL variations and financial fragility is arguably non-linear, since banks can manage small increases in NPL using interest margins and capital buffers. The choice of the threshold raises two main issues: first, the relevant threshold is hardly drawn from theories; second, this non-linearity is probably different for advanced and developing economies.[5] We therefore create several dummies (called banking sector fragility, BSF henceforth), equal to one if the annual change of this ratio exceeds a threshold c (from 1 to 5 percent)

$$BSF(c)_{it} = \begin{cases} 1, \ if \ \Delta \left(NPLs_{it}/Loans_{it} \right) \geq \left\{ c = 1; 2; 3; 4; 5 \right\} \\ \\ 0, \ otherwise \end{cases}$$

Our calculations are based on individual bank data drawn from the commercially available Bankscope database. An advantage of the Bankscope database is its coverage of low-income countries.[6] The Bankscope database covers 32,000 banks from almost all countries in the world over the period 2000–2016 (even if time coverage is more limited before the mid-2000s in low-income countries). Some filter rules are applied. We concentrate on banking systems and 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

1 An alternative to extend time period consists on assign the first value available (mid-2000s) on previous period, as done by Büyükkarabak and Valev (2012). This approach assumes that the feature of the credit information sharing institutions are stable over time. While this assumption is perhaps valid for high-income countries, Figure A1 tends to prove the opposite for emerging and developing countries.

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). The limited occurrence of such events does not allow us to apply a robust econometric model.

4 There are different bank-level indicators of financial stability used in the literature, including Z-score, capital ratio, assets quality and bank defaults. These indicators cannot easily be transformed into a macro-indicator and are less relevant than an NPL based indicator in giving policy recommendations, since they are either less transparent and/or less linked to the lending policy (equity ratios).

5 We thank a reviewer to raise these points.

6 Until recently, the coverage of banks in low-income countries by Bankscope was limited, but many improvements have been made over the past decade. There is an alternative database, namely the Financial Soundness Indicators (FSI) database from the IMF. The FSI database covers fewer countries than Bankscope, especially among low-income countries. In a robustness check, we replicate our results using the FSI database instead of Bankscope (see Tables A4 and A5 in the Appendix).

Table 1
Distribution of annual change of NPLs to loans ratio and of credit to GDP ratio.

	Obs	Mean	Median	Std. Dev	75th	90th	Mean + sd	Median + sd
Panel A: Annual variation of NPLs to loans ratio (percentage points)								
All	977	0.360	0.027	4.896	1.194	3.859	5.256	4.923
Advanced	499	0.706	0.098	4.707	1.444	3.691	5.413	4.805
Developing	478	−0.002	−0.048	5.065	1.065	4.041	5.063	5.017
Panel B: Annual variation of credit to GDP ratio								
All	977	0.910	0.793	6.558	2.802	5.681	7.468	7.351
Advanced	499	0.705	0.764	8.514	3.291	7.158	9.219	9.278
Developing	478	1.122	0.825	3.536	2.352	4.608	4.658	4.361

75^{th} refers to the third quartile and 90^{th} to the last decile.

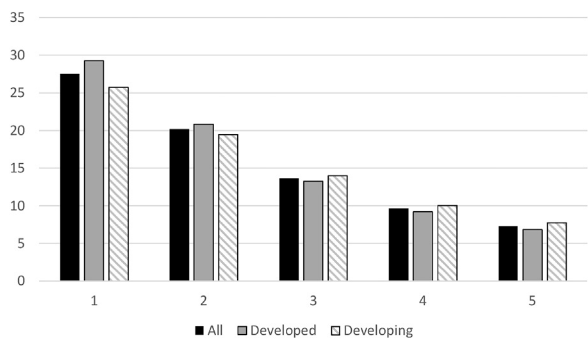

Fig. 2. Distribution of banking system fragility (BSF) variable, by group of countries and different thresholds (1–5).
The figure reports the percent of observations for those BSD equals to one according to the different thresholds retained and by group of countries.

