

International Banking Flows and Credit Booms: Do Booms Go with the Flow?*

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Abstract

This paper analyzes the impact of international banking flows on domestic credit booms and examines the drivers of the composition of banking flows by type of borrower: banking sector and non-banking sector. First, using a panel of 80 countries from 1980 to 2012, I find that international bank flows to the banking sector increase the probability of credit booms, while flows to the non-banking sector do not. Second, the paper shows that the composition of these flows is partly driven by the monitoring effort of the international bank lender. Using a partial equilibrium CAPM model, I find that, since monitoring is costly, international banks find it optimal to place more funds on the sector that requires less monitoring. I test this theoretical result and show that countries with mechanisms in place to make their banking sector less likely to fail - such as government guarantees, fiscal capacity to execute them and high institutional quality - attract more international bank funds to their banking sector. Thus, mechanisms to make the banking sector safer should be properly designed to reduce the distortions they may generate on the lending behavior of international banks.

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1 Introduction

Bank interconnections across countries have increased dramatically over the last 20 years bringing new opportunities but also new challenges for the real economy. The last global financial crisis generated some sort of vilification of the international activity of banks, which were blamed for transmitting financial instability across countries. As a result, there is an increased interest among researchers and policy-makers in understanding the effects of global banking on the real economy in order to design regulations that reduce the negative aspects of banking globalization without reducing its benefits.

I analyze the impact of banking globalization on economic outcomes by analyzing whether the international activity of banks generates excessive credit growth. This question is relevant because, as recent work has shown, the international activity of banks has played a major role in the expansion of credit in countries receiving the international bank funds (Bruno and Shin, 2013; BIS, 2010). Yet, the impact of this credit expansion is not clear and the theoretical priors inconclusive. On the one hand, international bank flows can have a positive impact because they help recipient countries meet their domestic demand for credit (Claessens and Horen, 2014). On the other hand, they may have a negative impact if they lead to excessive credit growth in the recipient country because credit surges are associated with financial instability, as the theoretical literature has argued for decades (Fisher, 1933; Minsky, 1977; Kindleberger, 1978) and the empirical literature has also shown (Demirgüç-Kunt and Detragiache, 1998; Kaminsky et al., 1998; Mendoza and Terrones, 2008; Schularick and Taylor, 2012; Laeven and Valencia, 2013). In fact, after the last 2008 financial crises, the evolution of credit is under the close scrutiny of financial regulators (OFR, 2014) because credit surges are associated with financial crises of more consequences for the real economy than crises that are not preceded by credit booms (Jordà et al., 2011; Schularick and Taylor, 2012).

The results of this paper contribute to the debate in two ways. First, the paper shows that the relation between banking globalization and credit booms depends on the type of borrowing sector: banking sector versus non-banking sector. International banking flows going to the banking sector increase the probability of credit booms in the recipient country, while banking flows to the non-banking sector do not. Second, the paper finds that the composition of international banking flows by borrowing sector is driven by the monitoring effort that international banks have to exert on each type of lender. Countries

with mechanisms in place to make the banking sector safer, such as government guarantees, better regulations and fiscal capacity will attract more international banking funds to their banking sector.

The core of the paper is empirical. The sample comprises 80 countries (26 high income, 23 middle income and 31 lower income countries) and annual data from 1980 to 2012. The paper is organized in two parts:

The first part of the paper examines whether international bank flows increase the probability of credit booms, where credit booms are defined as episodes in which private credit over GDP is substantially above its country-specific historical trend¹. I differentiate between credit booms that have a soft landing (“good booms”) from the ones that result in financial crises (“bad booms”) because policy makers because they are particularly interested in preventing and mitigating the effects of bad credit booms. Financial crises for the purpose of this paper are defined as banking, currency or debt crises. There are a total of 94 credit booms in the sample, 39 of which result in financial crises (i.e., 39 out of 94 credit booms are bad booms)².

International bank flows are defined as changes in cross-border bank claims from banks located in a particular country vis-a-vis the rest of the world. Data are compiled by the Bank of International Settlements (BIS) Locational Banking Statistics which contain the flows of funds channeled through the banks residing in a particular country vis-à-vis more than 200 countries. Data is provided at country level after aggregating banks’ individual positions. These country aggregated bank positions include: (i) loans and deposits; (ii) holdings and own issues of debt securities; and (iii) other assets and liabilities³. The destination of the funds can either be the banking sector or the non-banking sector (i.e., non-bank financial corporations, non-financial corporations, government entities, and households).

¹The series of private credit over GDP is decomposed into its permanent and cyclical component using an HP filter. Deviations of the cyclical component above certain boom thresholds determine the existence of the boom in a certain country at a certain period. See Section 2.1 for a detailed definition.

²If instead of 3 types of crises I had taken only one type, the number of bad booms would have barely changed because different types of financial crises tend to duplicate or precede each other, as documented in Kaminsky and Reinhart (1999), and a bad boom is defined as the episode that results in any type of financial crisis.

³Loans represent the largest share of total cross-border claims (73 percent), followed by debt securities (18 percent), and other positions (9 percent). These percentages have been calculated using data from 2009 only because there is no break down information prior to that date.

Using a logit model and differentiating by type of borrower, I find that international bank flows to the banking sector of the recipient country increase the probability of credit booms while flows to the non-banking sector do not. These results apply to high and middle income countries but lower income countries do not receive enough banking flows to generate credit booms. These results are robust to the introduction of controls (other capital flows, macro fundamentals, and global factors) and alternative econometric specifications. These findings are interesting on their own because show that not all banking flows across borders are problematic but only the banking flows directed to the banking sector.

In the second part of the paper, I take one step further and analyze the drivers of the composition of international bank positions by borrowing sector (i.e., banking and non-banking sector). Descriptive analysis shows that high income countries receive a larger share of bank to bank funds than bank to non-bank funds which, combined with the previous result, indicates that advanced economies are more prone to credit booms. I argue that this counterintuitive result derives from a moral hazard problem generated by asymmetric information in financial transactions. Asymmetries of information motivate the intermediation of banks which, with their inherent monitoring capacity, reduce the problems derived from these asymmetries. I argue that mechanisms to make the banking sector less likely to fail reduce the incentive of international investors to monitor the banking system of the borrowing country.

Using a partial equilibrium capital asset pricing model (CAPM), I show that, since monitoring is costly, it is optimal for international bank lenders to place more funds on the sector that requires less monitoring. I test this hypothesis and find that countries with mechanisms in place to make the banking sector less likely to fail -such as banking regulations, implicit and explicit government guarantees and fiscal capacity to execute them- will receive a larger share of international bank positions into their banking sector. This result holds even after controlling for other potential explanations, such as the size and leverage of the banking system. Therefore, safety mechanisms may distort the behavior of international banks by making them overlend to other banks across borders.

One potential caveat of this paper is to restrict the analysis to just banking flows, which are a sub-component of debt flows⁴. However, several factors justify this decision. First, there is enough evidence in the literature suggesting that the impact of international

⁴The BIS data do not include funds flowing into a country from non-bank institutions.

financial flows depends on the type of flow and, therefore, a more granular analysis is required to understand their effects⁵. Second, the international activity of banks has increased dramatically over the last 20 years⁶ and its impact, which has attracted policy-makers in recent years, is not clear: before the 2008 global financial crisis, international banking had been associated with better regulations, more competition and better access to finance (Claessens et al., 2001; Beck et al., 2004) but, after the crisis, it has been associated with the transmission of negative shocks across borders (Gourinchas et al., 2012; Obstfeld, 2012b; Kalemli-Ozcan et al., 2013; Claessens and Horen, 2014). Last, international lending tends to be intermediated by financial institutions with increasing levels of complexity and size, which poses new challenges on regulatory agencies because supervision and resolution procedures become more complicated and the too-big-to-fail problem more acute (Cetorelli and Goldberg, 2011; Claessens and Horen, 2014; Cetorelli and Goldberg, 2014; Cetorelli et al., 2014).

In any case, I address this potential caveat in two ways: in the descriptive analysis, I show that the share of bank flows over total debt flows is substantial and, therefore, worth studying on their own. In the econometric analysis, I show that the results are robust to controlling for non-bank debt flows.

Related Literature

This paper relates to three lines of research: the effects of external factors on domestic outcomes, the drivers of credit booms and the literature on global banking.

The distinction between external or “push” factors and internal or “pull” factors has been extensively studied in the literature since the seminal paper of Calvo et al. (1993)⁷. For example, Kaminsky and Reinhart (1999); Kaminsky et al. (2004) show that global imbalances increase macro vulnerabilities and credit booms. Bruno and Shin (2013) build a theoretical model linking capital flows and private credit through procyclical bank leverage. Reinhart and Reinhart (2008) show that net inflows into emerging economies generate domestic credit

⁵See Kose et al. (2006) for a review on the impact of financial globalization in general.

⁶Banking globalization, defined as the sum of international asset and liability positions of international banks, has grown from 30 percent of GDP in mid 1990s to almost 60 percent of GDP in 2012 (Milesi-Ferretti and Tille, 2011; Brunnermeier et al., 2012; Rey, 2013). The definition of banking globalization taken from Lane and Milesi-Ferretti (2007). Data on international assets and liabilities positions of banks are from the BIS Locational Banking Statistics.

⁷Calvo et al. (1996); Chuhan et al. (1998); Fratzscher (2012) and related literature.

expansion, which amplifies the potential weaknesses of their banking sector and, as a result, leads to a higher probability of financial crises. There is a consensus on this literature that not all types of international capital flows have the same impact. Debt flows are more associated with credit booms and financial fragility than other flows (Borio and Disyatat, 2011; Jordà et al., 2011; Schularick and Taylor, 2012; Gourinchas and Obstfeld, 2012; Obstfeld, 2012a; Calderón and Kubota, 2012; Rey, 2013; Bruno and Shin, 2013; Hale and Obstfeld, 2014)⁸. I contribute to this literature by showing that a sub-component of debt flows, banking flows to the banking sector, is the one that increases the probability of credit booms.

The second strand of literature this paper relates to is the work on credit booms. On the theoretical side, Minsky (1977); Kindleberger (1978) argue that economic expansions increase optimism that fuels credit growth that can result in financial and economic crises. The financial accelerator models show that an increase in the value of the collateral reduces the borrower's credit constraints, which leads to more lending and higher asset prices, all of which ends up raising the vulnerability of the banking system (Kiyotaki and Moore, 1997). On the empirical side, Gourinchas et al. (2001); Barajas et al. (2007); Mendoza and Terrones (2012); Calderón and Kubota (2012) find that booms tend to be preceded by surges in capital inflows and followed by financial crises. Calderón and Kubota (2012) show that bank inflows, in particular, have better predictive ability than other type of capital flows. I expand this literature by showing that not all banking debt across borders contributes to the generation of credit booms but just the interbank positions. This result echoes the generalized idea that cross-border interbank lending is more destabilizing than other types of cross-border lending and shows it in the context of credit booms⁹.

Last, I contribute to the literature on the composition of global banking which, so far, only relates it to bank efficiencies and barriers of entry (Kerl and Niepmann, 2014). I find that the composition of international banking flows across borrowers is determined by the international lenders' monitoring effort, which is distorted by government guarantees to the

⁸Calderón and Kubota (2012) find that gross "other investment" and portfolio investment inflows increase the probability of credit booms, while foreign direct investment (FDI) reduces it. Caballero (2012) finds that debt and portfolio-equity increase the probability of systemic banking crises. Furceri et al. (2012) use impulse response functions to show that debt inflows generate the largest effect on domestic credit.

⁹Schnabl (2012) finds that the transmission of the negative liquidity shock from 1998 Russian default to Peru affected Peruvian banks that borrowed internationally from other banks more than it affected locally interbank funded banks. McCauley et al. (2012) find that banking models that are less reliant on cross-border wholesale funding were less disrupted during the 2008 crisis. Reinhart and Riddiough (2014) shows that interbank lending is withdrawn in larger quantities than other types of lending when global risk is high.

banking sector and other mechanisms that make the banking sector safer. As a result, banks will be less monitored than other non-guaranteed borrowers which will make international lender overlend to the banking sector. This finding aligns with the literature relating asymmetric information and the lending behavior of banks. Dell’Ariccia and Marquez (2006) use an adverse selection model to show that during expansions banks find it optimal to reduce their monitoring, which results in a portfolio deterioration and higher probability of crises. The literature on moral hazard show government guarantees as a source of moral hazard but focuses on the behavior of the banks receiving the guarantee¹⁰. My contribution to this literature is to show that moral hazard also affects the behavior of the international banks lending to the guaranteed banks.

Policy implications

Two policy implications derive from this chapter. First, policy-makers should place more attention on interbank transactions across borders because those are the banking transactions that contribute to the generation of credit booms. Second, mechanisms that contribute to make the banking sector safer may also attract destabilizing international flows because these mechanisms distort the monitoring and lending decisions of international bank lenders. This paper does not suggest the removal of these mechanisms but alert about the need to design and target them appropriately to reduce the moral hazard problem they generate.

Outline

This chapter is structured as follows. Section 2 contains the description of the data, examination of the empirical regularities around booms, and the econometric analysis. Section 3 addresses the second part of the paper which includes a theoretical subsection on the drivers of the composition of international banking flows and empirical tests. Section 4 concludes and provides the policy recommendations.

¹⁰Theoretical works show that government guarantees are a source of moral hazard (Allen and Gale, 1998; Bhattacharya et al., 1998; Chari and Jagannathan, 1988). Empirical work documents that guaranteed banks take on more risks (Afonso et al., 2014; Brandao Marques et al., 2013).

2 Empirical Analysis

This section defines the data, provides descriptive evidence of the behavior of external and domestic factors around credit booms and contains the econometric analysis.

2.1 Data

The sample covers an unbalanced panel of 87 countries with annual data from 1980 to 2012. After dropping the off-shore centers, Luxembourg and Ireland, for having extreme values of banking flows due to taxation purposes¹¹, the final sample comprises 80 countries, 26 of which are high income countries, 23 are middle income countries and 31 are lower income countries -following to the World Bank classification by income¹². The list of countries is in Appendix Table A.1.

Credit booms

Credit booms per country are defined as episodes in which private credit over GDP is substantially above its country-specific historical trend¹³. This definition follows the “threshold method” of Gourinchas et al. (2001), also applied by Calderón and Kubota (2012) and Barajas et al. (2007). To identify credit booms, I decompose the series of private credit into its trend and cyclical component using the Hodrick-Prescott filter with $\lambda = 100$ as the smoothing parameter¹⁴. A credit boom occurs when the cyclical component rises above a

¹¹The off-shore countries dropped are Barbados, Hong Kong, Mauritius, Panama, and Seychelles. Similar studies also drop these countries (Lane and McQuade, 2014; Bruno and Shin, 2013).

¹²The World Bank classification is based on the 2012 GNI per capita. The income groups are: low income, \$1,035 or less; lower middle income, \$1,036 to \$4,085; upper middle income, \$4,086 to \$12,615; and high income, \$12,616 or more. I re-group the countries into three income groups: “High” for high income countries, “Middle” for upper-middle income countries, and “Lower” for lower-middle and low income countries. Country list is in the appendix.

¹³The advantage of the ratio of private credit to GDP is that it relates private credit to the size of the economy and corrects for the procyclicality in bank lending. The caveat of private credit to GDP is that it only captures bank credit and does not include the credit going through non-bank financial intermediaries, which leads to underestimate the frequency of booms, especially in more financially developed countries, like the US. The data source is the World Bank Financial Development and Structure database.

¹⁴Backus et al. (1992) suggest a smoothing parameter of the Hodrick-Prescott filter (HP filter) of $\lambda = 100$ for annual frequency, which is the λ value commonly used in this literature.

certain *boom threshold*. The boom threshold selected in this paper is 1.65 standard deviations of the cyclical component because the critical value for a 95 percent one-tailed test is 1.65. To account for different magnitudes of the excessive credit growth, I use 1 and 2 standard deviations as thresholds. The duration of the boom is determined by the time span between the beginning and the end of each boom, which are determined by a *limit threshold* of 0.5 standard deviations. The *peak* of the boom is the period at which the difference between the cyclical component and the boom threshold is the largest. See Figure 1 for a graphical illustration using the example of Algeria -first country from an alphabetical order.

In the sample, there are a total of 94 credit boom episodes and they last an average of four years¹⁵. I differentiate normal (or good) booms from bad booms. Normal booms are the episodes of excessive credit growth that have a soft landing, while bad booms are the ones that result in any type of financial crisis -systemic banking crises, currency crises or debt crises- within two years after the end of the boom. See Fig. 2 for an illustration.

Data on bank and currency crises are from Laeven and Valencia (2013) and data on debt crises from Reinhart and Rogoff (2009) -updated by Broner et al. (2013). There are 194 financial crises and, in 20 cases, more than one type of crisis coincides in the same country at the same time period. After removing the duplications, there are 174 years with some type of crises. Some of these crises occur sequentially, which aligns with Kaminsky and Reinhart (1999) who show that banking crises tend to precede currency crises. After grouping the crises that occur within 1 or 2 years from each other, the total number of financial crises is 120, 39 of which coincide with a credit boom and 82 of them are not credit related (Table 1). That is, 33 percent of the financial crises in the sample are credit related. Figure 3 shows the number of credit booms and crises per year.

Out of the 94 credit booms, 39 of them result in financial crises. Since booms last an average of four years, in order to count the number of booms per year without duplicating them, I pick one year per episode to represent the credit boom. I consider the most representative year to be the peak of the boom. Figure 4 shows the number of booms per year (i.e., the number of peaks) differentiating between good and “bad” booms. One interesting feature illustrated in Fig. 4 is that credit booms tend to be clustered around certain time

¹⁵The duration of the “bad” booms tends to be slightly longer than good booms: 4.5 versus 3.8 years, respectively. In middle income countries, average duration of bad booms is 4.3 years while good booms last 2.8 years. In lower income countries, bad booms last 5 years while good booms 3.9 years.

periods: beginning of the 1990s, late 1990s and 2008-2009. This synchronization aligns with the global business cycle literature and motivates the selection of global factors as potential explanatory variables¹⁶.

The analysis across income levels provides interesting insights. In high and middle income countries, around half of the credit booms have a hard landing (Table 2). In contrast, in lower income countries only 25 percent of the booms result in financial crises. This fact does not mean that there are more crises in high income countries but that crises are more likely to come out of a credit boom. In lower income countries, however, financial crises seem to occur for reasons other than credit booms¹⁷. Lower income countries may have less bad booms because the growth of credit in these countries is more likely to be driven by true financial deepening and convergence with the rest of the economies than by speculative reasons.

International banking flows

International banking flows are defined as changes in cross-border bank claims from banks located in a particular country vis-à-vis another country. Data are taken from the BIS Locational Banking Statistics which contain the flow of funds channeled through the banking system broken down by residency of the counterparty after aggregating banks' individual positions per country¹⁸.

Since the goal of the paper is to analyze whether the flow of funds received from international banks increase the probability of credit booms, banking *inflows* are the ones examined. In particular, I use *gross* inflows, which are the total amount of flows received by a country from banks located in the other BIS reporting countries, as opposed to net inflows, which are the difference between gross inflows and gross outflows, because net flows tend to

¹⁶Studies on the global business cycle include Backus et al. (1992); Kose et al. (2003); Heathcote and Perri (2004); Ayhan Kose et al. (2008); Del Negro and Otrok (2008); Ueda (2012) among others.

¹⁷In the high income group, 47 percent of financial crises are credit related while, in lower income countries, it is only 20 percent.

¹⁸The BIS Locational Banking Statistics record bank positions on an unconsolidated basis and include flows vis-à-vis own affiliates in other countries. On the contrary, the BIS Consolidated Banking Statistics collect data on international banking positions on a consolidated basis. In all cases, amounts outstanding at end t and $t-1$ are converted into their original currency components using the respective end-of-period exchange rates. The differences between these individual components are subsequently converted back into US dollar using average exchange rates during the period. Data are expressed in millions of US dollars.

be less volatile by construction and omit information that is useful for the current analysis. Recent literature on capital flows has also shifted the attention towards gross rather than net flows¹⁹.

The BIS data disaggregate the data by borrowing sector: banking sector and non-banking sector. The banking sector comprises deposit money banks, related offices (subsidiaries and branches) and central banks²⁰. The non-banking sector includes non-bank financial institutions²¹, non-financial corporations, households, and general government (or public sector). Claims on the public sector account for approximately 18 percent of all the international banks' positions in developed countries, 23 percent in the case of emerging countries and 7 percent in the case of off-shore centers²².