loans (and is thus a weighted average of bank NPL ratio). Table 1 provides detailed descriptive statistics on the distribution of this NPL ratio and Fig. 2 displays the financial fragility measures (dummies) derived from it by group of countries. We observe in Table 1 that the standard deviation is relatively high but mainly driven by extreme episodes. NPLs jumps exceed one point in one quarter of observations, 3 points in ten percent of observations and 5 percent in 7 percent of observations. We observe in Fig. 2 that distributions of NPLs jumps do not strongly differ between advanced and developing countries. As a baseline, we therefore consider a jump of NPLs of 3 points to detect an episode of financial fragility. As robustness checks, we will consider alternative thresholds from 1 to 5 points.

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 types of information provided or the coverage of information sharing mechanisms. To circumvent this limitation, 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.[7] Doing Business also provides 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 depth and coverage to proxy the development of information sharing mechanisms.[8]

2.4. Credit booms

In the literature, different methods have been employed to detect credit booms, ranging from statistical observations to econometric filter methods (see Dell'Ariccia et al., 2016). Considering a filter method requires to have sufficient time coverage to econometrically assess the trend and to identify deviation. Unfortunately, for many low-income countries, time coverage is rather limited. 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 growth in credit over GDP that averages more than five per cent (the cut-off is also taken from Gorton and Ordoñez, 2016). Again, since the choice of the relevant threshold of credit booms is tricky and may be different between developing economies and others, we test in the robustness check alternative measures of credit boom (average expansion of one to four per cent on three consecutive years). Data about credit to GDP ratios are 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 and Valev, 2010, 2012). Variables are grouped in two categories: financial system and macroeconomic factors.

First, we control for the degree of financial development by adding the ratio of total credit over GDP. 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 body of literature has studied the impact of bank competition on financial stability. The degree of bank competition has an ambiguous impact on financial fragility. The majority of papers using country-level

[7] Since 2013, Doing Business has provided 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 previous 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).

[8] We do not employ the duration since the implantation of a PCR and a PCB because it is not a good indicator of quality. Many IS institutions are not well-developed in spite of a long history. After collecting data on date of implementation from Djankov et al. (2007), we compute correlation coefficients between IS development and their age. We show that depth of credit information is negatively correlated with age (ρ = -0.29) and the coverage of IS is not correlated with age (ρ = -0.07).

data and a 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 Herfindahl-Hirschman 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).[9]

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.[10] In addition, we control for changes of nominal exchange rate.[11] Rapid exchange rate depreciation raises repayment costs for foreign currency loans and could induce less repayment (Gourinchas and Obstfeld, 2012). 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 financial fragility. The theoretical effect of inflation is ambiguous, since inflation reduces the real value of debt service but can also reduce borrowers' income. Empirical literature identifies a negative impact of GDP growth on the likelihood of a banking crisis (Demirgüç-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 the consumer price index (CPI). We expect that financial fragility is more likely in periods 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:

$$Pr(BSF_{it}=1)=\alpha+\beta IS_{it-1}+\Gamma\mathbf{X}_{it-1}+\mu_t+\varepsilon_{it} \quad (1)$$

where subscripts *i* and *i* refer to country and year respectively. *BSF* is a dummy variable equal to one if a country experienced a situation of financial fragility (see Section 2.2) and 0 otherwise. *IS* is a measure of the development of credit information sharing mechanisms (depth index and coverage), $\mathbf{X}$ is a matrix of control variables and μ_t time dummies. We expect that $\beta<0$; in other words, we expect that the likelihood of experiencing financial fragility decreases with the depth and coverage of information sharing.