The distinction by borrowing sector is done based on the issuer of the claim. For example, a bond issued by a company in Germany (e.g., BMW) bought by a bank in the US (e.g., Citibank) implies a movement of funds from a bank in the US to a non-bank in Germany. Therefore, it is a bank to non-bank inflow for Germany. Or, for example, a bond issued by Banco Santander in Spain which is bought by Bank of America in the US is a bank to bank inflow for Spain. If Barclays Bank in the UK buys a German government bond from Deutsche Bank in Germany (i.e., Deutsche bank has bonds from the German government in its books and Barclays buys them), it would be bank to non-bank inflow for Germany because the German government is a non-bank institution²³ Figure 5 illustrates the evolution of international banking flows by borrowing sector: banking and non-banking.

The funds raised internationally through non-bank institutions are not included in the

¹⁹Borio and Disyatat (2011); Calderón and Kubota (2012); Forbes and Warnock (2012); Milesi-Ferretti and Tille (2011); Broner et al. (2013); Bruno and Shin (2013).

²⁰Related offices are entities that belong to the same banking group or to the same controlling parent institution.

²¹The non-bank financial institutions include special purpose vehicles, hedge funds, securities brokers, money market funds, pension funds, insurance companies, central clearing counterparties, development banks, and other financial auxiliaries.

²²The break-down by sector is an estimation based on data from the BIS Consolidated Banking Statistics (Table 8), ultimate risk basis, from 2005 till 2012 because there is no such break-down in the BIS Locational Banking Statistics.

²³The purchase of a mortgage backed security, for example, should be reported as a claim on the issuer of the security, which can be a bank or a non-bank financial institution and not on the ultimate borrower who is the household holding the mortgage.

BIS data (see Figure 6). For example, funds raised by banks in the international bond market that are bought by non-banks are not included in the BIS data²⁴. Leaving out these sources of funds may raise a concern. However, I address this concern in two ways: in the descriptive analysis, I show that bank-debt flows are an important share of total debt flows and, therefore, worth studying on their own. In the econometric analysis, I control for the non-bank debt flows and show that the estimates of both bank debt and non-bank debt are robust to this change.

Banks' positions include: (i) loans and deposits; (ii) holdings and own issues of debt securities; and (iii) other instruments. Despite the BIS data is not broken-down by instrument until 2009, I calculate the share of each type of position using data from 2009 to 2012 to have an idea of the importance of each instrument²⁵. The loans represent 73 percent of all positions and are allocated to the country of residence of the borrower. Debt securities represent 18 percent of all positions and comprise claims in all negotiable debt instruments except equities and bonds held on a purely custodial basis. The holding of debt securities are allocated to the country of residence of the issuers. The last category, other instruments, account for 9 percent of all positions and comprise equity securities, retained earnings and any other residual on-balance sheet financial instruments.

The BIS Locational Banking Statistics track banks' exposure at country level in a way consistent with the Balance of Payments (BOP) methodology, which have the advantage of making the data comparable to data on other type of capital flows. Another advantage is the large coverage of the BIS data, which goes as far back as 1977. The disadvantage is their lack of granularity or break-down by type of instrument, maturity of each position or ultimate borrower.

Other factors

Other factors that the literature has associated with credit booms are international capital flows, macroeconomic fundamentals and global factors. I analyze the evolution of these other factors around credit booms and control for them in the econometric analysis.

²⁴A bond issued by Google USA that is bought by a Japanese insurance company is a debt inflow for the US that is NOT captured in the BIS data.

²⁵This approximation is likely to be close to the true value because, according to the BIS, loans have always been the dominant position although debt positions have increased over the last few years (McGuire and Tarashev, 2006).

International capital flows include foreign direct investment (FDI), portfolio equity, and debt -following the classification of Lane and Milesi-Ferretti (2007)²⁶. The data is from Lane and Milesi-Ferretti (2007)’s database and all the flows are scaled by GDP.

Macroeconomic fundamentals include real GDP, real exchange rate, and banking leverage - defined as bank credit over bank deposits. All the macro variables are transformed into annual percentage change. Data sources are the World Bank Development Indicators, IMF’s International Financial Statistics (IFS) and the World Bank Financial Development database.

Global variables comprise global liquidity -which is defined as the sum of M2 of the main important financial centers (Forbes and Warnock, 2012)- and global risk -measured by the VXO volatility index. Data from the IFS and the Chicago Board Options Exchange, respectively. The detailed description of variables and sources can be found in Table A.3.

2.2 Empirical Regularities around Booms

This section examines the evolution of the domestic and external factors around credit booms. The goal of this subsection is to identify the factors that contain valuable information to be included in the econometric analysis that comes next. Since the average duration of booms is 4 years, I show the evolution of these factors over a seven year window centered at the peak of the boom. I distinguish between normal and bad booms with the goal of examining whether these variables behave differently around bad booms, which are the most interesting from the policy perspective.

Figure 7 shows the dynamic behavior of private credit around good booms (left graphs) and “bad” booms (right graphs) across income levels. The top row illustrates that, in high income countries, the level of private credit is higher in the build-up of the bad booms than of the good booms, while there is almost no difference in the middle and lower income groups.

²⁶FDI is a category of cross-border investment associated with a resident in one country having control or a significant degree of influence on the management of an enterprise that is resident in another economy. However, portfolio equity investment has less of a role in the decision making of the firm the non-resident is investing in. Debt investment in Lane and Milesi-Ferretti (2007) comprise two BOP categories: “portfolio debt” and “other investments” -which include deposits, loans, trade credit and other account receivable/payable.

The next row shows the evolution of the annual percentage change in private credit and illustrates that the volatility of private credit is larger around bad booms, especially in lower income countries.

Since banking flows are a sub-set of debt flows, I analyze them in the context of capital flows. Figure 8 shows the evolution of the three types of capital flows -foreign direct investment (FDI), debt, and portfolio equity - around good booms (top graphs) and bad booms (bottom graphs). These graphs reveal interesting insights. First, debt flows are substantially larger and more volatile than FDI and portfolio equity, especially, in high income countries. The growth of debt inflows in the build-up of the boom is much larger than the other two types of capital flows. Second, FDI and portfolio equity do not show a large difference around good and bad booms. These graphs indicate that the study of credit booms should be focused on debt flows²⁷.

Next, I disaggregate debt flows into bank debt and non-bank debt flows by subtracting bank-debt from the total debt, as in Milesi-Ferretti and Tille (2011). This disaggregation is not exact because the BIS data on banking flows also include equity positions which, in the BOP classification fall under the portfolio equity category. However, this caveat does not invalidate this descriptive analysis because the equity category represents only around 9 percent of all banking flows. Figure 9 shows that, in high and middle income countries, there is little difference in the evolution of bank and non-bank debt flows but, in high income countries, bank debt flows are more volatile than non-bank debt flows. Second, low income countries receive small amount of international capital flows, in general, and of bank-debt flows, in particular, which may derive from the fact that these countries tend to be less financially open and less financially developed than the other two income groups.

Then, I analyze banking flows in more detail and disaggregate them by type of borrower: bank and non-bank. Figure 10 illustrates that, first, banking flows are larger and more volatile around bad booms; and second, bank flows to the banking sector (B-B) are substantially more volatile around bad booms than around normal goods, reaching 8 percent of GDP at the peak of the bad boom and falling abruptly to negative 12 percent of GDP. As before, lower income countries receive a negligible amount of international banking flows and

²⁷Banking flows include mainly loans and debt investment and only less than 10 percent of equity investment. Debt flows mainly comprise portfolio debt, loans, and deposits (see Section 2.1 for a detailed description of the data).

do not show different patterns around good and bad booms. At this stage of the descriptive analysis, it is evident that banking flows and, in particular, those to the banking sector (B-B) can play a role in generating bad credit booms.

I examine the evolution of domestic and global factors that the literature relates to credit booms. Figure 11 shows the macroeconomic factors around normal credit booms (left graphs) and bad credit booms (right graphs). The top graphs show the evolution of real GDP across income levels. Real GDP is transformed into an index for homogenization purposes. The index is set to 100 at T-4, where T is the peak of the boom, and I apply the annual growth rate of real GDP to the index to calculate its evolution around credit booms. Real GDP behaves slightly different around good and bad booms: the starting level of GDP is higher in the build-up phase of bad booms in middle income countries, and slows down or stagnates after bad booms. However, in normal booms, there is no change in the GDP trend. The second row shows the evolution of government debt over GDP. The graphs illustrate the deterioration of the fiscal position after bad booms. The real exchange rate shows an appreciation in the build-up phase of the boom and a depreciation in the downward phase. The exchange rate is much more volatile around bad than good booms, especially in middle and lower income countries. The bottom graphs show the evolution of bank leverage, defined as the ratio of bank credit over bank deposits. The level and change in leverage is higher around bad booms than around normal goods at all income levels.

The evolution of global factors, which is motivated by the synchronization of credit booms around certain time periods (Fig. 4), shows that the level and growth of global liquidity and global volatility before a bad boom is slightly larger than around bad booms (Fig. 12).

2.3 Econometric Analysis

This section examines the impact of international banking flows on credit booms. I describe the estimated model, provide the results of the analysis and check the robustness of my results.

Methodology

I assess the role of gross banking flows in the probability of having a credit boom in

the recipient country by estimating the following probabilistic model of a credit boom event occurring in country i at time t :

$$P(e_{it} = 1) = \alpha_i + \beta_1(L)BF_{it} + \beta_2(L)\mathbf{X}_{it} + \varepsilon_{it} \quad (1)$$

where $P(e_{it} = 1)$ is the probability of the event, e_{it} , which is a credit boom dummy variable that takes the value of 1 when there is a credit boom and 0 otherwise; α_i captures the persistent unobserved country-specific factors; BF_{it} is gross international banking flows scaled by GDP; L is the lag operator; \mathbf{X}_{it} is the matrix of control variables, which comprise other capital flows (portfolio equity, FDI and non-banking debt), macroeconomic variables (real GDP, real exchange rate, and banking leverage), and global factors (global liquidity and global risk); and ε_{it} is the error term.

I estimate equation (1) using a logit model; that is, $P(e_{it} = 1)$ is the logit function or the log of the odds ratio that a credit boom occurs relative to a non-boom²⁸. The advantage of the logit approach is that it is particularly adequate for low frequent events. In our case, there are 94 credit booms, which represent only around 5 percent of the whole sample. Since the logit is a distribution with fatter tails than alternative non-linear models (such as the probit), it is considered the most appropriate estimation method for this type of analysis and the most commonly used in the literature (Demirgüç-Kunt and Detragiache, 2002; Schularick and Taylor, 2012; Jordà et al., 2011). The disadvantage of using a logit approach is the incidental parameter problem, which occurs when too many parameters are estimated in a non-linear context, reducing the statistical power of the coefficients. To minimize this problem, I do not split the sample across income levels but use the whole sample.

The dummy captures each boom episode and takes the value of 1 per credit boom. Since booms last an average of four years and I need to pick only one year to identify each boom episode, I select the peak year as the representative year of the boom. I am not trying to predict a turning point but to select the most appropriate year of the dummy. As a robustness check, I select the year before the peak (i.e., T-1, where T is the peak year) as the year of the boom and the results do not significantly change, as it is shown later. The years of the boom other than the dummy year -i.e., the build-up and drop-down years- cannot be considered a 1 because I would be overfilling my sample with ones but they cannot enter as

²⁸ $logit(p_{it}) = \ln \frac{p(e_{it} = 1|BF_{it}, X_{it})}{p(e_{it} = 0|BF_{it}, X_{it})}$.

a 0 either because they are not normal or non-boom years either. Then, I drop them from the left hand side of Eq. (1) in the estimations.

The independent variables are introduced with two lags to account for reverse causality issues; that is, to account for the possibility that a credit boom is causing the surge in banking flows. Despite this work does not do any causation claim, the introduction of lags in the explanatory variables reduces the potential reverse causality problem. Based on the AIC and BIC lag selection tests, the selected number of lags is two.

The key explanatory variable is banking flows measured as gross inflows. I start the analysis using total banking flows and, then, I differentiate by type of borrower: banking sector (B-B) and non-banking sector (B-NB). The analysis is done for the whole sample and sub-samples: high, middle and lower income countries.

I estimate four specifications of the model, one for each of the four types of booms: all booms, good booms, bad booms and conditional bad booms. Specification (1) in each table includes the 94 credit booms in the sample. Specification (2) estimates only the booms that have a soft landing; i.e., 55 booms. Specification (3) estimates the probability of a bad boom and specification (4) estimates the probability of a ‘conditional bad boom’ which is the probability of a bad boom out of all the credit booms. For the conditional bad booms estimations, I only select the credit boom years and estimate whether banking flows affect the probability of those booms ending badly.

Control variables

There are other factors besides international banking flows that can affect the probability of credit booms. To account for these factors, first, I introduce country fixed effects. This way, I capture the general time-invariant country specific factors. Then, I control for three sets of variable: other international capital flows, macroeconomic factors and global variables. The choice of variables have been motivated by the already presented empirical regularities around credit booms (Section 2.2) and supported by the literature.

Other international capital flows include non-bank debt, portfolio equity and foreign direct investment (FDI). The macroeconomic factors comprise real GDP, real exchange rate and bank leverage -all of them in annual percentage change. The global variables are motivated by the observed clustering of credit booms around certain time periods. Following the

literature (Forbes and Warnock, 2012), the chosen variables to control for global factors are global liquidity and global risk. The detailed description and sources of each variable can be found in Table A.3.

Despite controlling for such a comprehensive set of factors improves the accuracy of the model, the possibility that something else is affecting the probability of credit booms can never be ruled out. However, even if there are some missing variables in the model, the fact that the control variables in this case tend to be highly correlated with each other reduces the potential implications of such omission (see correlations in Appendix Table A.5.)

2.4 Results

In this section I present the results of the estimations. First, I provide the results of the estimations in which the only explanatory variable is total banking flows (inflows). Then, I introduce control variables into the equation. Last, I show the results of the specifications in which the explanatory variables are banking flows to the banking sector (B-B) and to the non-banking sector (B-NB). All the result tables show the coefficient of each of the two lags as well as the linear combination of both lags. I conclude this section presenting the robustness checks.

Table 3 shows the results of the estimations in which total banking flows is the only explanatory variable. The first four columns show the results for the whole sample of countries and the other set of four columns shows the results for each of the three income subsamples. The coefficients of the sum of the lags are positive and statistically significant in all the credit boom types, which means that international banking flows increase the probability of a credit boom event. In particular, the coefficient of the sum of the lags of column (1) is 0.22, which means that a rise of banking inflows by 1 percent of GDP increases the log of the odds ratio of having a credit boom by 22 percent. The probability of bad booms is estimated in column (3) and the coefficient is slightly higher, 0.23, and also statistically significant. It indicates that the rise of banking inflows by 1 percent of GDP increases the log of the odds ratio of having a bad boom by 23 percent.

The results across income levels are presented in columns (5) to (16) of Table 3 and show that international banking flows significantly increase the probability of credit booms in high and middle income countries but do not affect credit booms in the lower income group. In

high income countries, banking flows increase the probability of all types of credit booms. In middle income countries, the coefficients are also positive and statistically significant, except for the estimation of the probability of good booms -column (10). None of the coefficients in the lower income regressions are significantly different from 0, which means that credit booms in lower income countries are not a banking flow driven story. This finding aligns with the small amount of banking flows going into lower income countries that was found in the descriptive analysis (section 3.2).

Since banking flows do not affect the occurrence of credit booms in lower income countries, the rest of the analysis is focused on high and middle income countries. I put together the sub-samples of high and middle income countries in order to increase the number of observations and statistical power of my results.

Table 4 introduces control variables in the joined sample of high and middle income countries. The coefficients of total banking flows are positive and statistically significant in all cases which means that international banking flows increase the probability of bad credit booms, even if we control for other factors. Columns (1)-(4) show the results of the estimations with for other capital flows as controls (non-bank debt, foreign direct investment (FDI), and portfolio equity), columns (5)-(8) add macroeconomic controls (real GDP, real exchange rate, and banking leverage), columns (9)-(12) show the results with other capital flows and global variables as controls, and columns (13)-(16) show the results controlling for all the above variables.

Next, I estimate the probability of credit booms having as explanatory variable each type of banking flow: flows to the banking sector (B-B) and flows to the non-banking sector (B-NB). The main finding is that banking flows to the banking sector (B-B) increase the probability of booms, while banking flows to the non-banking sector (B-NB) are not significantly associated with them. Table 5, columns (1)-(4) show that the coefficient on banking flows to the banking sector (B-B) are positive and statistically significant at 1 percent level, while the estimate on banking flows to the non-banking sector (B-NB) is positive but smaller and not statistically significant. These results are robust to controlling for other capital flows, columns (5)-(8); macro factors, columns (9)-(12), and global variables, columns (13)-(16).

I test whether the coefficient of B-B are significantly different from B-NB²⁹. The results

²⁹Results available upon request.

indicate that the difference between B-B and B-NB is statistically significant only for the specifications that estimate all the booms; that is, columns (1), (5), (9) and (13) in Table 5. For the rest of specifications, the point estimates remain positive but the significance level declines -most likely because the number of observations is too small for the estimations to have statistical power. Therefore, despite the statistical power of these checks does not allow for a strong claim, the size and sign of the estimates allow concluding that B-B flows are the ones that increase the probability of bad booms.

Robustness checks

This section explores whether the results are robust to an alternative selection of the dummy year, the exclusion of the last global financial crisis, the use of alternative methodologies and the selection of different boom thresholds.

The previous results had the peak year as the year of the boom dummy. As a robustness check, I select the period right before the peak as the year of the dummy. That is, the dummy equals 1 at (T-1), where T is the peak of the boom. In appendix Table B.1, columns (1) to (4) show the results for the specifications without controls, and columns (5)-(16) show the results with controls. In all cases but in (10) and (14), the coefficient for bank to bank flows (B-B) is positive and statistically significant, while bank to non-bank (B-NB) flows do not significantly affect the probability of credit booms, which confirms the benchmark results. Columns (10) and (14) estimate the probability of a normal boom with control variables. The results indicate that neither B-B nor B-NB are statistically significant.

Next, I check whether the benchmark results are driven by the last global financial crisis. I eliminate years 2006 to 2012 from the analysis and find that most of the benchmark results are robust to this change. Table B.2 shows the results for the specifications with total banking flows as the key explanatory variable. The results indicate that the benchmark results are robust except for bad credit booms in the high income group, where the estimates are still positive but not significant. These results derive from the fact that most of the high income bad booms in my sample occurred in the 2006-2012 period. Therefore, removing those years reduces the statistical power of my results. Yet, the remaining estimates confirm the benchmark results. Table B.3 shows the results of the regressions with control variables. All the specifications give positive and statistically significant results except for the estimations of normal goods, columns (2), (6) and (10). Yet, the benchmark results are robust in the case of bad and conditional bad credit booms, which are the boom episodes that attract

more policy interest.

Third, I check the sensitivity of my results to alternative methodologies: logit with random effects and population average. In the benchmark specifications, I use country fixed-effects because it is appropriate to capture persistent country specific factors and is common in this literature³⁰. As a robustness check, I use alternative fixed effects assumptions. Table B.4 collects the estimates, which indicate that the benchmark results are robust to these alternative choices in most of the cases, although the point estimates and statistical power become smaller.

Last, I change the boom thresholds from 1.65 standard deviations of the cyclical component (benchmark) to 1 and 1.96 standard deviations to account for the different magnitude of the surge in credit. The results do not change significantly under the 1.96 standard deviation threshold but they become less significant because of the smaller number of credit booms that result from the more stringent threshold definition. Under the 1 standard deviation threshold, the number of booms increases to 156 credit booms (64 bad and 92 good booms). As in the benchmark, the results show that banking flows significantly increase the probability of all types of booms (see appendix Table B.5). The main difference with respect to the benchmark resides in the coefficients of the two types of flows. Under the 1 threshold, the estimates of bank to bank flows (B-B) are very similar to those of bank to non-bank (B-NB) while, in the benchmark case, the B-B estimates are the only ones statistically significant (see appendix Table B.6). This may be due to the larger number of booms, which increases the level of significance of the bank to non-bank (B-NB) coefficients and, therefore, reduces the difference between B-B and B-NB that was found in the benchmark regressions. However, when other controls are introduced into the estimation, B-B estimates are larger than B-NB estimates and the only ones statistically significant, as in the benchmark (see columns (9) to (11) of table B.6).

³⁰A logit with country fixed effect estimates the effect of changes in the regressor with respect to each country mean on the probability of boom events. If fixed effects were not included, the model would be estimating the effect of the level of each regressor rather than the change from each country's mean.

2.5 Discussion

The results indicate that international banking flows increase the probability of credit booms in the recipient country in the case of high and middle income countries. This result applies to all types of credit booms: normal booms and bad booms (i.e., the booms that result in financial crises). Distinguishing the type of banking flow by borrowing sector (banking and non-banking sector), I find that bank to bank flows (B-B) significantly increase the probability of credit booms while bank to non-bank flows (B-NB) do not.

One of the reasons for B-B flows, rather than B-NB flows, to increase the probability of credit booms may be that bank claims on the real sector (B-NB) tend to be more market driven than the claims on the banking sector. Bank to non-bank flows seem to respond more to a real demand for funds, while flows to the banking sector may be due to any other reason rather than real demand, such as carry-trade or other speculative motives.

One potential criticism of these results derives from the way credit booms are identified. Credit booms are defined as episodes in which credit from domestic banks to the private sector is substantially above its long-run trend. Unfortunately, the measure does not include foreign credit to the private sector for lack of available data. Thus, one could think that banking flows to the banking sector are the only ones that could possibly trigger a credit boom because flows to the non-banking sector are excluded from the boom measure -i.e., there seems to be a tautology. However, the banking literature has shown in other contexts that bank to bank lending tends to be more destabilizing than other types of lending. My results indicate that, in the international context as well, bank to bank lending may give rise to financial instability. Also, descriptive statistics show that there is a high and significant correlation between B-B and B-NB positions (Table A.5) which means that, if international banks are lending large quantities to the banking sector of a foreign country, they are also placing large amounts of funds in its non-banking sector.

Then, I address the tautology concern by estimating whether banking flows increase the probability of financial crises. Table B.7 (left panel) shows that international banking flows increase the probability of financial crises in all countries except for low income countries. This result aligns with my findings. Next, I test whether B-B flows are special contributors to financial crises. Since B-B and B-NB are highly correlated, there should not be a difference between the contribution of B-B and B-NB to financial crises. However, distinguishing by type of banking flow (B-B and B-NB), I find that bank to bank flows (B-B) have a positive

and statistically significant coefficient (column (5) of Table B.7), while B-NB flows do not, which indicates that B-B flows are special -especially in high income countries³¹.

In line with the tests on the probability of credit booms, I check whether international banking flows increase the probability of crises that are credit boom-related (i.e., the ones that occur around credit booms) and crises that are not credit boom-related. Interestingly, I find that banking flows do not affect the crises that are not related with a surge in credit but do significantly increase the probability of crises that are credit related in high and middle income countries (Table B.8). These results also serve as a motivation of this paper which started with the premise that there could be a relation between international banking flows, credit booms and financial crises.

In conclusion, there must be something special about international banking flows and, in particular, about bank to bank flows (B-B) that generates financial instability in high income countries. These bank to bank flows are either associated with credit booms, increase the probability of financial crises, or both. In the next section, I further expand the analysis and examine the drivers of the composition of banking flows.

3 Determinants of the Composition of Banking Flows

The previous section concluded that banking flows to the banking sector increase the probability of booms, while banking flows to the non-banking sector do not. Then, the next step is to analyze the drivers of the composition of banking flows by borrowing sector, which is what I do in this section.

Simple descriptive analysis shows that the composition of banking flows by borrowing sector varies across income levels. High income countries receive a larger share of international banking funds being placed in their banking sector than in their non-banking sector but, as the level of income declines, this relation inverts. Figure 13 illustrates that higher income countries receive a larger share of banking funds into their non-banking sector while

³¹In middle income countries, there is no difference between B-B and B-NB. There is no point in analyzing lower income countries by type of flows because the total flows are not significant in this case.

lower income countries receive more funds in their non-banking sector³².

This fact combined with the finding of the previous section yields what may seem a counterintuitive result: high income countries' banking sector receive more international banking funds than their non-banking sector, which makes them more prone to credit booms. However, this result may have several explanations, some of which already exist in the literature. I am contributing to this literature by providing a new hypothesis based on an asymmetric information problem.

3.1 Hypothesis

I argue that the composition of international banking flows by type of borrower is based on the information asymmetries that exist in financial markets. When one party in a financial transaction has more information than the other party, adverse selection and moral hazard problems that motivate the intermediation of banks in the financial transactions may arise (Akerlof, 1970; Stiglitz, 1983; Hellmann et al., 2000). Relationship banking and banks' monitoring of the borrowers, two activities inherent to banks, reduce these adverse selection and moral hazard problems. In the international context, asymmetries of information may even be more salient. As a result, the monitoring effort of international banks will play a crucial role in reducing the asymmetric information problem in international financial transactions.

International bank lenders will likely exert less monitoring effort on the borrowers that are less likely to fail because they entail less counterparty risk. Then, since monitoring is costly, international bank lenders will place more funds on the "safer" sector. In the context of this analysis which differentiates the type of borrower, banks and non-banks, if one borrowing sector is considered to be less likely to fail because, for example, it is beneficiary of implicit or explicit government guarantees or subject to more stringent screening by local regulators, international lenders will place more funds on that sector.

My hypothesis is that countries with mechanisms in place to make the banking sector

³²This pattern holds throughout all the sample period. I split the sample into 5 year periods and the pattern of high income countries receiving a more B-B than B-NB funds and lower income countries receiving more B-NB than B-B funds remains.

safer - such as better regulations, government guarantees, and fiscal capacity of the government to execute those guarantees- will receive a larger share of international bank flows into their banking sector. Next, I provide theoretical support for this hypothesis and test it empirically.

3.2 Theoretical Framework

A representative domestic bank has to decide the amount to invest in three types of assets: domestic loans (L), foreign loans to the banking sector (L_B^*), and foreign loans to the non-banking sector (L_{NB}^*).

The bank raises deposits domestically and whatever is not invested in loans is invested in a riskless asset. The bank balance sheet is as follows:

Balance Sheet of a Representative Bank

ASSETS	LIABILITIES
L^* , Domestic Loans	D , Domestic Deposits
L_B^* , Foreign Loans (B)	B_B^* , Interbank Borrowing
L_{NB}^* , Foreign Loans (NB)	W , Endowment
R , Riskless Asset	

The model assumes that the market for assets is competitive, which implies that the bank takes the returns of these investments as given. The returns are stochastic because they depend on the state of the economy.

Then, the stochastic profit of the bank is:

$$\tilde{\Pi} = \tilde{r}_L L + (\tilde{r}_{LB}^* - c_B) L_B^* + (\tilde{r}_{LNB}^* - c_{NB}) L_{NB}^* + r_F R - r_D D - r_{BB}^* B_B^* \quad (2)$$

where \tilde{r}_L , \tilde{r}_{LB}^* , \tilde{r}_{LNB}^* , are the stochastic returns on the bank portfolio; and r_D , r_F , and r_{BB} are the deterministic deposit rate, risk-free return, and interbank borrowing rate. L , L_B , and L_{NB} are the amount lent domestically, to the foreign banking sector, and to the foreign non-banking sector, respectively. R is the riskless asset; D are the deposits, and B_{*B} is

the international interbank borrowing. The costs of monitoring the foreign banking and non-banking sector are c_B and c_{NB} , respectively.

The bank's objective function follows the standard finance model of risk aversion; i.e., the mean-variance type developed by Sharpe (1964), Lintner(1965) and Markowitz(1952)³³:

$$U = E(\tilde{\Pi}) - \frac{1}{2}\gamma\sigma^2(\tilde{\Pi}) \quad (3)$$

where $\gamma > 0$ is the degree of risk aversion and σ^2 is the portfolio variance.

After solving for the optimal amount of lending (see Appendix C), the comparative statics with respect to the monitoring costs reveal that:

$$\frac{\partial L^{OPT}}{\partial c} = \frac{1}{-\gamma(1 - 2\rho^*)\sigma^2} < 0 \quad (4)$$

where ρ is the vector of expected returns. This result means that it is optimal for the banks to place more funds in the sector that requires less monitoring.

3.3 Empirical Test

I take the hypothesis to the data and test whether the monitoring effort exerted by international banks determines the composition of the international bank lending positions. This analysis considers the total positions outstanding (stocks rather than flows) because the theoretical model provides the results in terms of the total amount of funds being lent.

I use the following OLS model to estimate the composition of bank positions:

$$\log \left[\left(\frac{\text{B-B}}{\text{B-NB}} \right)_{it} \right] = \mathbf{X}'_{it}\beta + \varepsilon_{it} \quad (5)$$

³³Sharpe, Lintner and Markowitz developed a model of optimal portfolio selection, the capital asset pricing model (CAPM), which assumes that investors' preference depends only on the first two moments of the random liquidation value of the portfolio; that is, the mean and variance. This assumption implies that investors have quadratic Von Neumann-Morgenstern preferences.

where the dependent variable is the natural logarithm of the ratio of international bank positions vis-à-vis the banking sector, B-B, over the international bank positions vis-à-vis the non-banking sector, B-NB. If there are more funds placed in the banking sector than in the non-banking sector; i.e., if $B-B > B-NB$, the left hand side of equation (5) will be positive. If $B-B < B-NB$, the left hand side of the equation will be negative. Thus, a positive coefficient, β , means that the explanatory variable increases the share of B-B over B-NB, while a negative β means that the explanatory variable increases the share of B-NB. \mathbf{X}_{it} is the vector of explanatory variables, all of which are lagged one period to address reverse causality issues, and ε_{ij} is the error term³⁴.

The explanatory variable should capture the monitoring exerted on each borrowing sector but there is no available data measuring the monitoring effort. Then, I assume that the extent of monitoring depends on the “safety” of the borrowing sector and assume that the sector that is less likely to fail will be monitored less. Factors that make the banking sector “safer” include proper regulations and rule of law, government guarantees, and fiscal capacity to execute those guarantees. The variables accounting for those factors are: institutional quality and government debt to GDP, which are defined as follows:

- **Institutional quality (IQ)** is an index that comprises the average of four IQ variables that may affect the composition of international bank claims (Frankel et al., 2013). These IQ variables are: (1) investment profile, that assesses investment risk not covered by other risks (political, economic and financial) and includes contract expropriation, profits repatriation and payment delays; (2) Law and order, that assesses the impartiality of the legal system and the quality of the rule of law; (3) Corruption, that assesses the corruption within the political systems; and (4) Bureaucratic quality, that assess the strength and expertise of the government. The IQ index ranges between 0 (lowest IQ) to 100 (highest IQ). Similar measures of IQ have been used to study international banking flows (Papaioannou, 2009) but this IQ index is the one more closely related to this analysis³⁵. The evolution of IQ over time across income levels is shown in the data appendix, Fig. 14. Data from the International Country Risk Guide dataset (ICRG), from the PRS group.

³⁴I do not control for country fixed effects because it would absorb the variation in some of the slow moving explanatory variables.

³⁵There are alternative IQ measures but the correlations among them are high (results available upon request), which means that using alternative IQs should not provide different results.

- **Government debt to GDP** captures the fiscal capacity of the government to bail-out banks if needed. The willingness of the government to do that is represented by the implicit and explicit guarantees, which are more related to regulations and the enforcement of those regulations; i.e., related to IQ. But the guarantees will only be credible if the country has the fiscal capacity of the government to execute these guarantees and bail-out the banks if needed. I capture this capacity with the government debt over GDP variable. Data from the IMF World Economic Outlook (WEO).

I control for other factors that could also affect the composition of international banking flows, as suggested by the literature (Papaioannou, 2009; Alfaro et al., 2008). These controls are: GDP per capita, country risk (S&P sovereign rating), and financial openness (Chinn-Ito index). Data from the IFS database and Bloomberg.

Alternative explanations

There are alternative explanations for why international banks may place more funds in the banking sector than in their non-banking sector. One explanation is based on the size of the banking sector, which is defined as banking assets over GDP. Figure 15 shows the evolution of banking sector size across income levels and illustrates the positive relation between the two. High income countries tend to have larger banking systems relative to the size of their economies. As a result, high income countries will receive a larger share of B-B than other countries with smaller banking systems³⁶. To control for this potential explanation, I introduce the size of the banking sector as a control in eq. (5).

Another explanation has to do with the fact that high international bank connectivity tends to be associated with high banking leverage, defined as bank credit over bank deposits. High income countries have more leveraged banking systems than emerging economies and several studies have shown that highly leveraged banking systems tend to rely more on wholesale funding, part of which comes from other banking institutions Bruno and Shin (2013); Hale and Obstfeld (2014). Thus, to account for the possibility that countries with more leveraged banks attract a larger share of interbank flows, I introduce bank leverage as a control variable in eq. (5).

Inter-office transactions

³⁶I would like to thank Nina Boyarchenko for this suggestion.

International transactions between banks can be motivated by the transmission of funds across affiliates belonging to the same banking group; i.e., subsidiaries and branches. Countries that are more active in the international expansion of their banks may have more interbank transactions due to the inter-office positions. However, I cannot eliminate those internal market transactions from my analysis because the BIS data used is based on a residence principle and do not disaggregate the inter-office positions. However, I can estimate the share of these transactions in the total interbank positions using less granular data provided by the BIS statistics, which is based on the nationality of ownership of the reporting bank. The data start in 1985 (BIS Table 8). I find that the inter-office transactions have increased over time, which aligns with the increased internationalization of domestic banking systems. In 1985, the inter-office transactions were 33 percent of all the interbank (B-B) transactions and reached 55 percent in 2012. On average, the inter-office transactions represented 44 percent of all B-B positions.

Despite the share of inter-office transactions in total B-B positions is substantial, my hypothesis is still valid because inter-office transactions are subject to a similar asymmetric information problem that the one that drives the composition of international bank funds among non-related parties. Transactions in the internal market do not occur in a frictionless way for two reasons. First, the moral hazard problem derived from the separation of ownership from control generates a principal-agent problem that affects banks within the same group. Rogue trading is the manifestation of this problem and there are several cases in recent history of individual rogue traders generating big losses to the parent institution, which motivates the need for monitoring banks' own foreign affiliates³⁷. Second, inter-office transactions depend on the specific business model of the bank (Cetorelli and Goldberg, 2012c). In some cases, the subsidiaries do not have much independence from the parent institution while, in other cases, they function more independently (e.g., the Spanish banks in Latin America). In the latter cases, internal market transactions follow very similar *modus operandi* as non-internal market transactions. Therefore, the fact that part of the B-B transactions are inter-office transactions does not mean that the monitoring argument is less valid.

³⁷Nick Leeson caused the collapse of the British investment bank, Barings Bank, in 1995 due to his fraudulent trading from the bank's Singapore office; Toshihide Iguchi was the trader of the Japanese Daiwa Bank responsible for causing 1.1 billion USD in trading losses from the NY office; and the "London Whale" made JP Morgan lose more than 2 billion USD in unauthorized CDS positions are examples of rogue trading.

3.3.1 Regression results

The results confirm the hypothesis that countries with better institutional quality (IQ) and more fiscal capacity receive more bank to bank funds (B-B) than bank to non-bank funds (B-NB). Column (1) of Table 6 presents the result of the specification without control variables. The coefficients for institutional quality (IQ) and government debt to GDP are statistically significant at 1 percent level and with the expected sign. IQ has a positive coefficient of 0.021 which means that a 10 point increase in the IQ index will increase the ratio of B-B (bank to bank) over B-NB (bank to non-bank) positions by 21 percent. The coefficient on government debt to GDP is negative, which means that an improvement in the fiscal capacity of the country increases the relative importance of B-B over B-NB. Columns (2) and (3) control for the other two alternative explanations: size of the banking sector and bank leverage. Column (2) shows that the size of the banking sector has a positive coefficient, which means that economies with larger banking systems will receive a larger share of B-B funds. Specification (3) adds bank leverage as another explanatory variable. The coefficient of leverage is also positive and statistically significant. In both cases, the coefficients of IQ and government debt are still significant. Thus, even controlling for the other two potential explanations of the composition of banking funds, my hypothesis still holds true.

Columns (4)-(5) of Table 6 introduce control variables that can also affect the ratio of B-B over B-NB. First, I introduce GDP per capita. When GDP per capita is the only explanatory variable of the ratio of B-B over B-NB, its coefficient is positive and highly statistically significant, which means that a higher GDP per capita leads to a larger share of B-B over B-NB funds³⁸. When I introduce GDP per capita as control variable, the coefficient of GDP per capita remains positive (0.057) but non-statistically significant - see column (4). This means that the other drivers of the composition of banking flows -i.e., IQ, government debt, and bank size and leverage- have already explained most of the share of B-B to B-NB. In column (5), I also control for country risk, which is measured by the existing Standard and Poors sovereign rating³⁹. The coefficient for country risk is not different from zero but the

³⁸A specification with log of B/NB on the left hand side and GDP per capita on the right hand side yields a coefficient of 0.32 which is significant at 1 percent level. Results available upon request.

³⁹The Standard and Poors sovereign ratings are the rating that a particular country has at the end of year. These ratings are converted from letters (AAA, BB+, etc.) into numbers by giving the number 1 to the best rating and adding a one to the next lower grade rating. The worst rating corresponds to number 55. Data from Bloomberg.

important point is that, even controlling for country risk, the estimates of IQ and government debt remain statistically significant and as large as without controls.

Last, I control for the level financial openness of the country. The selection of this variable is motivated by the limited literature on the composition of global banking. Kerl and Niepmann (2014) argues that barriers of entry will lead banks to serve the foreign market through interbank lending rather than opening subsidiaries or lending to the real sector directly. This means that closer countries will receive more bank to bank (B-B) funds. However, I find that lower income economies, which tend to be financially closer, receive a larger share of B-NB flows. To solve this puzzle, I argue that there is a minimum level of openness for the story of Kerl and Niepmann (2014) to hold true because global banks would not even be able to serve a market through interbank transactions if the country is closed. To show this, I split the sample into two open-level groups: open and closer economies. I do it using the Chinn-Ito index and following Goldberg (2009)'s binary classification of openness⁴⁰. Column (1) of Table 7 shows the results for the “open” group, column (1). The sign of the financial openness coefficient in open countries is negative, which aligns with the above cited paper. However, in closer economies, the coefficient for openness is positive, which means that as countries remove their financial barriers, the share of B-B increases -see column (2). The coefficient of openness is not significant but the coefficients of the main explanatory variables confirm the key result that better institutional quality and fiscal space receive more bank to bank funds.

Robustness checks

I test whether the benchmark result about the drivers of the composition of banking funds are robust to different income levels and alternative methodologies.

Table B.11 shows the benchmark results in column (1): countries with better institutional quality and fiscal capacity receive a larger share of bank to bank (B-B) funds. Columns (2) and (3) split the sample by income groups: OECD and non-OECD⁴¹. The co-

⁴⁰Goldberg (2009) generates binary variables of openness by defining “open” countries as those with a Chinn-Ito *kaopen* index greater than 0.15 (which is around 35 percent of my sample); “midopen” countries are those with a *kaopen* index between -1.15 and 1.2; and “closed” economies those with a *kaopen* index below -1.15.

⁴¹The results splitting the sample in three groups -high, middle, and lower income countries- are very similar but the standard errors are larger due to the loss of statistical power when using smaller samples.

efficients of the main explanatory variables remain significant and with the same sign as in the benchmark specification.

I use country fixed effects instead of the random effects applied in the benchmark model. Columns (4)-(6) are equivalent to (1)-(3) but using country fixed effects. Again, the benchmark results are robust to the specification with country fixed effects. The only difference is that the estimates under the country fixed effects specification are smaller and lose significance level compared to the benchmark specification, except for the government debt coefficient.

4 Conclusion

This paper examines whether international banking flows affect the probability of credit booms. The question is important because, first, banking globalization has increased dramatically over the last 20 years but its impact is unclear; second, international lending tends to be intermediated by financial institutions with increasing levels of complexity and size, which poses new challenges on policy-makers; and, third, credit booms are under the close scrutiny of financial regulators for having being associated with financial crises which have more negative effects than non-credit related financial crises.