3.2. Transmission channels

In the second step of analysis, we investigate the transmission channels through which information sharing affects financial fragility. As expressed above, we paid special attention to credit booms (Fig. 1). Firstly, we study whether information sharing exerts an impact on financial fragility through an additional channel to credit booms (dashed arrows in Fig. 1). We therefore estimate the following equation:

$$Pr(BSF_{it}=1)=\alpha+\beta IS_{it-1}+\delta CB_{it-1}+\Gamma\mathbf{X}_{it-1}+\mu_t+\varepsilon_{it} \quad (2)$$

We expect that $\delta>0$, indicating that a situation of financial fragility 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:

$$Pr(BSF_{it}=1)=\alpha+\beta IS_{it-1}+\delta CB_{it-1}+\gamma IS_{it-1}{}^{*}CB_{it-1}$$
$$+\Gamma\mathbf{X}_{it-1}+\mu_t+\varepsilon_{it} \quad (3)$$

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

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

where *CB* is a dummy equal 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 of observing a credit boom by avoiding borrowers borrowing 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 (μ_t) to control for common shocks (such as the 2008 global financial crisis). The specifications employ independent variables lagged by one-year to reduce endogeneity. With the exception of Eq. (3), we use a random-effect probit due to the binary nature of the dependent variable and to control for unobserved country heterogeneity. For Eq. (3), we employ a linear random-effect model.[12] Indeed, the interpretation of interaction poses some challenges in non-linear models, especially for the random-effect probit model (Greene, 2010).

Finally, insofar as we are particularly concerned with 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 was above US$ 4,125 in 2014) and for less developed countries (79, whose GNI per capita was below US$ 4,125 in 2014).

4. Results

4.1. Descriptive statistics

Table 2 provides some summary statistics. These statistics document that episodes of rapid degradation of loan quality are frequent. Table 2 points out that the correlation coefficient between BSF_3% and a (one-year lagged) credit boom seems moderate; however, such a correlation is not always informative due to the

[9] A large empirical literature has investigated the effect of capital regulation, restrictions on bank entry, restrictions on non-lending activities (Barth et al., 2004) or deposit insurance schemes (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 et al. (2004) and/or the deposit insurance database provided by Demirgüç-Kunt et al. (2015). The use of this variable will significantly reduce the sample of developing countries, on which we focus.

[10] It should be noted that this variable may also capture changes in international flows regulation.

[11] Considering real exchange rate would 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.

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

Table 2
Summary statistics.

	Bank fragility	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	32.71	8.25	54.00	6.34	3.68	0.11	0.02	973.52
Std. Dev	0.34	0.31	2.47	36.87	1.58	44.72	8.39	4.35	0.35	0.09	2041.04
Min	0	0	0	0	5.00	0.30	−30.61	−15.09	−2.27	−0.18	0.72
Max	1	1	6	100	11.36	253.45	103.82	25.05	4.96	0.68	10000
Correlations											
BSF	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

nature of the variables (dummies). We scrutinize this relationship in more detail. Among 133 episodes of rapid loan quality degradation (BSF_3%), one third (43) are preceded by a credit boom in the previous year. This ratio reaches almost 50 per cent in the case of developed and emerging countries (30 out of 66 episodes), which can be explained by recent financial crises. For developing countries, 20 per cent of financial distresses were preceded by a credit boom (13 out of 67).

Scrutinizing credit information sharing data, we observe that both coverage and depth of credit information sharing are higher in high income countries. However, developing economies—especially middle income countries—have experienced a rapid expansion of information sharing institutions over the last ten years. The rate of coverage of public and private institutions, as well as the quality of information, has increased in middle income countries over the last decade (see Fig. 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, which has almost tripled for both groups of countries over the past decade. After a long period of stagnation, low-income countries 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, but remains very weak.

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 3 using a 3% threshold for NPL ratio variations (BSF_3%)). The two first columns consider all countries, while columns [3] and [4] concentrate on countries whose GNI per capita exceeded US$ 4,125 in 2014 and columns [5] and [6] on countries whose GNI per capita exceeded US$ 4,125 in 2014 (called "developing countries"). We consider two measures of credit information sharing: the depth of information provided and the coverage of credit bureaus and credit registries. The bottom of Table 3 reports the usual tests of model validity. The LR test validates our decision to take into account unobserved country heterogeneity.

The baseline model provides two main messages. Firstly, 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 statistically significantly) associated with the likelihood of experiencing a period of rapid loan quality degradation. Not only is the impact of credit information sharing development statistically significant, but the effect is also economically significant. The results indicate that a one-standard deviation of the credit depth index reduces the likelihood of observing a financial crisis episode by 3.5 percentage points and a one-standard deviation of the coverage of information sharing by four percentage points. Secondly, credit information sharing mechanisms exert a role on both developed and developing countries. Given the limited number of low-income countries that have implemented IS systems, this result is driven by lower-middle income countries, but it has useful implications for LICs since they share many structural characteristics with lower MICs. 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, but this impact is larger in developing economies.

Table 4 provides estimates for the full range of thresholds, but only for variables of interest. [13] We consider NPLs jumps from 1 percent to 5 percent. Table 4 shows that the impact of IS in developing countries is the most significant on BSF(2%) and BSF(1%) ; which implies that IS is more efficient to dampen small NPL ratio jumps than larger ones. This may reflect that ability to contain NPLs jumps is lower in low-income countries and the development of IS may help lenders to manage NPLs. As far as advanced countries are concerned, the impact of IS is smaller and uniform across financial fragility indicators. We also consider a measure of NPL growth defined by change of NPLs to loans ratio from t-1 to t. This measure does not allow to capture the non-linearity that we expect (i.e. no impact of small variations) but econometric results (in columns [11]) point out that our main conclusion is confirmed, even if statistical significance is reduced when we consider the coverage of information sharing.

We also study whether private credit bureaus and public credit registries differently impact financial fragility. For doing so, we consider the depth and coverage of each mechanism separately. Results are reported in the Appendix (Table A3).[14] In a nutshell, our baseline findings are not altered by the type of credit information sharing mechanisms. Both depth and coverage remain negative and statis-

[13] We thank a reviewer to invite us to consider this question.
[14] Results by group of countries are available upon request.

Table 3
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 equal to one if a country experienced financial fragility episode in year t (BSF(3%)). All explanatory variables are includes with a one-year lag. Year dummies are included but not reported. Random effect probit model is used. LR statistic tests 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 *** indicate significance level of 10%, 5% and 1% respectively.

tically significant when we consider only PCR or PCB. It should be noted that the presence of a PCR or a PCB (dummy) does not affect financial stability. Put differently, it is the level of development of each credit information sharing infrastructure that matters rather than its presence or its organization (public and private).

Regarding control variables, the likelihood of experiencing an episode of financial fragility is reduced in countries with higher GDP per capita, a limited sized financial system, with high growth and in competitive banking markets. It should be noted that some of these results hold for developed countries but they tend to vanish when we consider only developing countries.[15]

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 a sensitivity analysis to be sure that our results are not driven by misspecification. Results are reported in the Appendix (Tables A4 and A5). Firstly, we exclude all control variables (column [1]). Secondly, we change the econometric method. The baseline model uses a random-effect probit model to control for country heterogeneity. An alternative method is a population-averaged probit model. An advantage of the population-averaged method is that it allows us to reduce the influence of outliers (column [2]). Thirdly, we also consider a fixed effect model. Credit information sharing could be a proxy for various influences on credit quality that are not captured by control variables. Rather than adding additional control variables, we add country fixed effect instead of relying on random effects. Indeed, many of potential cofounding variables are time invariant (such as legal origin) and are therefore capture by country fixed effect. Results, reported in column [3] indicate that coefficients associated with IS remain negative, even if not always statistically significant (at the usual thresholds but significant at 15%-level).[16] The reduction of statistical significance could be explained by the fact that the major source of variation occurs between countries and not within country. Two additional tests of sensitivity focus on the sample considered. On the one hand, we exclude the year following the start of the banking system fragility (column [4]), following the literature on financial crisis (e.g., Büyükkarabacak and Valev, 2012). 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 in NPLs might only capture the difficulties faced by one bank. We re-estimate our model on these sub-samples (column [5]). Our findings are unchanged, both statistically and economically. Another robustness test focuses on the database considered to compute our dependent variable. As the baseline, we use the Bankscope database because we are able to extract NPL ratios for a large range of countries. However, the Bankscope database is open to criticism (errors, limited coverage in some countries, etc.). To be sure that our results are not driven by the database considered, we consider data from the Financial Soundness Indicators (FSI) provided by the IMF.[17] The FSI covers fewer (mainly developing) countries than the Bankscope database. However, in contrast to Bankscope, first hand data are obtained by supervision agencies and are more likely to cover all