The paper is mainly empirical and is organized in two parts. In the first part, I examine whether international bank flows increase the probability of credit booms. For the purpose of this analysis, I follow the literature and define credit booms as episodes in which private credit to GDP is substantially above its country-specific historical trend. I differentiate between normal credit booms -those that have a soft landing- from “bad” credit booms - those that result in financial crises (banking, currency or debt crises). International banking flows are defined as changes in cross-border bank claims from banks located in a particular country vis-à-vis the rest of the world and compiled on the basis of the residence of the bank, as in the Balance of Payment statistics. Banking data are from the BIS Locational Banking Statistics which contain the flows of funds channeled through the banking system at country level after aggregating banks’ individual positions. These positions include loans and

Results available upon request.

deposits, debt securities and other positions. All positions are broken down by borrowing sector: banking sector and non-banking sector.

The sample consists of 87 countries that, after removing the off-shore centers and outliers, results in 80 countries and annual data from 1980 to 2012. There are a total of 94 credit booms in the sample, 39 of which end in financial crises. Using a logit model and differentiating by type of borrower, I find that international bank flows to the banking sector increase the probability of credit booms in the recipient country while flows to the non-banking sector do not. These results apply to high and middle income countries and are robust to controlling for other capital flows, macroeconomic fundamentals and global factors.

The second part of the paper analyzes the composition of banking positions across borrowing sectors: banks and non-banks. High income countries receive more banking funds into the banking sector which, combined with the previous result, indicates that high income countries are more prone to credit booms. I argue that this counterintuitive finding may be explained by the monitoring effort exerted by the international bank lenders on each type of borrowing sector. Using a partial equilibrium CAPM, I find that, since monitoring is costly, it is optimal for international banks to place more funds in the borrowing sector that requires less monitoring. I argue that countries with mechanisms in place to make the banking sector “safer” -such as better regulations, implicit and explicit government guarantees or fiscal space to bail-out their banks if needed- will be perceived as less likely to fail and, as a result, will attract more funds from international bank lenders. I test this hypothesis empirically and the results indicate that countries with better institutional quality and more fiscal capacity attract a larger share of cross-border banking positions into their banking sector.

Two policy implications derive from these findings. First, policy-makers should place more attention on interbank transactions across borders. Second, mechanisms that contribute to make the banking sector safer may also attract destabilizing flows from abroad because these mechanisms may distort the incentives of international lenders to monitor their borrowers. Thus, international bank lenders may overlend to the banking sector of foreign countries. I do not suggest the removal of mechanisms that make the banking sector safer but alert policy-makers about the need to design and target these mechanisms properly to reduce the distortions they may generate.

Last, this study provides direction for future work on this subject. On the theoretical

side, it would be interesting to enrich the model by endogeneizing the amount of monitoring based on the guarantees received by the borrowing banking sector and introducing risk variation. On the empirical side, it would be informative for policy-makers to analyze the impact of bank-specific capital controls and examine whether they are effective reducing the likelihood of credit booms and, especially, bad credit booms.

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Table 1: Financial Crises: credit-related and non-credit related

	Crises (with boom)		Crisis (no boom)		Total	
	n.	%	n.	%	n.	%
High income	17	47	19	53	36	30
Middle income	14	32	30	68	44	37
Lower income	8	20	32	80	40	33
Total	39	33	81	68	120	100

A financial crisis (banking, currency or debt crisis) is credit-related if the crisis occurs during the boom episode or within two years after the end of it. Duplication of crises has been removed by computing one crisis per boom even if there were more than one type of financial crisis in the same year or in consecutive years during the boom period -or within two years after the end of it. Sample of 80 countries from 1980-2012.

Table 2: Credit Booms: bad and good (normal) (1980-2011)

Countries		Bad booms		Good booms		Total	
n.		n.	%	n.	%	n.	%
26	High income	17	0.47	19	0.53	36	0.38
23	Middle income	14	0.54	12	0.46	26	0.28
31	Lower income	8	0.25	24	0.75	32	0.34
80		39	0.41	55	0.59	94	1

A credit boom is defined as an episode in which private credit to GDP is above 1.65 standard deviations the cyclical component of the series. A “bad” boom is defined as a credit boom that results in any type of financial crisis -banking, currency or debt crisis- at the end of the boom or within two years after the end of it. A normal or good credit boom is the boom that has a soft landing. Sample of 80 countries from 1980 to 2011. Year 2012 has been removed because it is not possible to know the length or type of ongoing credit boom with the data.

Table 3: Impact of Total International Banking Flows on Credit Booms

	ALL COUNTRIES				HIGH INCOME				MIDDLE INCOME				LOWER INCOME			
	(1) Any	(2) Good	(3) Bad	(4) Bad(con.)	(5) Any	(6) Good	(7) Bad	(8) Bad(con.)	(9) Any	(10) Good	(11) Bad	(12) Bad(con.)	(13) Any	(14) Good	(15) Bad	(16) Bad(con.)
Banking flows(-1)	0.07*** (0.02)	0.07** (0.03)	0.07* (0.04)	0.07* (0.04)	0.05*** (0.02)	0.05 (0.03)	0.05*** (0.02)	0.05*** (0.02)	0.15** (0.06)	0.08 (0.08)	0.39** (0.18)	0.84** (0.35)	0.19** (0.08)	0.18* (0.10)	0.21 (0.14)	0.24 (0.16)
Banking flows (-2)	0.14*** (0.03)	0.10** (0.04)	0.16*** (0.04)	0.17*** (0.05)	0.15*** (0.03)	0.11** (0.05)	0.15*** (0.04)	0.15*** (0.05)	0.21*** (0.07)	0.13 (0.10)	0.19 (0.12)	0.47* (0.26)	-0.05 (0.09)	0.02 (0.11)	-0.20 (0.14)	-0.15 (0.15)
Sum of lags	0.22*** (0.04)	0.17*** (0.05)	0.23*** (0.05)	0.24*** (0.06)	0.20*** (0.04)	0.16*** (0.06)	0.20*** (0.06)	0.20** (0.06)	0.36*** (0.09)	0.20 (0.14)	0.58*** (0.16)	1.31*** (0.45)	0.14 (0.11)	0.21 (0.13)	0.01 (0.15)	0.08 (0.15)
<i>N</i>	1794	1110	879	434	624	380	404	224	498	248	284	140	672	482	191	70
pseudo <i>R</i> ²	0.08	0.04	0.13	0.16	0.14	0.09	0.17	0.18	0.13	0.03	0.27	0.50	0.03	0.03	0.06	0.08
<i>AIC</i>	495.5	308.4	204.8	150.6	175.8	97.8	94.0	75.3	130.8	74.0	59.1	31.5	187.4	142.6	47.3	33.3
<i>BIC</i>	506.5	318.4	214.4	158.7	184.7	105.7	102.0	82.1	139.2	81.0	66.4	37.4	196.4	151.0	53.8	37.8

Logit. Country fixed effects. Standard errors in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Dependent variable: probability of a credit boom event. There is one type of boom event per specification: (1) estimates the probability of all credit booms; (2) estimates the probability of good booms; (3) estimates the probability of bad booms; and (4) conditional bad booms, which are the booms that result in a crisis conditional on the existence of a credit boom. The coefficient of interest is total international banking inflows. The explanatory variables enter with two lags. The results shown in the table are the coefficients of the sum of those two lags (i.e., the linear combination of both lags). No control variables. Estimations for the whole country sample and across income levels.

Table 4: Impact of Banking Inflows on Credit Booms: with control variables

	CONTROLS (Other Capital flows)				CONTROLS (Macro factors)				CONTROLS (Global factors)				CONTROLS (All factors)			
	(1) Any	(2) Good	(3) Bad	(4) Bad(con.)	(5) Any	(6) Good	(7) Bad	(8) Bad(con.)	(9) Any	(10) Good	(11) Bad	(12) Bad(con.)	(13) Any	(14) Good	(15) Bad	(16) Bad(con.)
B. flows (-1)	0.05** (0.02)	0.05 (0.04)	0.06** (0.03)	0.08** (0.04)	0.06 (0.04)	0.09 (0.06)	0.04 (0.03)	0.06 (0.04)	0.07** (0.03)	0.09* (0.05)	0.06** (0.03)	0.09* (0.05)	0.08* (0.04)	0.21** (0.09)	0.02 (0.03)	0.03 (0.04)
B. flows (-2)	0.17*** (0.04)	0.13** (0.05)	0.18*** (0.05)	0.19*** (0.06)	0.21*** (0.06)	0.24*** (0.09)	0.17** (0.07)	0.20** (0.08)	0.16*** (0.04)	0.14** (0.06)	0.16*** (0.05)	0.16** (0.07)	0.19*** (0.06)	0.27** (0.13)	0.16** (0.07)	0.15* (0.09)
Sum of lags	0.22*** (0.05)	0.19*** (0.07)	0.23*** (0.06)	0.27*** (0.08)	0.27*** (0.07)	0.33*** (0.10)	0.21*** (0.08)	0.25** (0.10)	0.23*** (0.05)	0.23*** (0.08)	0.22** (0.07)	0.25*** (0.08)	0.27*** (0.07)	0.48*** (0.17)	0.18** (0.08)	0.18* (0.11)
CONTROLS	Other Capital Inflows				Other Capital Inflows Δ real GDP Δ Real exchange rate Δ Bank Leverage				Other Capital Inflows Global liquidity Global risk				Other Capital Inflows Δ real GDP Δ Real exchange rate Δ Bank Leverage Global Liquidity Global Risk			
<i>N</i>	843	493	536	304	589	385	378	224	706	388	444	269	489	295	308	193
pseudo <i>R</i> ²	0.14	0.11	0.21	0.27	0.19	0.24	0.25	0.31	0.17	0.24	0.24	0.37	0.21	0.43	0.32	0.45
<i>AIC</i>	256.3	143.6	133.1	103.2	203.5	115.9	112.1	90.8	238.1	123.1	130.1	94.9	191.3	93.6	107.0	81.8
<i>BIC</i>	294.2	177.2	167.4	132.9	264.8	171.3	167.1	138.5	292.8	170.7	179.2	138.1	266.8	160.0	174.1	140.5

Logit. Country fixed effects. Standard errors in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Dependent variable is the probability of a credit boom event. Sample countries: high and middle income countries. Each specification estimates the probability of a different type of boom: (1) all credit booms; (2) good booms; (3) bad booms; and (4) conditional bad booms, which are the booms that result in a crisis conditional on the existence of a credit boom. The coefficient of interest is total international banking inflows. The explanatory variable enters with two lags. The results shown in the table are the coefficient of the sum of those two lags (i.e., the linear combination of both lags). The control variables include three types: (i) international capital flows other than banking flows: non-bank debt flows, portfolio equity, and foreign direct investment (FDI); (ii) macroeconomic variables: GDP, real exchange rate, and bank leverage; (iii) global variables: global liquidity and risk.

Table 5: Impact of Banking Inflows on Credit Booms: by type of borrowing sector

	NO CONTROLS				CONTROLS (Other capital flows)				CONTROLS (Macro factors)				CONTROLS (Global factors)			
	(1) Any	(2) Good	(3) Bad	(4) Bad(con.)	(5) Any	(6) Good	(7) Bad	(8) Bad(con.)	(9) Any	(10) Good	(11) Bad	(12) Bad(con.)	(13) Any	(14) Good	(15) Bad	(16) Bad(con.)
Bank to Bank flows(-1)	0.08*** (0.02)	0.07 (0.04)	0.06** (0.03)	0.07** (0.03)	0.08** (0.04)	0.13** (0.07)	0.06** (0.03)	0.10** (0.04)	0.09* (0.05)	0.15 (0.09)	0.04 (0.03)	0.07 (0.04)	0.11** (0.05)	0.33** (0.14)	0.02 (0.04)	0.04 (0.05)
Bank to Bank flows(-2)	0.23*** (0.04)	0.16** (0.07)	0.21*** (0.05)	0.24*** (0.07)	0.23*** (0.05)	0.12* (0.07)	0.22*** (0.07)	0.26*** (0.09)	0.29*** (0.08)	0.20* (0.12)	0.24*** (0.09)	0.30** (0.12)	0.27*** (0.08)	0.26 (0.17)	0.21** (0.09)	0.23* (0.13)
Bank to NonBank flows(-1)	0.06 (0.06)	0.02 (0.08)	0.16 (0.10)	0.17 (0.11)	-0.03 (0.09)	-0.17 (0.13)	0.12 (0.13)	0.07 (0.14)	-0.05 (0.11)	-0.22 (0.19)	0.15 (0.14)	0.12 (0.16)	-0.01 (0.11)	-0.32 (0.27)	0.18 (0.15)	0.10 (0.17)
Bank to NonBank flows(-2)	0.04 (0.07)	0.04 (0.08)	0.02 (0.12)	0.05 (0.12)	0.04 (0.08)	0.15 (0.12)	-0.02 (0.13)	0.03 (0.14)	0.11 (0.11)	0.37** (0.18)	-0.12 (0.17)	-0.05 (0.17)	0.07 (0.12)	0.51* (0.26)	-0.14 (0.18)	-0.05 (0.19)
Sum of lags(B-B)	0.30*** (0.06)	0.23*** (0.08)	0.27*** (0.07)	0.31*** (0.09)	0.31*** (0.07)	0.26*** (0.10)	0.29*** (0.08)	0.36** (0.12)	0.37*** (0.10)	0.35*** (0.13)	0.28*** (0.11)	0.36** (0.15)	0.38*** (0.10)	0.59*** (0.22)	0.23** (0.11)	0.27* (0.16)
Sum of lags(B-NB)	0.10 (0.09)	0.06 (0.12)	0.18 (0.13)	0.22 (0.13)	0.01 (0.11)	-0.02 (0.17)	0.10 (0.15)	0.10 (0.18)	0.05 (0.14)	0.15 (0.23)	0.03 (0.18)	0.07 (0.18)	0.06 (0.14)	0.19 (0.33)	0.04 (0.19)	0.05 (0.20)
CONTROLS					Other Capital Inflows				Other Capital Inflows Δ real GDP Δ Real exchange rate Δ Bank Leverage				Other Capital Inflows Δ real GDP Δ Real exchange Rate Δ Bank Leverage Global Liquidity Global Risk			
<i>N</i>	1122	628	688	364	843	493	536	304	589	385	378	224	489	295	308	193
pseudo <i>R</i> ²	0.14	0.07	0.19	0.23	0.16	0.14	0.23	0.28	0.20	0.27	0.29	0.35	0.22	0.48	0.36	0.47
<i>AIC</i>	304.7	170.7	157.0	117.6	256.0	144.0	134.1	105.4	204.1	116.2	112.1	91.3	192.3	92.5	107.5	84.1
<i>BIC</i>	324.8	188.5	175.1	133.2	303.3	186.1	176.9	142.5	274.2	179.5	175.1	145.9	276.1	166.3	182.1	149.3

Logit. Country fixed effects. Standard errors in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Dependent variable is the probability of a credit boom event. Sample: high and middle income countries. Estimations per type of boom: (1) probability of all credit booms; (2) probability of good booms; (3) probability of bad booms; and (4) probability of bad booms conditional on the existence of a credit boom. The coefficients of interest are: international banking flows to the banking sector (B-B) and to the non-banking sector (B-NB). The explanatory variables enter with two lags. The results shown in the table are the coefficient of the sum of those two lags. The control variables include three types of factors: (i) international capital flows other than banking flows: non-bank debt flows, portfolio equity, and foreign direct investment (FDI); (ii) macroeconomic variables: GDP, nominal exchange rate and banking leverage; (iii) global variables: liquidity and risk.

Table 6: Determinants of the composition of international banking flows

	(1)	(2)	(3)	(4)	(5)
	B-B/B-NB	B-B/B-NB	B-B/B-NB	B-B/B-NB	B-B/B-NB
Institutional Quality (-1)	0.021*** (0.005)	0.017*** (0.005)	0.016*** (0.005)	0.015** (0.006)	0.020*** (0.008)
Government debt to GDP (-1)	-0.005*** (0.001)	-0.005*** (0.001)	-0.004*** (0.001)	-0.004*** (0.001)	-0.006** (0.002)
Size of banking sector (-1)		0.005*** (0.001)	0.004*** (0.001)	0.004*** (0.001)	0.003** (0.001)
Banking leverage (-1)			0.002* (0.001)	0.002** (0.001)	0.002* (0.001)
Log of real GDP pc (-1)				0.057 (0.077)	0.050 (0.142)
Country risk (-1)					-0.000 (0.011)
Constant	-1.294*** (0.392)	-1.357*** (0.373)	-1.526*** (0.396)	-1.900*** (0.542)	-2.032* (1.211)
Observations	1263	1223	1192	1186	902
R^2	0.30	0.40	0.38	0.38	0.42

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

Dependent variable: log of the ratio of bank to bank positions (B-B) over bank to bank to non-bank positions (B-NB) received by a country; i.e., $\log(B-B/B-NB)$. Main independent variables: institutional quality (from the ICRG), government debt to GDP. Other independent variables: size of the banking sector (bank assets over GDP), and bank leverage (bank assets over bank deposits). Controls: GDP per capita and country risk (from sovereign ratings of S&P). All of the explanatory variables are lagged one period to account for potential endogeneity issues.

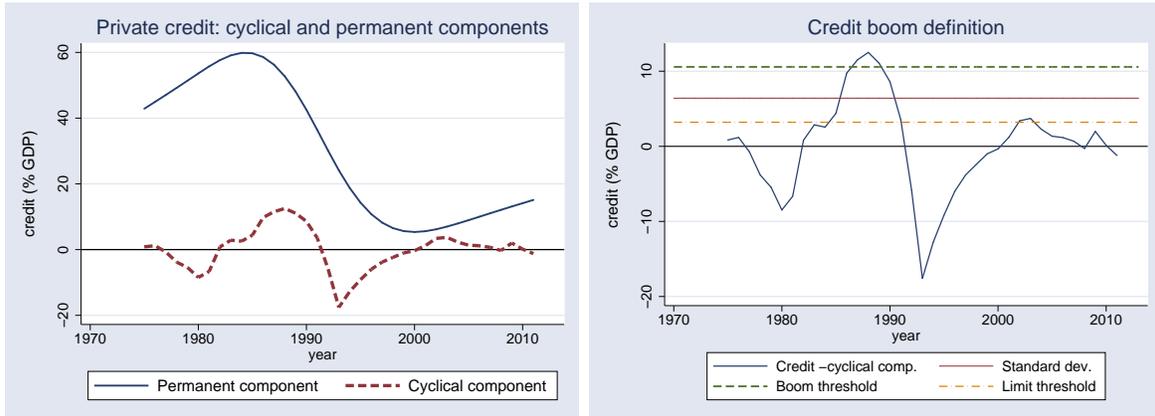
Table 7: Composition of international banking flows: by openness level

	Open	Low-open
	(1)	(2)
	B-B/B-NB	B-B/B-NB
Institutional Quality (-1)	0.017* (0.009)	0.012* (0.007)
Government debt to GDP (-1)	-0.003 (0.002)	-0.003 (0.002)
Size of banking sector (-1)	0.003** (0.001)	0.009*** (0.002)
Banking leverage (-1)	0.002** (0.001)	0.003* (0.002)
Log of real GDP pc (-1)	0.082 (0.132)	0.072 (0.103)
Financial openness (-1)	-0.122 (0.086)	0.049 (0.069)
Constant	-2.007*** (0.655)	-2.229*** (0.805)
Observations	631	493
R^2	0.40	0.32

Random effects. Robust standard errors. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

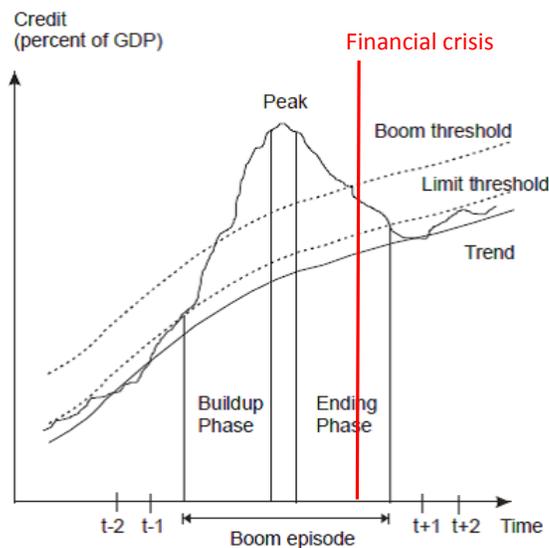
Dependent variable: log of the ratio of bank to bank positions (B-B) over bank to bank to non-bank positions (B-NB) received by a country; i.e., $\log(\text{B-B}/\text{B-NB})$. Column (1) shows the results for the sub-sample of open countries (those with Chinn-Ito index above 0.15), and column (2) shows the results for those that are not in the “open” group. Main independent variables: institutional quality (from the ICRG database), government debt to GDP. Other independent variables: size of the banking sector (bank assets over GDP), and bank leverage (bank assets over bank deposits). Controls: GDP per capita and financial openness (Chinn-Ito index -the larger the index, the more financially open the country is). All of the explanatory variables are lagged one period to account for potential endogeneity issues.