[15] In an alternative model, we consider macroprudential policies as control variables (in all specifications). Data are extracted from Cerutti et al. (2017) 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 countries is greatly reduced from 159 to 96 countries due to missing data. 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.

[16] Non-linear models are subject to incidental parameter issue when fixed effects are included. To limit this issue, we report results using a simple linear model with country fixed effects. Econometric results are rather similar when the binary structure of dependent variable is considered (conditional probit model). In addition, coefficients associated with control variables are largely similar.

[17] Data of FSI are reported in the Global Financial Development Database, the last updated version of which (June 2016) is available at: http://data.worldbank.org/data-catalog/global-financial-development

Table 4
Alternative definition of dependent variable.

Panel A: All countries

	BSF(1%)		BSF(2%)		**BSF(3%)**		BSF(4%)		BSF(5%)		D(NPL)	
	[1]	[2]	[3]	[4]	**[5]**	**[6]**	[7]	[8]	[9]	[10}	[11]	[12]
Depth of IS	−0.038***		−0.034***		**−0.015*** **		−0.012***		−0.008**		−0.145*	
	(-3.73)		(-4.13)		**(-2.75)**		(-2.94)		(-2.51)		(-1.78)	
Coverage of IS		−0.0021***		−0.0015***		**−0.0011*** **		−0.0007***		−0.0005**		−0.007*
		(-2.90)		(-2.54)		**(-2.70)**		(-2.56)		(-1.96)		(-1.70)
# Obs.	977	977	977	977	**977**	**977**	977	977	977	977	977	977
# countries	159	159	159	159	**159**	**159**	159	159	159	159	159	159
# events	269	269	197	197	**133**	**133**	94	94	71	71	–	–
Pseudo R^2	0.074	0.070	0.062	0.052	**0.056**	**0.056**	0.056	0.055	0.044	0.041	–	–

Panel B: Countries those GNI exceeds US$ 4,125 in 2014

	BSF(1%)		BSF(2%)		**BSF(3%)**		BSF(4%)		BSF(5%)		D(NPL)	
	[1]	[2]	[3]	[4]	**[5]**	**[6]**	[7]	[8]	[9]	[10}	[11]	[12]
Depth of IS	−0.036**		−0.024**		**−0.009** **		−0.010**		−0.005*		−0.264**	
	(-2.39)		(-2.16)		**(-2.07)**		(-2.46)		(-1.74)		(-2.21)	
Coverage of IS		−0.0017**		−0.0009*		**−0.0006** **		−0.0005**		−0.0003*		−0.008
		(-1.98)		(-1.64)		**(-2.07)**		(-2.10)		(-1.66)		(-1.30)
# Obs.	499	499	499	499	**499**	**499**	499	499	499	499	499	499
# countries	80	80	80	80	**80**	**80**	80	80	80	80	80	80
# events	146	146	104	104	**66**	**66**	46	46	34	34		
Pseudo R^2	0.074	0.072	0.050	0.048	**0.042**	**0.042**	0.037	0.036	0.035	0.034		

Panel C: Countries those GNI is below US$ 4,125 in 2014

	BSF(1%)		BSF(2%)		**BSF(3%)**		BSF(4%)		BSF(5%)		D(NPL)	
	[1]	[2]	[3]	[4]	**[5]**	**[6]**	[7]	[8]	[9]	[10}	[11]	[12]
Depth of IS	−0.047***		−0.047***		**−0.023** **		−0.016**		−0.012**		−0.265**	
	(-3.30)		(-4.01)		**(-2.43)**		(-2.50)		(-2.30)		(-2.21)	
Coverage of IS		−0.0031**		−0.0036***		**−0.0020** **		−0.0015**		−0.0009*		−0.010
		(-2.22)		(-2.89)		**(-2.04)**		(-2.09)		(-1.64)		(-0.82)
# Obs.	478	478	478	478	**478**	**478**	478	478	478	478	478	478
# countries	79	79	79	79	**79**	**79**	79	79	79	79	79	79
# events	123	123	93	93	**67**	**67**	48	48	37	37	–	–
Pseudo R^2	0.025	0.019	0.036	0.028	**0.034**	**0.032**	0.042	0.041	0.035	0.032	–	–

The dependent variable is a dummy variable taken value one if variation of NPLs exceeds 1 point in columns [1-2], 2 points in columns [3-4], 3 points in columns [5-6] (baseline estimates reported in bold), 4 points in columns [7-8] and 5 points in columns [9-10]. In columns [11-12], we consider a continuous variable defined as the difference in the ratio of NPLs to loans from t-1 to t as dependent variable. 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 [11-12]. Marginal effects are reported and z-stat are in brackets. For more details, see Section 4.2.1
*, **, and *** indicates significance level of 10, 5 and 1% respectively.

Table 5
Extended model (including 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	−0.0132**		−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 equal to one if a country experienced financial fragility episode in year t (BSF3%). All explanatory variables are includes with a one-year lag. Control variable and year dummies are included but not reported. Random effect probit model is used. LR statistic tests 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 *** indicate significance levels of 10%, 5% and 1% respectively.

banks in a country. In column [6], we present estimations using the FSI to compute our dependent variable. Our sample is reduced from 159 countries to 120 countries, including 72 developed and (only) 48 developing economies. However, our findings are largely unchanged. Both credit information sharing mechanisms limit the occurrence of financial distress episodes. It should be noted that economic impact is reduced in comparison with the baseline model and that statistical significance is also reduced for developed countries.

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 the instrumental strategy proposed by Büyükkarabacak and Valev (2012) considering the total population and urbanization rate.[18] For the 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 ten 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.

4.3. Transmission channels

The baseline model points out that information sharing mechanisms limit the risk of experiencing an episode of financial fragility for a country. In addition, this result hold for both developing and developed countries, but is more clear-cut and focused on small NPL jumps in developing economies. In a second step of analysis, we shed light on transmission channels. As documented in Fig. 1, IS might exert a role on financial fragility through at least three channels. We test each channel in separate models.

[18] We also test another instrument, namely share of the 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 provides 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.

4.3.1. 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 an independent effect. To test this hypothesis, we run Eq. (2), which consists of the baseline model with an additional variable, namely credit boom (CB). Results are reported in Table 5. Firstly, we document that a credit boom in previous years induces a higher probability of observing financial fragility episode, in line with previous studies. A 5% credit boom increases the likelihood of observing a 3% NPL jump by almost five percentage points. When we focus on sub-samples of developed and developing countries, our results are largely unchanged, but, interestingly, the impact of a credit boom on financial fragility is higher for developing countries. A credit boom episode increase the likelihood to observe an episode of financial distress by 17 percent for developing countries and by 5 percent for advanced economies. 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 channels other than credit booms. We run the same battery of sensitivity analyses as those presented in Tables A4 (and A5). In addition, we consider alternative indicators of credit boom and of financial fragility (increase by one point to five points). We employ all 25 (5×5) possible combinations for both measures of information sharing (depth and coverage) and for the three sample (all countries, developed countries and developing countries). Our main results are not altered by these changes. Therefore, not only does IS act directly on financial fragility by improving the portfolio quality, but credit booms are also important drivers of financial fragility. Moreover, we observe that only large credit booms (> 5%) affect financial fragility in advanced countries, while almost all shocks (from 2% to 5%) hurt developing economies.