Figure 1: Credit boom definition



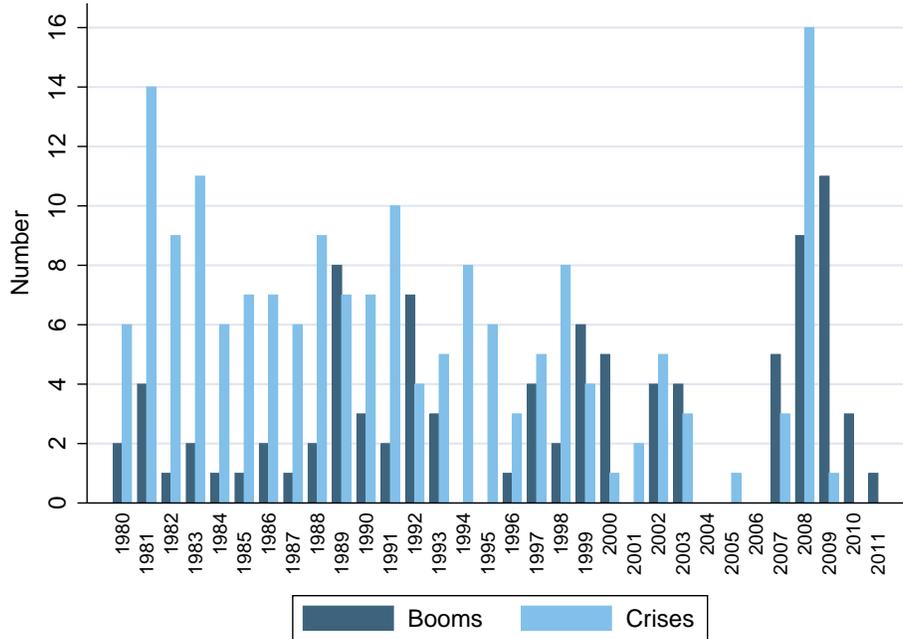
A *credit boom* is an episode in which private credit over GDP is above certain *boom threshold* over a country specific long-run trend. In this paper, the boom threshold is 1.65 standard deviations of the cyclical component. Cyclical and permanent components have been calculated using HP filter with smoothing parameter of $\lambda = 100$. The beginning of the boom is considered the year the private credit series is above a *limit threshold*, which is 0.5 standard deviations of the cyclical component. The end of the boom is the year the private credit series crosses back the limit threshold. The *peak* of the boom is the point where the difference between the private credit series and the long-run trend is the largest. A credit boom that has a financial crisis in the ending phase of the boom or within two years after the end of it is considered to be a *bad boom*. The financial crisis can be a systemic banking crisis, a currency crisis or a debt crisis. Data on private credit to GDP from the World Bank Financial Development and Structure database.

Figure 2: “Bad” credit boom definition



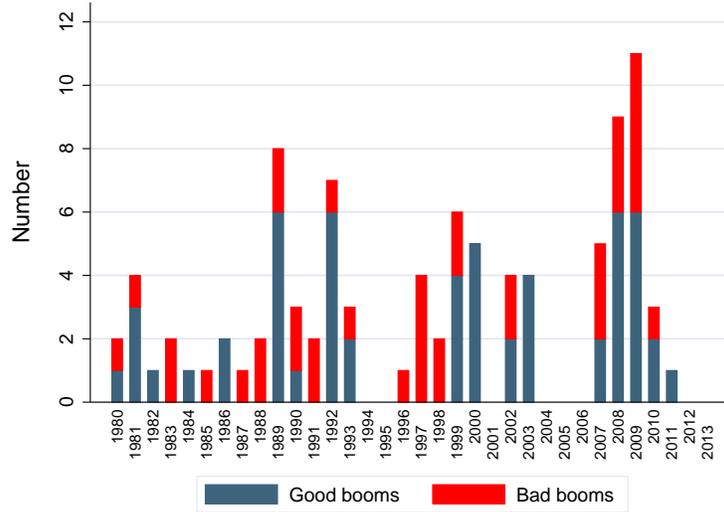
Note: Picture borrowed from Figure 1 of Gourinchas et al., 2001

Figure 3: Credit booms and financial crises



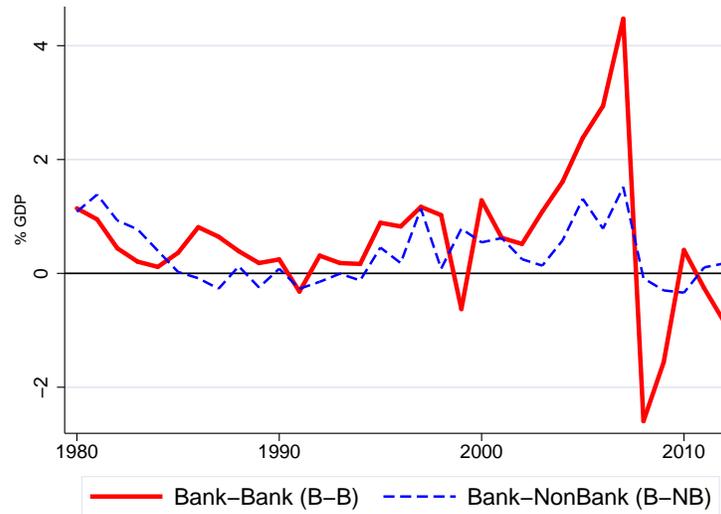
Credit booms, defined in the note of Fig. 1, last an average of 4 years in my sample. To count the number of booms, I select the peak year. The figure shows the number of booms and crises per year. Booms include both good and bad booms. Financial crises can be systemic banking crises, currency crises and debt crises. A systemic banking crisis is defined as an episode in which a country’s financial sector has large number of defaults or a sharp increase in number of defaults and most of the banking system capital is exhausted. Data from Laeven and Valencia (2013). A currency crisis is defined, following Frankel and Rose (1996) as episode in which a country’s nominal depreciation of the exchange rate is at least 30 percent and represents at least a 10 percent increase in the annual rate of depreciation over the previous year. Data from Laeven and Valencia (2013). A debt crisis refers to both external and internal debt crisis and is defined as the episodes in which downgrades to default levels occur for the sovereign local currency debt (domestic) or for the sovereign foreign currency debt (external), as in Reinhart and Rogoff (2009) updated by Broner et al. (2013). Data on credit booms derives from own calculations using private credit to GDP from the WB Financial Development and Structure database (see Section 2.1 for a detailed description of the data).

Figure 4: Credit booms: good and bad



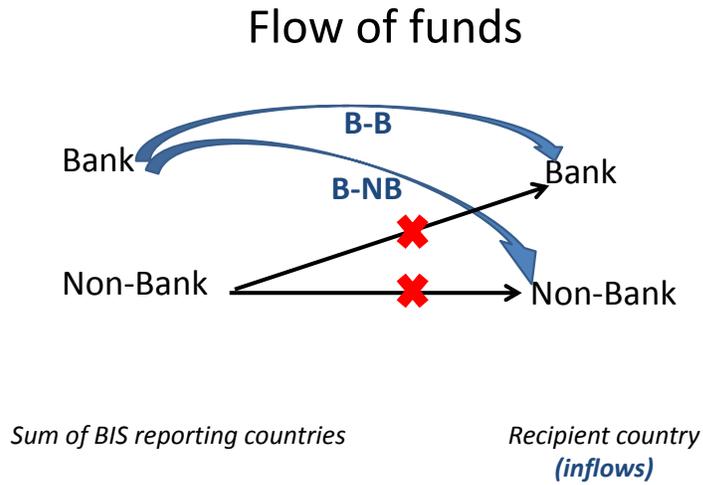
Credit booms are represented by their peak year. Credit booms can result in financial crisis (bad booms) or not (normal or good booms). Then, a “bad” boom is defined as a credit boom and a financial crisis coinciding in the same country i at the same time period t or within two years after the end of the boom.

Figure 5: Evolution of international bank flows



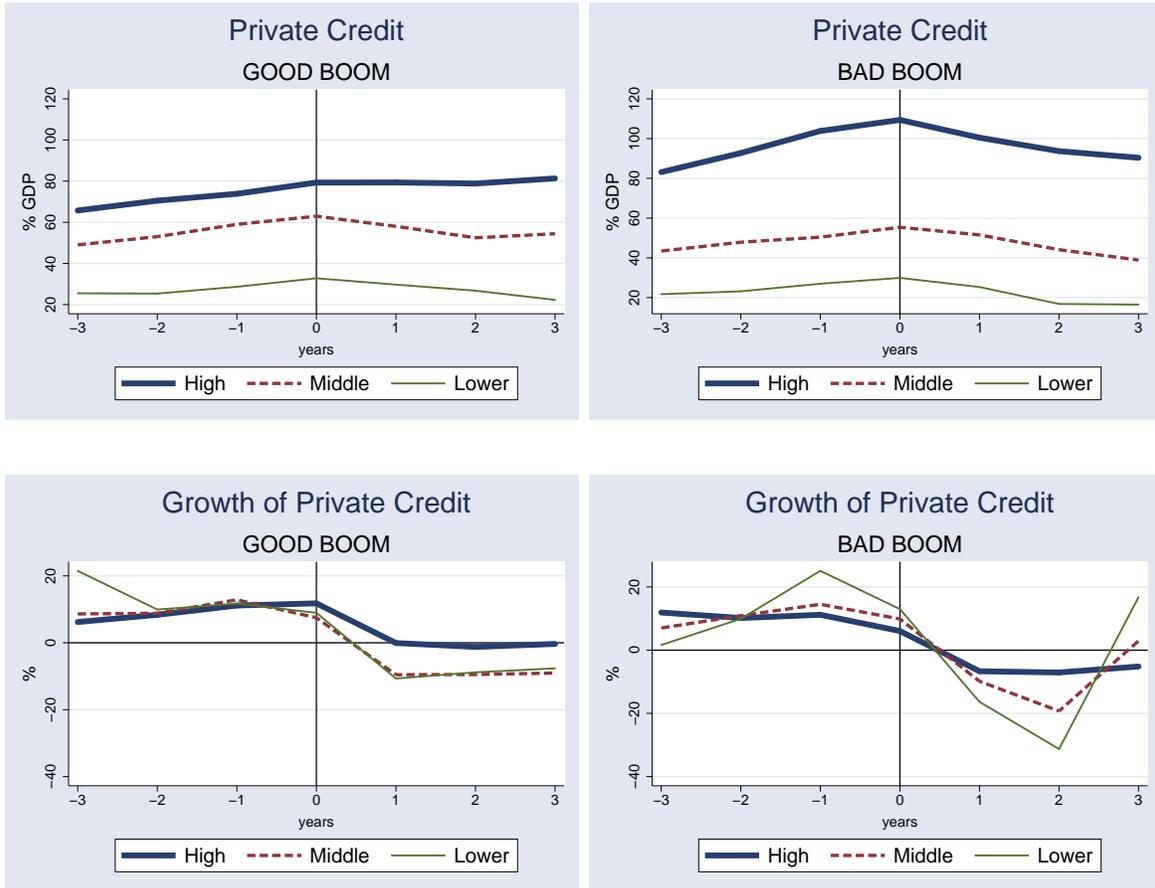
International banking flows are defined as changes in cross-border bank claims from banks located in a particular country vis-à-vis another country. The claims include loans and deposits, holdings and own issues of debt securities, and other assets and liabilities. The flows are broken down by destination sectors: (1) banking flows to the banking sector (B-B) and (2) to the non-banking sector (B-NB). The non-banking sector includes households, non-financial corporations, non-bank financial corporations, and government entities. Data from the BIS Locational Banking Statistics -Table 6.

Figure 6: Description of the International Banking Flows



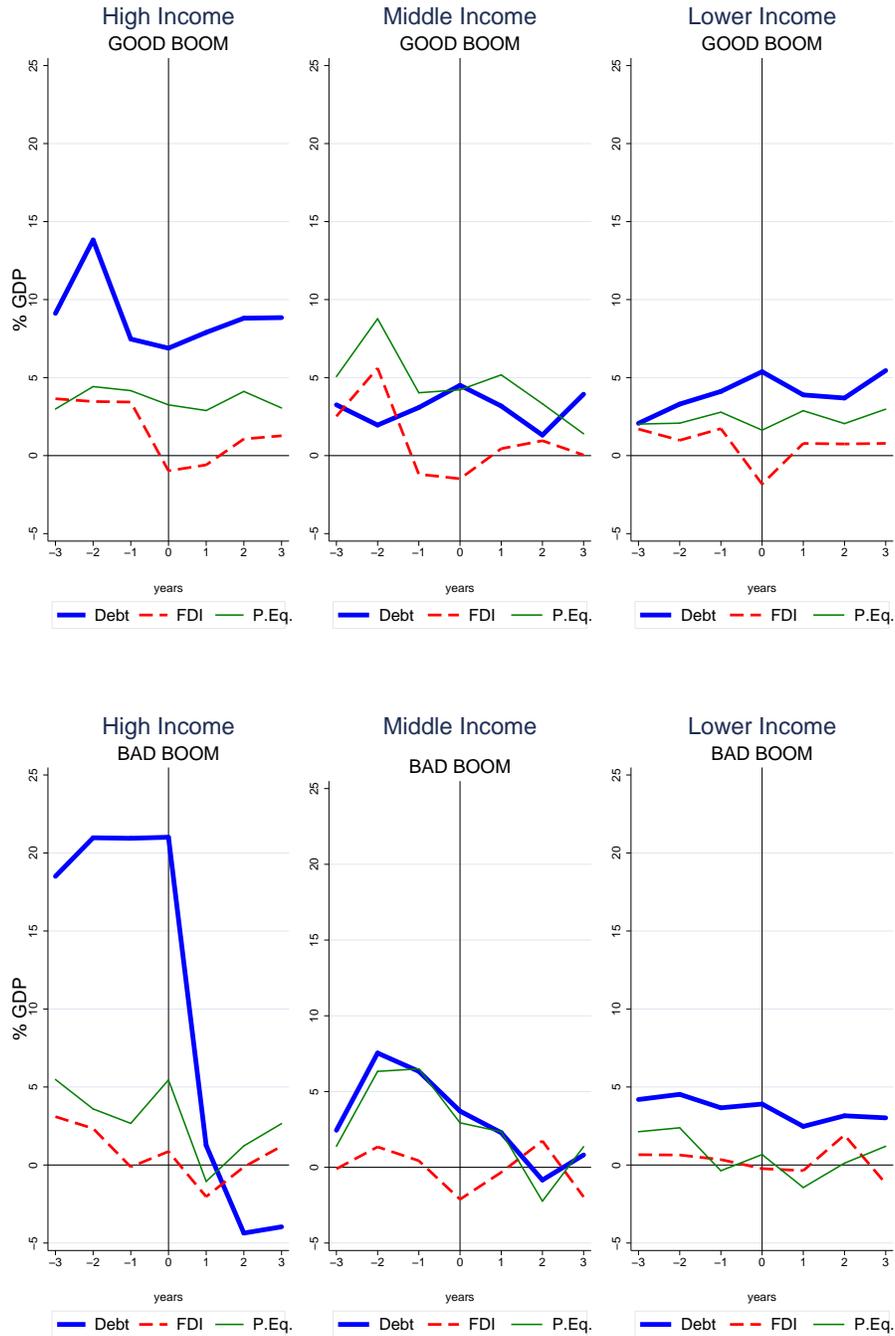
The BIS data captures the flow of funds going from the banking sector in BIS reporting countries vis-à-vis another country. The data are aggregated by the BIS. Thus, the funds received by a particular country (inflows) come only from banks. The banks' claims against the recipient country are aggregated by country and the sum of all those positions is the total gross inflows. The destination of the funds in the recipient country can be the banking sector (B-B) or the non-banking sector (B-NB). However, funds channeled through the non-banking sector are not included in the BIS data. These funds are, therefore, non-bank debt flows.

Figure 7: Evolution of private credit around credit booms



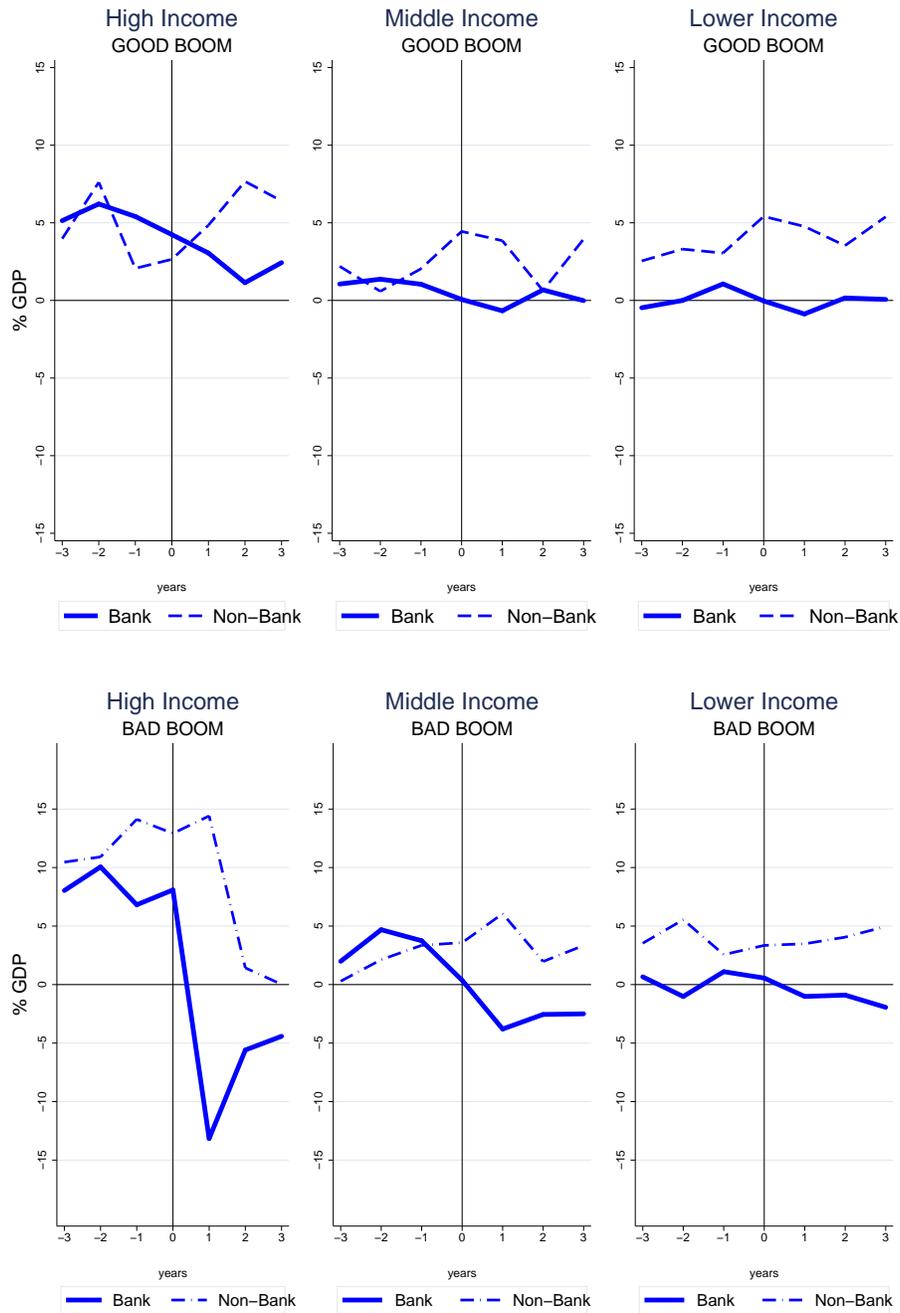
Evolution of private credit to GDP (upper panel) and annual change of GDP (lower panel) around normal booms (left) and bad booms (right). The center of each graph is the year of the peak. The graphs show a window of 3 years before and after the peak of each type of boom. Each line represents the average across income levels: High, middle and lower income countries. Data from the WB Financial Development database.

Figure 8: Evolution of capital flows around credit booms



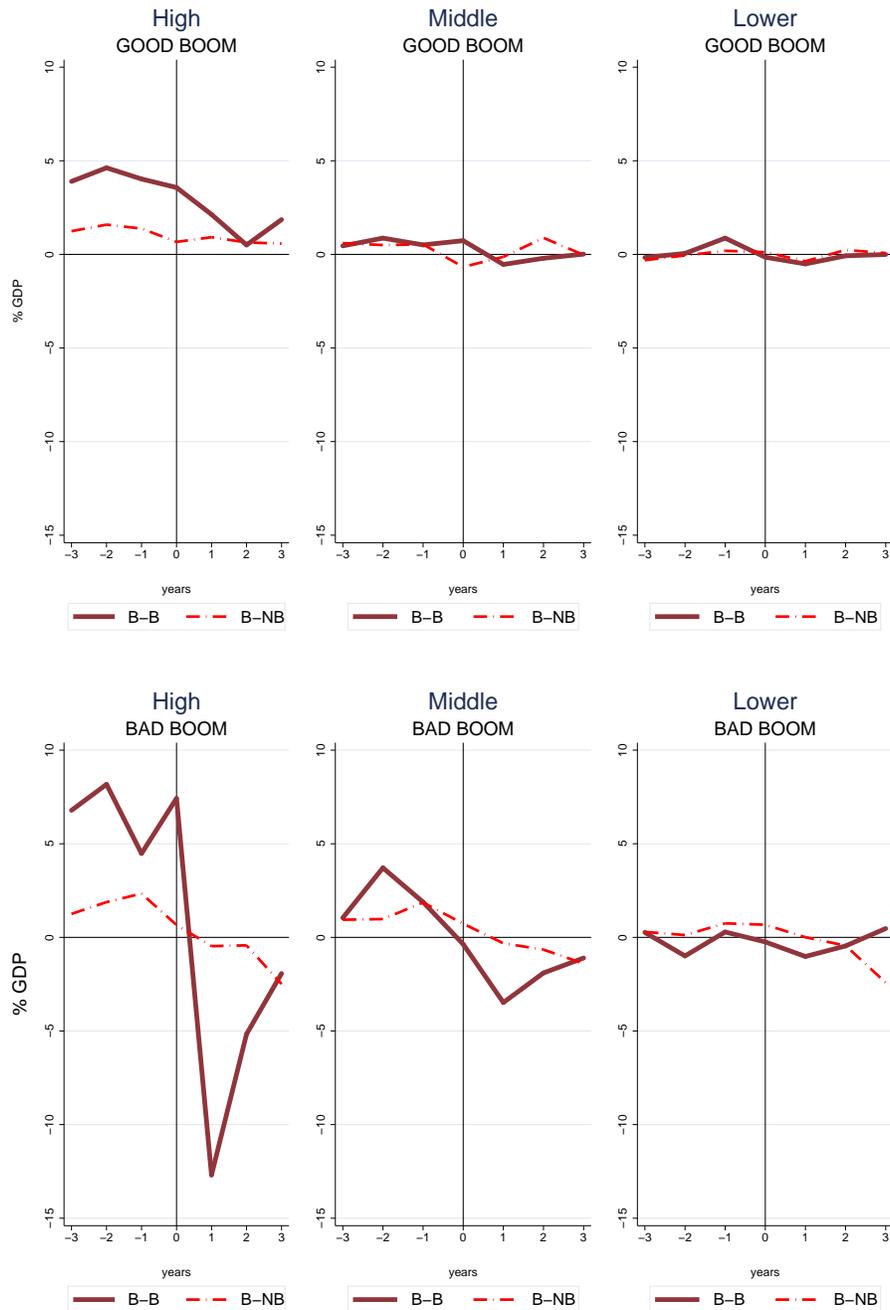
Evolution of international capital flows around good booms (upper panel) and bad booms (lower panel) across income levels: high income (left), middle income (center) and lower income (right). The graphs show a window of 3 years before and after the peak of each type of boom (year=0). The charts show capital flows going from the rest of the world to the recipient country (gross inflows) for the three types of flows: debt flows, foreign direct investment (FDI) and portfolio equity. Data from the Wealth of Nations database of Lane and Milesi-Ferretti (2007). The flows are expressed as a percentage of GDP.

Figure 9: Evolution of debt flows around credit booms: bank and non-bank debt



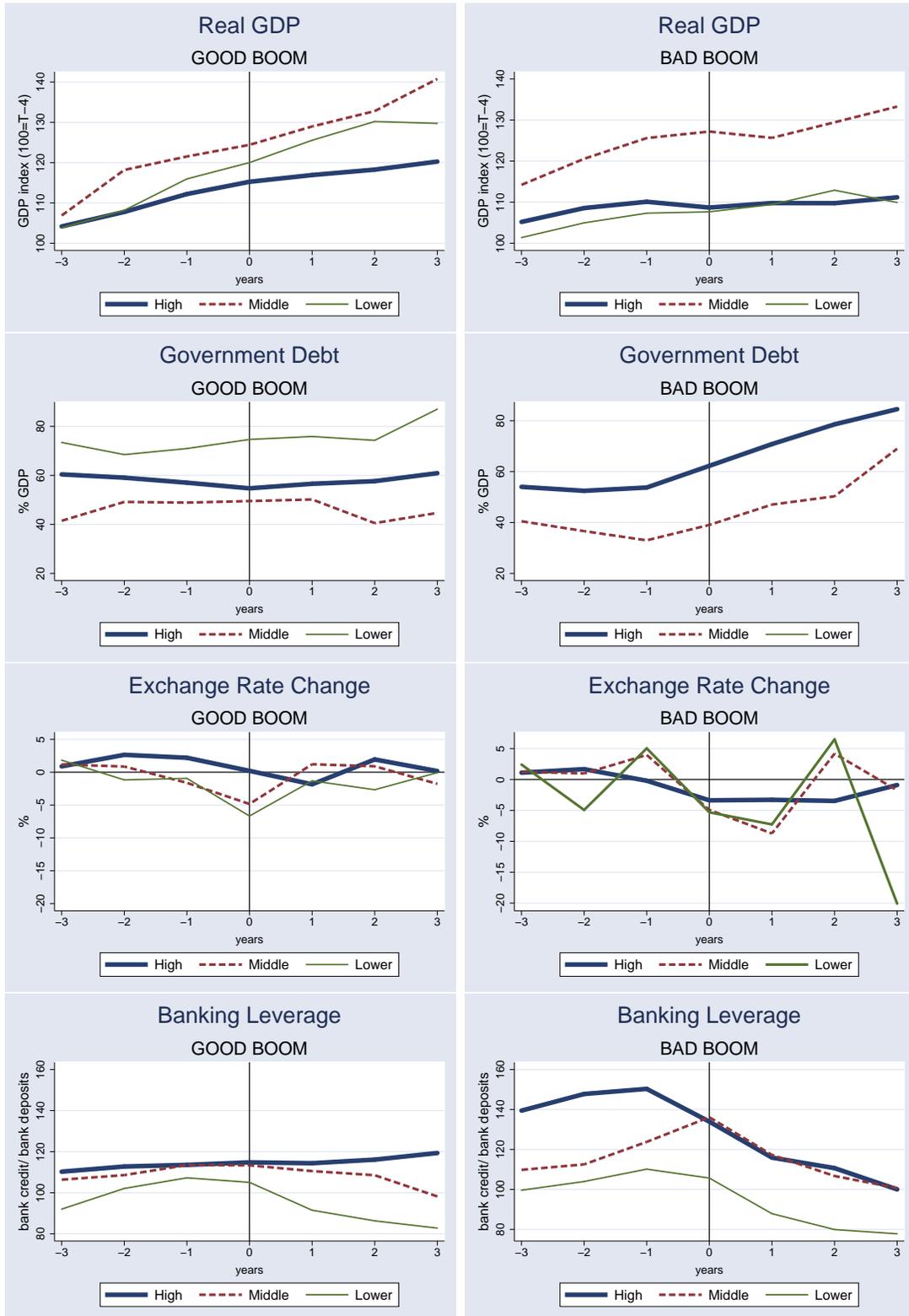
Evolution of debt flows around good booms (upper panel) and bad booms (lower panel) across income levels: high income (left), middle income (center) and lower income (right). The graphs show a window of 3 years before and after the peak of each type of boom (year=0). Debt flows are broken down by counterparty: bank and non-bank. Data on banking flows from the BIS Locational Banking Statistics. Non-banking debt inflows are calculated subtracting banking debt flows from total debt inflows, using data on total debt inflows from The Wealth of Nations database. The flows are expressed as a percentage of GDP.

Figure 10: Evolution of banking flows by counterparty: banks (B-B) and non-banks (B-NB)



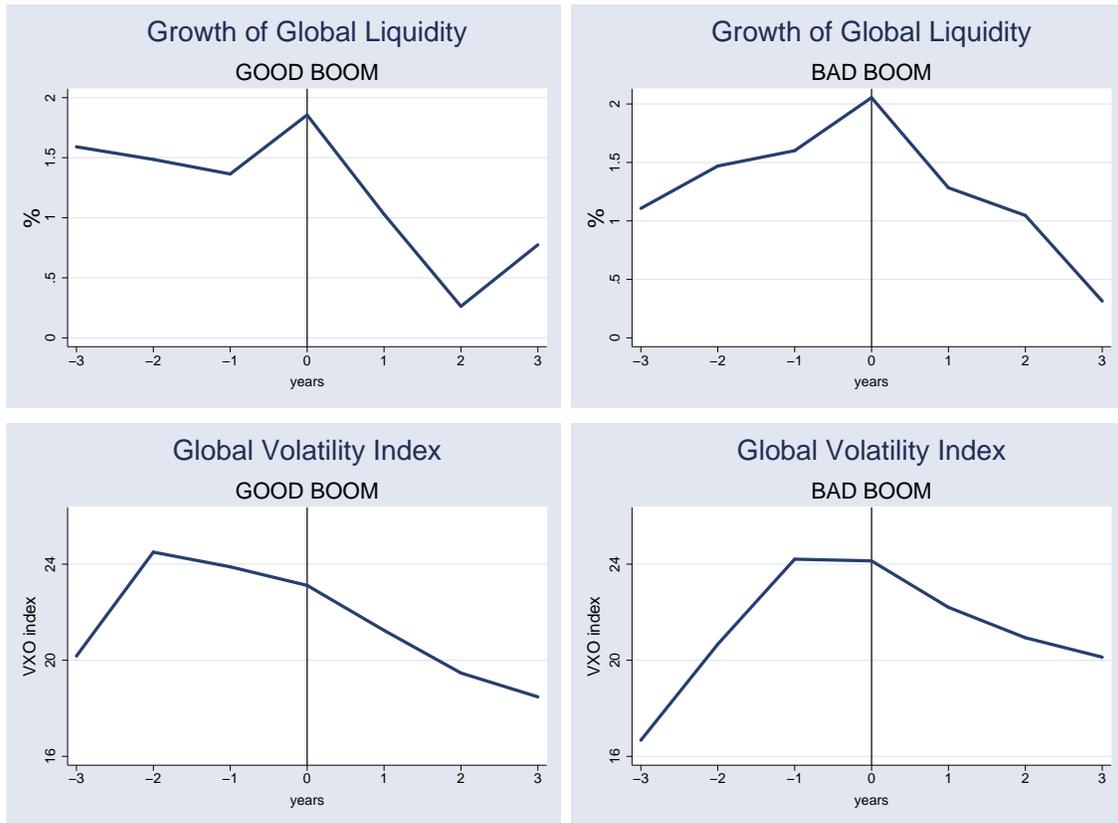
Evolution of international banking flows around good booms (upper panel) and bad booms (lower panel) across income levels: high income (left), middle income (center) and lower income (right). The graphs show a window of 3 years before and after the peak of each type of boom (year=0). The banking flows are broken down by borrowing sector: banking (B-B) and non-banking (B-NB) - includes households, non-bank financial corporations, non-financial corporations and government. The distinction by destination sector is done based on which is the issuer of the debt security. For example, the reporting bank should report purchases of government debt from a bank in another country as a claim on the government issuing that debt instrument, not as a claim on the bank. Source: BIS Locational Banking Statistics.

Figure 11: Evolution of macro factors around credit booms



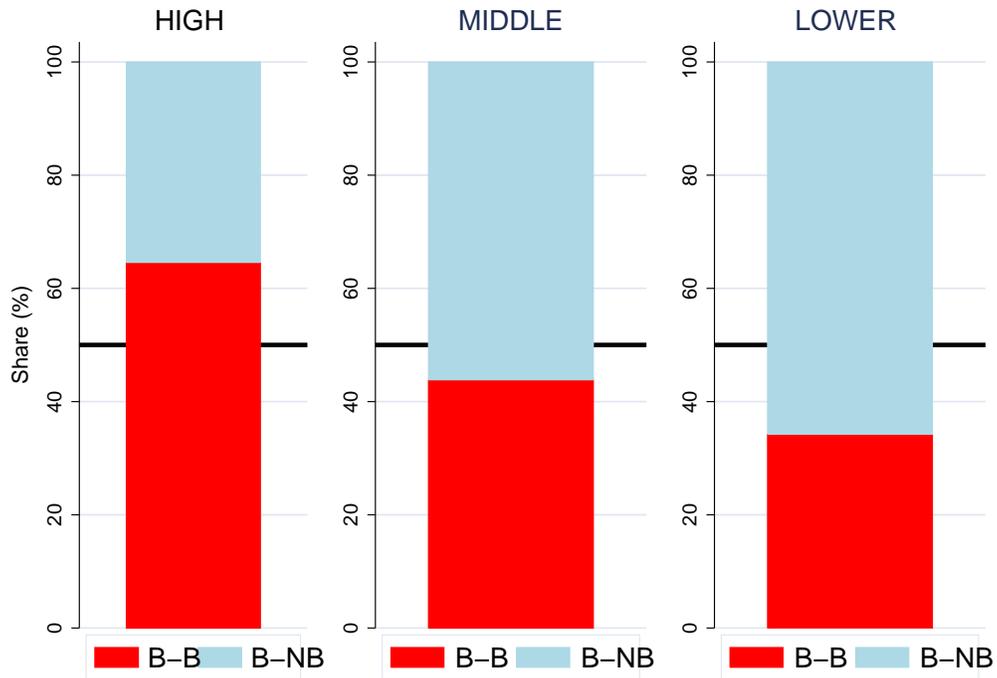
Evolution of macro factors around good booms (left) and bad booms (right) across income levels. The macro variables are: Real GDP (top panel) is indexed to 100 at the beginning of the boom period (ie, 4 years before the peak); government debt to GDP (second panel); real exchange rate (third panel); and bank leverage (lower panel).

Figure 12: Evolution of global variables around credit booms



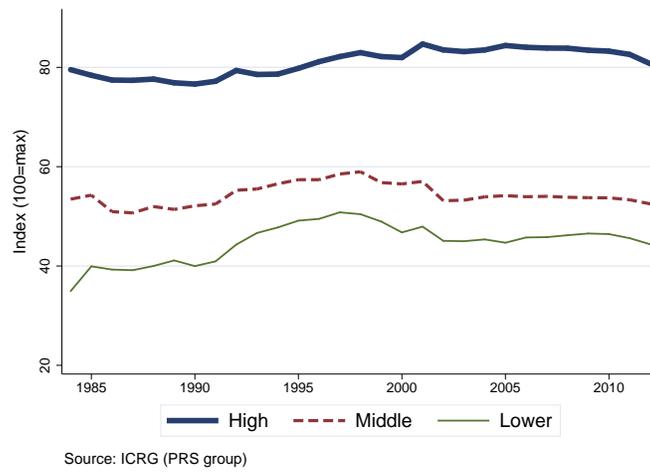
Evolution of global factors around good booms (left) and bad booms (right) across income levels. The global variables are: global liquidity (top panel), which is defined as the sum of M2 in the United States, Eurozone, Japan and United Kingdom, following Forbes and Warnock (2012); and global risk (bottom), which is defined as the volatility index (VXO) from the Chicago Board Options Exchange. M2 data from the IFS.

Figure 13: Composition of international bank positions across income levels



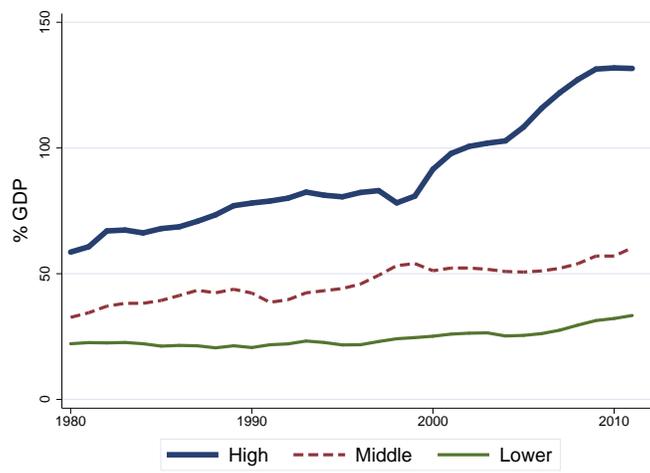
Share of international banking claims by counterparty: bank to bank positions (B-B) and bank to non-bank positions (B-NB), which include households, non-financial corporations, non-bank financial corporations, and government entities. Sample average across income levels: high income (left), middle income (center), and lower income countries (right). The claims include loans and deposits, holdings and own issues of debt securities, and other assets and liabilities. Data from table 6 of the BIS Locational Banking Statistics.

Figure 14: Institutional Quality (IQ) across income levels



Evolution of the institutional quality index (IQ) across income levels over the sample period. The IQ index comprises the average of four IQ variables from the International Country Risk Guide dataset (from PRS group). These variables are: (1) investment profile, that assesses investment risk not covered by other risk (political, economic and financial) and includes contract expropriation, profits repatriation and payment delays; (2) Law and order, that assesses the impartiality of the legal system and the quality of the rule of law; (3) Corruption, that assesses the corruption within the political systems; and (4) Bureaucratic quality, that assess the strength and expertise of the government. See section 3.3 for details.

Figure 15: Size of the banking sector across income levels



Evolution of the size of the banking sector over time across income levels. The size of the banking sector is measured by the ratio of deposit money banks assets to GDP; i.e., claims on domestic real non-financial sector by deposit money banks as a share of GDP. Data from the World Bank Financial Development and Structure database (with raw data from the IMF's IFS).

Appendices

A Data Appendix

Table A.1: Country list by income group

HIGH INCOME	MIDDLE INCOME	LOWER INCOME
Australia	Algeria	Bolivia
Austria	Argentina	Burkina Faso
Belgium	Botswana	Burundi
Canada	Brazil	Cameroon
Denmark	China	Central African Republic
Finland	Colombia	Cote d'Ivoire
France	Costa Rica	Egypt, Arab Rep.
Germany	Dominica	El Salvador
Greece	Dominican Republic	Gambia, The
Iceland	Ecuador	Ghana
Israel	Gabon	Honduras
Italy	Grenada	India
Japan	Hungary	Indonesia
Korea, Rep.	Jamaica	Kenya
Netherlands	Jordan	Madagascar
New Zealand	Malaysia	Malawi
Norway	Mexico	Morocco
Poland	Peru	Nepal
Portugal	South Africa	Niger
Slovenia	Suriname	Nigeria
Spain	Thailand	Pakistan
Sweden	Tunisia	Papua New Guinea
Trinidad and Tobago	Turkey	Paraguay
United Kingdom		Rwanda
United States		Senegal
Uruguay		Sri Lanka
		Sudan
		Swaziland
		Syrian Arab Republic
		Togo
		Uganda

There are 80 countries in the sample, 26 of which are high income, 23 middle income, and 31 lower income countries according to the World Bank classification, which is based on the 2012 GNI per capita. The income groups are: low income, \$1,035 or less; lower middle income, \$1,036 to \$4,085; upper middle income, \$4,086 to \$12,615; and high income, \$12,616 or more. I re-group the countries into three income groups: "High" for high income countries, "Middle" for upper-middle income countries, and "Lower" for lower-middle and low income countries.