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 obtain the impact of interaction by observing the sign and significance of the coefficient. Results are reported in Table 6. The

Table 6
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 equal to one if a country experienced financial fragility episode in year t (BSF3%). All explanatory variables are includes with a 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 *** indicate significance levels of 10%, 5% and 1% respectively.

two first columns report econometric results for the sample of all countries. We observe that not only are the variables related to the development of IS significant and negative, but their interactions with credit booms are also negative 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 ten percentage points in a country with a moderately developed credit information sharing mechanism (i.e. IS whose level of development equals the average, namely a depth index of three and coverage of 32 per cent). 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. The information provided is instructive. For countries whose GNI exceeds US$ 4,125, the positive effect of IS on financial stability tends to be related to their role during credit booms. Indeed, we observe that variables of IS in levels do not remain statistically significant, albeit the 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 significant only for developed and emerging economies.[19]

4.3.3. Determinants of credit booms

The previous sub-section has documented that IS plays 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 light on the impact of IS on the likelihood of observing a credit boom. We test this potential hypothesis by investigating the determinants of a credit boom (Eq. (4)). Table 7 reports the determinants of credit booms. The results are interesting: the depth of credit information sharing tends to reduce the likelihood of observing a credit boom. This result occurs in the different specifications (all countries, developed and developing sub-samples), but is smaller and less significant in developing economies. The results indicate that a one-standard deviation of credit depth index reduces the likelihood of observing 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 per cent. As previously, the impact of the quality of credit information sharing is higher for developed countries (reduction by 3.5 percentage points). In contrast, the coverage of credit information sharing has no statistical impact on the occurrence of credit booms.

4.3.4. Household credit boom versus firm credit boom

Finally, a recent literature has highlighted the importance to distinguish between household credit and firm credit to explain financial instability (Büyükkarabacak and Valev, 2010; Jordà et al., 2015). In particular, recent papers document that household credit expansion is more detrimental for financial stability. Using a new database compiling household credit and firm credit in a large range of developed and developing countries (Léon, 2018a,b) [20], we test whether our results are different for household credit and firm credit. We define household credit boom and firm credit boom using the same methodology than that employed for total credit boom. We then include household credit boom and firm credit boom and their interactions with information sharing characteristics (depth of IS in Panel A and coverage of IS in Panel B). Econometric results are reported in Table 8 using the mid-range measure of financial fragility (BSF(3%)). In column [1], we report baseline results without credit booms (because the number of observations has been reduced to 689 observations and 117 countries when we consider the new database). In the three following columns, we include household credit boom (column [2]), firm credit boom (column [3]) and both credit booms (column [4]). Finally, we add interaction between IS and household credit boom (columns [5]), IS and firm credit boom (column [6]), and IS with both credit booms (columns [7]). Econometric results provide very interesting findings. First, both household credit boom and firm credit

[19] As previously, we consider alternative combinations of financial fragility threshold and credit boom threshold (from 1% to 5%, 25 combinations). We document that IS alleviates credit booms especially if we restrict to dramatic changes in NPLs (superior to 3 points) and if credit boom is defined as increase of credit to GDP above or equal to 2 points per year. We confirm that mitigation effect occurs only in developed and emerging countries.

[20] Data are available on the author's website (https://sites.google.com/site/florianleon/research/data).

Table 7
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 equal to one if a country experienced a credit boom in year t. All explanatory variables are includes with a one-year lag. Year dummies are included but not reported. Random effect probit model is used. LR statistic tests 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 *** indicate significance levels of 10%, 5% and 1% respectively.

Table 8
Household credit vs. firm credit.