Table A.2: Country list of credit booms (1980-2012)

Country	year		Country	year	
Algeria	1988		Jordan	2007	
Argentina	1981	1999	Kenya	1980	
Australia	1989	2008	Korea, Rep.	1998	
Austria	1981		Madagascar	1981	1992
Belgium	1992	2007	Malawi	1992	
Bolivia	1999		Malaysia	1986	1997
Botswana	1993	2009	Mexico	1992	
Burundi	2003		Morocco	2000	2009
Cameroon	1991		Nepal	2010	
Canada	1981		Netherlands	1980	2000
Central African Republic	1984		New Zealand	1989	
China	2003		Nigeria	2009	
Colombia	1998		Norway	1989	2007
Costa Rica	2009		Pakistan	1986	2008
Cote d'Ivoire	1992		Papua New Guinea	1990	2009
Denmark	2009		Paraguay	2011	
Dominican Republic	2002		Peru	1999	
Ecuador	1999		Poland	2008	
Egypt, Arab Rep.	2002		Portugal	2000	2009
El Salvador	1985		Rwanda	1989	
Finland	1991		Senegal	1993	
France	1989	2009	Slovenia	2009	
Gabon	1987		South Africa	2008	
Gambia, The	2003		Spain	2007	
Germany	2000		Sri Lanka	1996	
Ghana	2000		Sudan	1982	
Greece	2008		Suriname	1992	
Grenada	1999	2010	Swaziland	1983	
Honduras	1999	2009	Sweden	1990	
Hungary	1990	2008	Thailand	1997	
Iceland	2007		Togo	1993	
India	2008		Trinidad and Tobago	2009	
Indonesia	1997		Tunisia	2002	
Israel	2003	2008	Turkey	1997	
Italy	1992	2010	United Kingdom	1989	
Jamaica	1989		United States	1988	2008
Japan	1989		Uruguay	1983	2002

Credit booms and “bad” booms are defined in the note of Fig.2. A total of 74 of the 80 countries in the sample have a credit boom at least. There are 94 credit booms, 39 of which are bad booms. Bad credit booms in red and bold.

Table A.3: Variables and sources

<i>Variable</i>	<i>Definition</i>	<i>Original source</i>
Private credit	Credit to the non-financial private sector by deposit money banks as a share of GDP	World Bank's Financial Development and Structure Database (updated Nov. 2013)
Credit boom	Episodes in which private credit exceeds the country's long run trend above a certain boom threshold (see Section 2.1)	Own calculations
Financial crises	Bank, currency, and debt crises (see Section 2.1)	Laeven and Valencia 2013 (banking and currency crises); Reinhart and Rogoff (debt crises -updated by Broner et al., 2013)
Banking flows	changes in cross-border bank claims from banks located in a particular country vis-à-vis another country (section 2.1)	BIS Locational Banking Statistics (table 6)
Capital flows	Difference in international assets and liability positions. They include: portfolio equity, foreign direct investment, and debt positions (portfolio debt and other investment).	The Wealth of Nations (updated 2013) -Lane and Milesi-Ferretti-with data from the IMF International Financial Statistics
Real GDP	Gross domestic product in constant 2005 USD.	World Development Indicators
Government debt	General government gross debt as a percentage of GDP	World Economic Outlook
Real exchange rate	Nominal effective exchange rate (a measure of the value of a currency against a weighted average of several foreign currencies) divided by a price deflator or index of costs.	IFS
Money supply (M2)	Money and quasi money comprise the sum of currency outside banks, demand deposits other than those of the central government, and the time, savings, and foreign currency deposits of resident sectors other than the gov.	IFS
Global liquidity	M2 growth of the main world economies (US, Japan, UK, Germany and France), following Forbes and Warnock (2012).	International Monetary Fund, International Financial Statistics and data files, and World Bank and OECD GDP estimates.
Global risk	VXO volatility index	Chicago Board Options Exchange (CBOT)
Interest rate spread	Interest rate charged by banks on loans to private sector customers minus the interest rate paid by banks for deposits.	IFS
Institutional quality	Average of four IQ variables: investment profile, law and order, corruption, and bureaucratic quality. It ranges between 0 (lowest) and 100 (highest). See section 3.3	International Country Risk Guide dataset (ICRG), from the PRS group.
Banking sector size	Claims on domestic real non-financial sector by deposit money bank assets as a share of GDP.	WB Financial Development and Structure Dataset
Bank leverage	Domestic private credit by deposit money banks as a share of deposits.	WB Financial Development and Structure Dataset (updated Nov. 2013)
Financial openness	"kaopen" is the Chinn-Ito index measuring a country's level of capital account openness.	Chinn-Ito Index
Country risk	Sovereign ratings at the end of the year from S&P. Ratings converted to a scale of 1(lowest risk) to 55 (highest risk)	Bloomberg

Table A.4: Descriptive statistics

Variable	Mean	St Dev	Min.	Max.	N.
High income countries					
Private credit	74.36	35.28	15.79	272.81	847
Bank claims on NB	13.58	11.22	0.56	79.71	835
Bank claims on B	24.75	27.68	0.47	268.45	835
Port. equity	13.09	17.77	0.04	168.45	753
FDI	23.89	26.47	0.25	204.46	815
Debt	83.69	79.18	9.83	901.49	815
Growth of real GDP(%)	2.47	2.92	-10.27	14.43	836
Gov. debt	61.69	35.06	8.6	243.22	670
Inflation-GDP deflator(annual %)	7.94	22.22	-27.63	390.68	862
KA openness(Chinn-Ito)	1.43	1.31	-1.86	2.44	809
M2 over GDP	85.10	49.23	20.11	241.18	693
Int. rate spread	7.02	31.44	-165.06	541.63	615
Real exchange rate	106.9	79	37.51	1123.83	792
Bank leverage	114.05	44.27	47.13	390.74	754
Middle income countries					
Private credit	40.74	32.93	2.51	170.89	711
Bank claims on NB	8.92	7.3	0.08	52.14	704
Bank claims on B	6.96	7.33	0	55.33	704
Port.equity	5.92	8.08	0.01	65.25	469
FDI	26.92	28.04	-1.32	209.55	720
Debt	49.09	30.35	2.29	197.6	733
Growth of real GDP(%)	3.78	4.47	-17.15	19.45	754
Gov. debt	52.02	33.6	0.97	219.73	438
Inflation-GDP deflator(annual %)	52.08	313.28	-26.3	5048.78	748
KA openness(Chinn-Ito)	-0.36	1.32	-1.86	2.44	722
M2 over GDP	53.86	34.02	10.08	187.58	755
Int. rate spread	13.79	102.2	-11	2334.96	567
Real exchange rate	117.72	49.92	51.24	448.52	462
Bank leverage	102.14	56.26	15.95	429.36	723
Lower income countries					
Private credit	18.42	12.26	1.21	74.52	983
Bank claims on NB	5.9	5.77	0	39.33	1010
Bank claims on B	3.07	3.4	0	21.91	1010
Port. equity	1.94	3.27	0	27.55	422
FDI	16.62	14.87	0.08	92.06	983
Debt	66.36	40.14	5.06	240.09	988
Growth of real GDP(%)	3.67	4.82	-50.25	35.22	1015
Gov. debt	64.96	44.66	9.55	454.86	498
Inflation-GDP deflator(annual %)	25.57	384.4	-9.82	12338.66	1045
KA openness(Chinn-Ito)	-0.59	1.15	-1.86	2.44	983
M2 over GDP	33.17	18.78	6.55	113.9	1014
Int. rate spread	8.67	7.13	-6.91	103.4	698
Real exchange rate	159.04	215.1	58.15	3579.12	495
Bank leverage	87.44	39.27	15.12	343.93	981

Table A.5: Cross-correlations of main variables

Variables	Credit	B-B claims	B-NB claims	Port.eq.	FDI	Debt	GDP	Gov.debt	Lever.	REER	Glob.liq.	Glob.risk
Private credit	1											
B-B claims	0.601***	1										
B-NB claims	0.351***	0.690***	1									
Port. equity	0.380***	0.385***	0.427***	1								
FDI	0.141***	0.440***	0.383***	0.216***	1							
Debt	0.406***	0.791***	0.701***	0.268***	0.433***	1						
GDP	0.175***	0.023	-0.017	0.109***	-0.155***	-0.032	1					
Gov. debt	0.024	0.146***	0.177***	0.005	-0.022	0.266***	0.225***	1				
Bank leverage	0.534***	0.291***	0.147***	0.154***	0.029	0.126***	-0.020	-0.358***	1			
Real exchange rate	0.007	-0.150***	-0.221***	-0.082**	-0.080**	-0.233***	0.037	-0.031	0.080**	1		
Global liquidity	0.014	0.061*	0.094***	0.079**	0.148***	0.069*	0.007	-0.054	-0.044	0.003	1	
Global risk	-0.007	0.005	0.035	-0.021	0.005	0.006	-0.00655	-0.026	-0.002	0.008	0.310***	1

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.6: Correlations of variables in Section 3

(1)							
	iqPRS	govdebt	dombanka	bcbd	gdppcr	kaopen	cnrisk
iqPRS	1						
govdebt	0.203***	1					
dombanka	0.597***	0.358***	1				
bcbd	0.271***	-0.296***	0.375***	1			
gdppcr	0.861***	0.276***	0.605***	0.260***	1		
kaopen	0.563***	0.294***	0.401***	0.0879***	0.610***	1	
cnrisk	-0.846***	-0.156***	-0.646***	-0.337***	-0.846***	-0.538***	1

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B Robustness Checks

Table B.1: Robustness: Impact of banking flows on credit booms at [peak-1].

	NO CONTROLS				CONTROLS (Other capital flows)				CONTROLS (Macro factors)				CONTROLS (Global factors)			
	(1) Any	(2) Good	(3) Bad	(4) Bad(con.)	(5) Any	(6) Good	(7) Bad	(8) Bad(con.)	(9) Any	(10) Good	(11) Bad	(12) Bad(con.)	(13) Any	(14) Good	(15) Bad	(16) Bad(con.)
Bank to Bank flows(-1)	0.17*** (0.04)	0.10* (0.06)	0.18*** (0.05)	0.22*** (0.08)	0.16*** (0.05)	0.08 (0.07)	0.18*** (0.06)	0.29*** (0.10)	0.20*** (0.07)	0.14 (0.12)	0.13** (0.07)	0.23** (0.11)	0.23*** (0.08)	0.18 (0.15)	0.12 (0.07)	0.25* (0.15)
Bank to Bank flows(-2)	0.15*** (0.05)	0.09 (0.08)	0.14** (0.07)	0.13 (0.08)	0.17*** (0.06)	0.12 (0.08)	0.13* (0.08)	0.10 (0.10)	0.16** (0.07)	0.04 (0.12)	0.17* (0.10)	0.13 (0.13)	0.18** (0.08)	0.01 (0.13)	0.14 (0.10)	0.13 (0.18)
Bank to NonBank flows(-1)	0.02 (0.06)	0.03 (0.08)	0.05 (0.12)	0.07 (0.12)	-0.01 (0.09)	0.06 (0.11)	-0.03 (0.14)	0.03 (0.15)	0.04 (0.12)	0.28 (0.19)	-0.11 (0.16)	-0.03 (0.17)	0.13 (0.13)	0.49* (0.27)	-0.08 (0.17)	0.06 (0.19)
Bank to NonBank flows(-2)	0.03 (0.07)	0.04 (0.09)	0.03 (0.12)	0.08 (0.12)	0.01 (0.09)	-0.00 (0.13)	0.03 (0.14)	-0.01 (0.16)	0.03 (0.11)	0.09 (0.18)	0.01 (0.15)	-0.05 (0.18)	-0.06 (0.13)	-0.03 (0.21)	0.07 (0.16)	-0.04 (0.23)
Sum of lags(B-B)	0.32*** (0.06)	0.19** (0.08)	0.32*** (0.07)	0.35*** (0.)	0.33*** (0.07)	0.20** (0.10)	0.31*** (0.08)	0.39*** (0.12)	0.37*** (0.09)	0.19 (0.14)	0.30*** (0.10)	0.36*** (0.13)	0.40*** (0.11)	0.18 (0.17)	0.26** (0.11)	0.39** (0.17)
Sum of lags(B-NB)	0.05 (0.09)	0.07 (0.12)	0.08 (0.14)	0.15 (0.15)	0.00 (0.11)	0.06 (0.15)	0.00 (0.17)	0.02 (0.20)	0.06 (0.14)	0.37 (0.23)	-0.10 (0.20)	-0.08 (0.24)	0.08 (0.16)	0.46 (0.35)	-0.01 (0.22)	0.02 (0.29)
CONTROLS					Other Capital Inflows				Other Capital Inflows Δ real GDP Δ Real exchange rate Δ Bank Leverage				Other Capital Inflows Δ real GDP Δ Real exchange Rate Δ Bank Leverage Δ Global Liquidity Global Risk			
<i>N</i>	1098	614	678	361	823	480	530	301	576	376	374	223	475	286	303	191
pseudo <i>R</i> ²	0.15	0.06	0.20	0.23	0.17	0.11	0.23	0.28	0.21	0.27	0.21	0.27	0.31	0.46	0.26	0.49
<i>AIC</i>	301.9	170.9	154.2	116.7	250.8	146.9	133.3	104.6	200.6	115.0	120.4	98.1	171.0	94.0	113.9	80.7
<i>BIC</i>	321.9	188.6	172.3	132.3	297.9	188.6	176.0	141.7	270.3	177.8	183.2	152.7	254.2	167.1	188.1	145.7

Logit. Country fixed effects. Standard errors in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Dependent variable: probability of a credit boom. Sample: high and middle income countries. The left hand side of the specifications represents the boom event. In this case, the year of the boom is not the peak year but the previous period (i.e., T-1, where T is the peak year). The explanatory variables enter with two lags. The control variables include international capital flows other than banking flows, macro, and global variables.

Table B.2: Robustness: Impact of banking flows on credit booms (1980-2005)

	ALL COUNTRIES				HIGH INCOME				MIDDLE INCOME				LOWER INCOME			
	(1) Any	(2) Good	(3) Bad	(4) Bad(con.)	(5) Any	(6) Good	(7) Bad	(8) Bad(con.)	(9) Any	(10) Good	(11) Bad	(12) Bad(con.)	(13) Any	(14) Good	(15) Bad	(16) Bad(con.)
BENCHMARK (1980-2012)																
Banking flows(sum of 2 lags)	0.22*** (0.04)	0.17*** (0.05)	0.23*** (0.05)	0.24*** (0.06)	0.20*** (0.04)	0.16*** (0.06)	0.20*** (0.06)	0.20** (0.06)	0.36*** (0.09)	0.20 (0.14)	0.58*** (0.16)	1.31*** (0.45)	0.14 (0.11)	0.21 (0.13)	0.01 (0.15)	0.08 (0.15)
<i>N</i>	1794	1110	879	434	624	380	404	224	498	248	284	140	672	482	191	70
pseudo <i>R</i> ²	0.08	0.04	0.13	0.16	0.14	0.09	0.17	0.18	0.13	0.03	0.27	0.50	0.03	0.03	0.06	0.08
WITHOUT LAST FINANCIAL CRISIS (1980-2006)																
Banking flows (sum of 2 lags)	0.20*** (0.05)	0.16** (0.07)	0.26*** (0.08)	0.36*** (0.11)	0.15** (0.07)	0.15** (0.08)	0.17 (0.14)	0.31 (0.19)	0.39*** (0.11)	0.21 (0.20)	0.53*** (0.16)	1.75*** (0.66)	0.08 (0.11)	0.18 (0.15)	-0.03 (0.14)	0.06 (0.14)
<i>N</i>	1144	696	475	262	355	234	123	80	324	128	221	119	465	334	131	63
pseudo <i>R</i> ²	0.05	0.04	0.08	0.14	0.09	0.14	0.05	0.12	0.15	0.03	0.24	0.52	0.02	0.02	0.08	0.09

Logit. Country fixed effects. Standard errors in parenthesis. Sample: 1980-2006. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Dependent variable: probability of a credit boom event. Sample period excludes the last global financial crisis. The top rows show the result for the whole sample and the bottom rows for the sample without the last financial crisis (1980-2006). The results shown in the table are the coefficients of the sum of those two lags of gross bank inflows. There is one type of event per specification: (1) all credit booms; (2) good booms; (3) bad booms; and (4) bad booms conditional on the existence of a credit boom.

Table B.3: Robustness: by type of banking flows (1980-2005)

	NO CONTROLS				CONTROLS (Other Capital flows)				CONTROLS (Macro factors)			
	(1) Any	(2) Good	(3) Bad	(4) Bad(con.)	(5) Any	(6) Good	(7) Bad	(8) Bad(con.)	(9) Any	(10) Good	(11) Bad	(12) Bad(con.)
BENCHMARK (1980-2012)												
Sum of lags(B-B)	0.30*** (0.06)	0.23*** (0.08)	0.27*** (0.07)	0.31*** (0.09)	0.31*** (0.07)	0.26*** (0.10)	0.29*** (0.08)	0.36** (0.12)	0.37*** (0.10)	0.35*** (0.13)	0.28*** (0.11)	0.36** (0.15)
Sum of lags(B-NB)	0.10 (0.09)	0.06 (0.12)	0.18 (0.13)	0.22 (0.13)	0.01 (0.11)	-0.02 (0.17)	0.10 (0.15)	0.10 (0.18)	0.05 (0.14)	0.15 (0.23)	0.03 (0.18)	0.07 (0.18)
<i>N</i>	1122	628	688	364	843	493	536	304	589	385	378	224
pseudo R^2	0.14	0.07	0.19	0.23	0.16	0.14	0.23	0.28	0.20	0.27	0.29	0.35
WITHOUT LAST FINANCIAL CRISIS (1980-2006)												
Sum of lags(B-B)	0.23*** (0.08)	0.17 (0.11)	0.38** (0.15)	0.65*** (0.23)	0.23** (0.10)	0.16 (0.15)	0.55** (0.24)	1.01** (0.39)	0.28** (0.13)	0.24 (0.21)	0.63** (0.30)	1.16* (0.63)
Sum of lags(B-NB)	0.18 (0.13)	0.12 (0.20)	0.25 (0.16)	0.50** (0.22)	-0.02 (0.18)	-0.31 (0.30)	0.19 (0.25)	0.50 (0.40)	-0.03 (0.23)	-0.29 (0.48)	0.12 (0.30)	0.54 (0.47)
<i>N</i>	679	362	344	199	505	297	234	155	341	234	133	95
pseudo R^2	0.11	0.09	0.15	0.27	0.14	0.23	0.21	0.38	0.15	0.41	0.25	0.38
CONTROLS					Other Capital Inflows				Other Capital Inflows Δ Real GDP Δ Real exchange Rate Δ Bank Leverage			

Logit. Country fixed effects. Standard errors in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Dependent variable: probability of a credit boom. Sample period excludes the last global financial crisis. The top rows show the result for the whole sample and the bottom rows for the sample without the last financial crisis (1980-2006). The coefficients of interest are: international banking flows to the banking sector (B-B) and to the non-banking sector (B-NB). The results shown in the table is the coefficient of the sum of those two lags. The control variables include three types: (i) international capital flows other than banking flows; and (ii) macroeconomic variables.