Panel A: Depth of IS

	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Depth of IS	−0.0242***	−0.0245***	−0.0242***	−0.0246***	−0.0437***	−0.0524***	−0.0487***
	(-2.97)	(-3.01)	(-2.97)	(-3.02)	(-3.48)	(-4.11)	(-3.76)
Household CB		0.0624**		0.0491*	0.0863*		0.0881*
		(2.27)		(1.73)	(1.80)		(1.82)
Depth of IS*Household CB					−0.0231*		−0.0311**
					(-1.75)		(-2.30)
Firm CB			0.0769***	0.0640**		0.0839*	0.0700
			(2.72)	(2.19)		(1.67)	(1.39)
Depth of IS*Firm CB						0.0111	0.0191
						(0.80)	(1.34)
# Obs	689	689	689	689	689	689	689
# Countries	117	117	117	117	117	117	117
R^2 (overall)	0.09	0.10	0.10	0.11	0.17	0.18	0.20
Wald test	–	64.65***	67.63***	70.70***	50.28***	52.75***	60.39***

Panel B: Coverage of IS

	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Coverage of IS	−0.00015***	−0.0015***	−0.0014***	−0.0014***	−0.0012**	−0.0016***	−0.0012**
	(-2.96)	(-3.00)	(-2.85)	(-2.90)	(-2.44)	(-3.00)	(-2.44)
Household CB		0.0624**		0.0494*	0.0859***		0.0767**
		(2.27)		(1.74)	(2.83)		(2.47)
Cov. of IS*Household CB					−0.0009*		−0.0011**
					(-1.81)		(-2.17)
Firm CB			0.0746***	0.0618**		0.0638**	0.0498
			(2.64)	(2.11)		(2.05)	(1.57)
Cov. of IS*Firm CB						0.0004	0.0006
						(0.77)	(1.14)
# Obs	689	689	689	689	689	689	689
# Countries	117	117	117	117	117	117	117
R^2 (overall)	0.09	0.10	0.10	0.11	0.10	0.10	0.11
Wald test	–	64.69***	66.93***	70.01***	66.02***	66.24***	72.51***

The dependent variable is a dummy equals to one if a country experienced a financial fragility episode 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. Wald test tests the significance of all explanatory variables. *, **, and *** indicates significance level of 10, 5 and 1% respectively.

boom are detrimental for financial stability as shown in columns [2-4]. Second, and maybe more interestingly, information sharing mechanisms are effective to mitigate the negative impact of household credit booms but not of firm credit booms as documented in columns [5-7]. In an unreported table, we test whether developing countries differ from developed and emerging economies but we fail to provide real difference. This finding can be explained by the specific characteristics of household credit that often are mortgage credit. We also documented that information sharing mechanisms have no impact on firm credit booms and household credit booms.

5. Conclusion

In this paper, we analyse the effect of credit information sharing on the financial vulnerability of a large sample of countries. Instead of a 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 fragility (jumps in NPL ratios) and not only the extreme ones (crises). Our first result confirms findings from other papers by highlighting the stabilizing impact of credit information sharing. We also document that this result holds for both less developed countries (whose GNI per capita is below US$ 4,125) and other countries (advanced and emerging). This stabilizing impact is larger for developing countries and more efficient on small shocks (2% NPL ratios jumps). 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) the higher the scope of information collected, the lower the likelihood of observing a credit boom (but the coverage of credit information sharing information does not matter); (iii) credit information sharing mitigates the detrimental effect of a credit boom but this result holds only for advanced and emerging countries and for household credit booms; and (iv) credit booms are strong predictors of financial vulnerability, especially in advanced and emerging countries.

Our results, although preliminary, have several policy implications. Firstly, credit growth is a key variable in conducting macroprudential policies in both developing economies and advanced economies. Secondly, 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. This result is particularly interesting for poor countries that have hitherto little used these information sharing systems. Our results also document that credit information sharing is less efficient on large NPL shocks than on smaller ones, and 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 and financial fragility. Finally, extending the coverage of information sharing systems is not enough, since the depth of information sharing is more effective in avoiding credit booms.

One limitation of our work is data availability. Due to the lack of data on both dependent and interest variables, we consider a relatively limited period. Further investigations should use national experience to confirm our results with longer time coverage.

Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.jfs.2018.08.004.

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