Table B.4: Impact of banking flows on credit booms: by methodology

	NO CONTROLS				CONTROLS (Other capital flows)				CONTROLS (Macro factors)				CONTROLS (Global factors)			
	(1) Any	(2) Good	(3) Bad	(4) Bad(con.)	(5) Any	(6) Good	(7) Bad	(8) Bad(con.)	(9) Any	(10) Good	(11) Bad	(12) Bad(con.)	(13) Any	(14) Good	(15) Bad	(16) Bad(con.)
BENCHMARK (WITH FIXED EFFECTS)																
Sum of lags(B-B)	0.30*** (0.06)	0.23*** (0.08)	0.27*** (0.07)	0.31*** (0.09)	0.31*** (0.07)	0.26*** (0.10)	0.29*** (0.08)	0.36** (0.12)	0.37*** (0.10)	0.35*** (0.13)	0.28*** (0.11)	0.36** (0.15)	0.38*** (0.10)	0.59*** (0.22)	0.23** (0.11)	0.27* (0.16)
Sum of lags(B-NB)	0.10 (0.09)	0.06 (0.12)	0.18 (0.13)	0.22 (0.13)	0.01 (0.11)	-0.02 (0.17)	0.10 (0.15)	0.10 (0.18)	0.05 (0.14)	0.15 (0.23)	0.03 (0.18)	0.07 (0.18)	0.06 (0.14)	0.19 (0.33)	0.04 (0.19)	0.05 (0.20)
WITH RANDOM EFFECTS																
Sum of lags(B-B)	0.16*** (0.03)	0.04 (0.03)	0.16*** (0.04)	0.15*** (0.05)	0.15*** (0.04)	0.06 (0.04)	0.15*** (0.05)	0.19*** (0.06)	0.17*** (0.06)	0.05 (0.05)	0.12** (0.07)	0.1* (0.07)	0.17*** (0.06)	0.07 (0.06)	0.12 (0.07)	0.11 (0.07)
Sum of lags(B-NB)	0.04 (0.06)	0.03 (0.09)	0.09 (0.09)	0.11 (0.10)	0.01 (0.09)	-0.01 (0.12)	0.05 (0.12)	0.04 (0.12)	-0.03 (0.09)	-0.02 (0.13)	0.01 (0.12)	0.00 (0.12)	-0.03 (0.09)	0.00 (0.14)	-0.00 (0.12)	0.02 (0.13)
WITH POPULATION AVERAGE																
Sum of lags(B-B)	0.13*** (0.04)	0.04 (0.02)	0.16*** (0.05)	0.15 (0.05)	0.13 (0.05)	0.06 (0.04)	0.14** (0.06)	0.18** (0.06)	0.09* (0.05)	0.05 (0.03)	0.12** (0.06)	0.13** (0.06)	0.15* (0.06)	0.07 (0.05)	0.12** (0.06)	0.11** (0.05)
Sum of lags(B-NB)	0.03 (0.06)	0.02 (0.07)	0.09 (0.08)	0.11 (0.12)	-0.01 (0.09)	-0.01 (0.06)	0.05 (0.12)	0.04 (0.13)	-0.03 (0.08)	-0.03 (0.08)	0.01 (0.12)	0.00 (0.12)	-0.08 (0.11)	-0.00 (0.09)	0.00 (0.12)	0.01 (0.13)
CONTROLS					Other Capital Inflows				Other Capital Inflows Δ real GDP Δ Exchange Rate Δ Banking Leverage				Other Capital Inflows Δ real GDP Δ Exchange Rate Δ Banking Leverage Δ Global Liquidity Global Risk			
<i>N</i>	1141	1291	1272	617	881	1005	990	521	803	911	900	479	673	774	759	414

Logit with fixed effects, random effects and population average. Standard errors in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Dependent variable: probability of a credit boom. Logit model with fixed effects (benchmark), with random effects (middle panel) and with population average (lower panel). The coefficients of interest are: international banking flows to the banking sector (B-B) and to the non-banking sector (B-NB). The results shown in the table is the coefficient of the sum of those two lags. The control variables include (i) international capital flows other than banking flows; and (ii) macroeconomic variables; and (iii) global variables.

Table B.5: Robustness: threshold of 1 standard deviation

	ALL COUNTRIES				HIGH INCOME				MIDDLE INCOME				LOWER INCOME			
	(1) Any	(2) Good	(3) Bad	(4) Bad(con.)	(5) Any	(6) Good	(7) Bad	(8) Bad(con.)	(9) Any	(10) Good	(11) Bad	(12) Bad(con.)	(13) Any	(14) Good	(15) Bad	(16) Bad(con.)
BENCHMARK: Boom threshold 1.65 st. deviations																
Banking flows(sum of 2 lags)	0.22*** (0.04)	0.17*** (0.05)	0.23*** (0.05)	0.24*** (0.06)	0.20*** (0.04)	0.16*** (0.06)	0.20*** (0.06)	0.20** (0.06)	0.36*** (0.09)	0.20 (0.14)	0.58*** (0.16)	1.31*** (0.45)	0.14 (0.11)	0.21 (0.13)	0.01 (0.15)	0.08 (0.15)
<i>N</i>	1794	1110	879	434	624	380	404	224	498	248	284	140	672	482	191	70
pseudo <i>R</i> ²	0.08	0.04	0.13	0.16	0.14	0.09	0.17	0.18	0.13	0.03	0.27	0.50	0.03	0.03	0.06	0.08
ROBUSTNESS: Boom threshold 1.0 st. deviations																
Banking flows (sum of 2 lags)	0.24*** (0.03)	0.17*** (0.04)	0.22*** (0.05)	0.16*** (0.05)	0.20*** (0.04)	0.15*** (0.05)	0.15*** (0.05)	0.09* (0.05)	0.40*** (0.09)	0.21** (0.10)	0.62*** (0.14)	0.67*** (0.22)	0.19** (0.09)	0.22** (0.11)	0.07 (0.14)	0.10 (0.15)
<i>N</i>	1664	1320	1157	485	576	448	448	195	437	261	335	127	651	611	374	163
pseudo <i>R</i> ²	0.08	0.04	0.12	0.10	0.14	0.07	0.19	0.17	0.16	0.05	0.27	0.28	0.02	0.02	0.03	0.02

Logit. Country fixed effects. Standard errors in parenthesis. Sample: 1980-2006. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Dependent variable: probability of a credit boom event. The top rows show the result for credit booms defined as episodes in which boom threshold is 1.65 standard deviations. The bottom rows show the results for booms defined using 1 standard deviation. The results shown in the table are the coefficients of the sum of those two lags of gross bank inflows. There is one type of event per specification: (1) all credit booms; (2) good booms; (3) bad booms; and (4) bad booms conditional on the existence of a credit boom.

Table B.6: Robustness: threshold of 1 standard deviation (by type of flow)

	NO CONTROLS				CONTROLS (Other Capital flows)				CONTROLS (Macro factors)			
	(1) Any	(2) Good	(3) Bad	(4) Bad(con.)	(5) Any	(6) Good	(7) Bad	(8) Bad(con.)	(9) Any	(10) Good	(11) Bad	(12) Bad(con.)
BENCHMARK: Boom threshold 1.65 st. deviations												
Sum of lags(B-B)	0.30*** (0.06)	0.23*** (0.08)	0.27*** (0.07)	0.31*** (0.09)	0.31*** (0.07)	0.26*** (0.10)	0.29*** (0.08)	0.36** (0.12)	0.37*** (0.10)	0.35*** (0.13)	0.28*** (0.11)	0.36** (0.15)
Sum of lags(B-NB)	0.10 (0.09)	0.06 (0.12)	0.18 (0.13)	0.22 (0.13)	0.01 (0.11)	-0.02 (0.17)	0.10 (0.15)	0.10 (0.18)	0.05 (0.14)	0.15 (0.23)	0.03 (0.18)	0.07 (0.18)
<i>N</i>	1122	628	688	364	843	493	536	304	589	385	378	224
pseudo R^2	0.14	0.07	0.19	0.23	0.16	0.14	0.23	0.28	0.20	0.27	0.29	0.35
ROBUSTNESS: Boom threshold 1.0 st. deviations												
Sum of lags(B-B)	0.27*** (0.05)	0.16*** (0.06)	0.19*** (0.07)	0.10 (0.07)	0.24*** (0.06)	0.13** (0.07)	0.20** (0.08)	0.08 (0.08)	0.34*** (0.08)	0.22** (0.08)	0.25** (0.12)	0.14 (0.14)
Sum of lags(B-NB)	0.20*** (0.07)	0.16* (0.09)	0.29*** (0.11)	0.24** (0.11)	0.14 (0.11)	0.17 (0.13)	0.20 (0.15)	0.24 (0.16)	0.07 (0.12)	0.17 (0.17)	0.09 (0.19)	0.29 (0.21)
<i>N</i>	1012	708	783	322	761	565	568	243	591	377	397	171
pseudo R^2	0.14	0.06	0.19	0.17	0.15	0.10	0.24	0.24	0.26	0.27	0.37	0.43
CONTROLS					Other Capital Inflows				Other Capital Inflows Δ Real GDP Δ Real exchange Rate Δ Bank Leverage			

Logit. Country fixed effects. Standard errors in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Dependent variable: probability of a credit boom event. The top rows show the result for credit booms defined as episodes in which boom threshold is 1.65 standard deviations. The bottom rows show the results for booms under the 1 standard deviation. The coefficients of interest are: international banking flows to the banking sector (B-B) and to the non-banking sector (B-NB), sum of two lags. Controls: other capital flows and macro variables.

Table B.7: Probability of financial crises

	Banking flows				Banking flows by borrowing sector			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Dep. var: CRISES</i>	All sample	High inc.	Middle inc.	Low inc.	All sample	High inc.	Middle inc.	Low inc.
Banking flows(-1)	0.04** (0.02)	0.04* (0.03)	0.04 (0.04)	0.04 (0.08)				
Banking flows(-2)	0.07*** (0.02)	0.07** (0.03)	0.13*** (0.04)	-0.02 (0.07)				
Sum of lags	0.12*** (0.03)	0.11** (0.03)	0.17*** (0.06)	0.02 (0.09)				
Bank to Bank flows(-1)					0.04* (0.02)	0.05 (0.03)	-0.08 (0.06)	0.10 (0.11)
Bank to Bank flows(-2)					0.09*** (0.03)	0.10** (0.04)	0.24*** (0.08)	-0.12 (0.08)
Bank to NonBank flows(-1)					0.06 (0.04)	0.02 (0.08)	0.12* (0.07)	-0.11 (0.12)
Bank to NonBank flows(-1)					0.05 (0.05)	-0.02 (0.09)	0.04 (0.08)	0.16 (0.11)
Sum of lags(B-B)					0.12*** (0.04)	0.15*** (0.05)	0.16* (0.09)	-0.01 (0.13)
Sum of lags(B-NB)					0.10 (0.06)	-0.00 (0.11)	0.16* (0.10)	0.04 (0.15)
<i>N</i>	2113	712	576	825	2107	712	576	819
pseudo R^2	0.03	0.08	0.03	0.00	0.03	0.09	0.06	0.02

Logit. Country fixed effects. Standard errors in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Dependent variable: probability of a financial crises (banking, debt, or currency crises). LEFT PANEL: Explanatory variable: all banking inflows (2 lags). All country sample (column 1), high income countries (column 2), middle income countries (column 3) and lower income countries (column 4). RIGHT PANEL: explanatory variables: bank to bank flows (B-B) and bank to non-bank flows (B-NB). Same split of country sample as in columns (1)-(4).

Table B.8: Probability of crisis: credit and non-credit related

<i>Dep. var: CRISES</i>	CRISES that are boom-related				CRISES that are NOT boom-related			
	(1) All sample	(2) High inc.	(3) Middle inc.	(4) Low inc.	(5) All sample	(6) High inc.	(7) Middle inc.	(8) Low inc.
Banking flows(-1)	0.12*** (0.04)	0.12** (0.05)	0.10 (0.08)	0.18 (0.14)	0.03 (0.02)	0.03 (0.03)	0.09 (0.07)	-0.04 (0.09)
Banking flows(-2)	0.15*** (0.04)	0.17*** (0.05)	0.20** (0.09)	-0.12 (0.15)	-0.00 (0.03)	0.00 (0.04)	0.01 (0.08)	-0.06 (0.08)
Sum of lags	0.27*** (0.05)	0.29** (0.07)	0.31*** (0.11)	0.05 (0.17)	0.03 (0.02)	0.03 (0.03)	0.09 (0.08)	-0.09 (0.11)
<i>N</i>	1074	466	352	256	1615	470	416	729
pseudo <i>R</i> ²	0.15	0.27	0.13	0.03	0.01	0.02	0.01	0.00

Logit. Country fixed effects. Standard errors in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Dependent variable: probability of a financial crisis that is credit related (LEFT PANEL), and probability of a financial crisis that is no credit related (RIGHT panel). Explanatory variable: all banking inflows (2 lags). All country sample (column 1), high income countries (column 2), middle income countries (column 3) and lower income countries (column 4). Idem for (5)-(8).

Table B.9: Coefficients of control variables: capital flows

<i>Dep. var: Credit booms</i>	Only capital flows				Bank flows and other capital flows			
	(1) Any	(2) Good	(3) Bad	(4) Bad(cond)	(5) Any	(6) Good	(7) Bad	(8) Bad(cond)
Banking flows					0.22*** (0.05)	0.19*** (0.07)	0.23*** (0.06)	0.27*** (0.08)
Debt(non-bank) flows					-0.01 (0.03)	-0.08* (0.05)	0.05 (0.04)	0.06 (0.05)
Debt flows	0.05*** (0.02)	0.01 (0.03)	0.11*** (0.03)	0.12*** (0.04)				
FDI flows	0.03 (0.03)	0.02 (0.06)	0.01 (0.04)	0.02 (0.04)	0.03 (0.03)	0.06 (0.06)	0.01 (0.04)	0.01 (0.04)
Port.equity flows	0.01 (0.03)	0.11* (0.06)	-0.04 (0.034)	-0.18* (0.09)	0.01 (0.03)	0.09 (0.06)	-0.04 (0.04)	-0.22** (0.11)
<i>N</i>	843	493	536	304	843	493	536	304
pseudo <i>R</i> ²	0.07	0.05	0.16	0.20	0.14	0.11	0.21	0.27
<i>AIC</i>	271.4	148.8	136.3	107.1	256.3	143.6	133.1	103.2
<i>BIC</i>	299.8	174.0	162.0	129.4	294.2	177.2	167.4	132.9

Logit. Country fixed effects. Standard errors in parenthesis.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Dependent variable: probability of a credit boom event. Sample: high and middle income countries. Explanatory variable in columns (1)-(4) are total capital flows split by instrument according to Lane and Milesi-Ferretti (2007): debt, foreign direct investment (FDI), and portfolio equity. Debt flows significantly increase the probability of credit booms, except for good booms, where the debt estimate is not significantly different from zero. Column (5)-(9) add international banking flows as another explanatory variables. Since banking flows are mostly debt flows, I enter the debt flow variable deducting the banking flows (i.e., debt (non-bank) flows=debt flows-bank flows). The coefficient of banking flows replicate Table 4, columns (1)-(4). The difference is that the current table also shows the coefficient of the controls: other capital flows. Interestingly, debt flows' estimates lose their significance and are close to zero, which indicates that banking flows are the subset of capital flows that affect the probability of credit booms the most.

Table B.10: Other variables coefficients: capital flows

<i>Dep. var: Credit booms</i>	Only capital flows				Bank flows and other capital flows			
	(1) Any	(2) Good	(3) Bad	(4) Bad(cond)	(5) Any	(6) Good	(7) Bad	(8) Bad(cond)
Banking flows					0.22*** (0.05)	0.19*** (0.07)	0.23*** (0.06)	0.27*** (0.08)
Debt(non-bank) flows					-0.01 (0.03)	-0.08* (0.05)	0.05 (0.04)	0.06 (0.05)
Debt flows	0.05*** (0.02)	0.01 (0.03)	0.11*** (0.03)	0.12*** (0.04)				
FDI flows	0.03 (0.03)	0.02 (0.06)	0.01 (0.04)	0.02 (0.04)	0.03 (0.03)	0.06 (0.06)	0.01 (0.04)	0.01 (0.04)
Port.equity flows	0.01 (0.03)	0.11* (0.06)	-0.04 (0.034)	-0.18* (0.09)	0.01 (0.03)	0.09 (0.06)	-0.04 (0.04)	-0.22** (0.11)
<i>N</i>	843	493	536	304	843	493	536	304
pseudo R^2	0.07	0.05	0.16	0.20	0.14	0.11	0.21	0.27
<i>AIC</i>	271.4	148.8	136.3	107.1	256.3	143.6	133.1	103.2
<i>BIC</i>	299.8	174.0	162.0	129.4	294.2	177.2	167.4	132.9

Logit. Country fixed effects. Standard errors in parenthesis.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Dependent variable: probability of a credit boom event. Sample: high and middle income countries. Explanatory variable in columns (1)-(4) are total capital flows split by instrument according to Lane and Milesi-Ferretti (2007): debt, foreign direct investment (FDI), and portfolio equity. Debt flows significantly increase the probability of credit booms, except for good booms, where the debt estimate is not significantly different from zero. Column (5)-(9) add international banking flows as another explanatory variables. Since banking flows are mostly debt flows, I enter the debt flow variable deducting the banking flows (i.e., debt (non-bank) flows=debt flows-bank flows). The coefficient of banking flows replicate Table 4, columns (1)-(4). The difference is that the current table also shows the coefficient of the controls: other capital flows. Interestingly, debt flows' estimates lose their significance and are close to zero, which indicates that banking flows are the subset of capital flows that affect the probability of credit booms the most.

Table B.11: Composition of international banking flows: by method

	Random effects (benchmark)			Country fixed effects		
	(1) All	(2) OECD	(3) Non-OECD	(4) All	(5) OECD	(6) Non-OECD
<i>Dep. var:</i> log (B-B/B-NB)						
Institutional Quality (-1)	0.020*** (0.008)	0.022** (0.009)	0.021* (0.011)	0.017** (0.008)	0.023** (0.010)	0.021* (0.012)
Government debt to GDP (-1)	-0.006** (0.002)	-0.003 (0.003)	-0.009*** (0.003)	-0.007*** (0.002)	-0.003 (0.004)	-0.009** (0.003)
Size of banking sector (-1)	0.003** (0.001)	0.004*** (0.001)	0.012*** (0.003)	0.003 (0.002)	0.004** (0.002)	0.009** (0.004)
Banking leverage (-1)	0.002* (0.001)	0.001 (0.001)	0.002 (0.002)	0.002 (0.001)	0.001 (0.001)	0.003 (0.002)
Log of real GDP pc (-1)	0.050 (0.142)	-0.938* (0.484)	-0.029 (0.151)	-0.032 (0.259)	-0.998 (0.616)	0.095 (0.286)
Country risk (-1)	-0.000 (0.011)	-0.002 (0.016)	0.001 (0.011)	0.005 (0.011)	0.002 (0.018)	0.003 (0.011)
Constant	-2.032* (1.211)	7.984* (4.505)	-1.908 (1.165)	-1.001 (2.274)	8.474 (5.761)	-2.847 (2.280)
Observations	902	402	500	902	402	500
Adjusted R^2	0.42	0.09	0.37	0.15	0.20	0.19

Random effects (left) and country fixed effects (right). Robust standard errors. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Dependent variable: log of the ratio of bank to bank loans over bank to bank to non-bank loans received by a country; ie, $\log(B-B/B-NB)$. Independent variables: institutional quality (from the ICRG), government debt to the banking sector, size of the banking sector (ie, assets over GDP), banking leverage (ie, bank assets over bank deposits), financial openness (Chinn-Ito index), and country risk (interest rate spread). All of the explanatory variables are lagged one period.

C Extended version of the Model

The objective function is:

$$\begin{aligned}
 U(L_i) = & E(\tilde{r}_L)L + E(\tilde{r}_B - c_B)L_B^* + E(r_{NB}^* - c_{NB})L_{NB}^* + r_F R - r_D D - r_B B \\
 & - \frac{1}{2} \rho \left[\text{var}(\tilde{r}_L)L^2 + 2\text{cov}(\tilde{r}_L, (\tilde{r}_B^* - c_B))LL_B^* + 2\text{cov}(\tilde{r}_L, (r_{NB}^* - c_{NB}))LL_{NB}^* \right] \\
 & - \frac{1}{2} \rho \left[\text{var}(\tilde{r}_B^* - c_B)L_B^{*2} + \text{var}(r_{NB}^* - c_{NB})L_{NB}^{*2} \right]
 \end{aligned} \tag{6}$$

The bank will choose L_i in order to maximize the utility function. The FOCs are:

$$\frac{\partial U}{\partial \mu} \frac{\partial \mu}{\partial L_i} + \frac{\partial U}{\partial \sigma^2} \frac{\partial \sigma^2}{\partial L_i} = 0 \tag{7}$$

or, equivalently,

$$\frac{\partial U}{\partial \mu} \rho_i + 2 \frac{\partial U}{\partial \sigma^2} \sum_j v_{ij} L_j = 0 \tag{8}$$

Let $\rho = (\rho_1, \dots, \rho_N)$ be the vector of expected returns and $V = (v_{ij})_{i,j=1,\dots,N}$ the variance-covariance matrix of risky assets, assumed to be invertible. Then, the FOC are:

$$-\lambda \rho + V\mathbf{L} = 0 \quad \text{or} \quad \mathbf{L} = \lambda V^{-1} \rho \tag{9}$$

where

$$\begin{aligned}
 \mathbf{L} &= \begin{pmatrix} L \\ L_B^* \\ L_{NB}^* \end{pmatrix} \\
 \lambda &= \frac{(\partial U / \partial \mu)}{2(\partial U / \partial \sigma^2)}; \\
 V &= \begin{pmatrix} \text{var}(\tilde{r}_L) & \text{cov}(\tilde{r}_L, \tilde{r}_B^* - c_B) & \text{cov}(\tilde{r}_L, \tilde{r}_{NB}^* - c_{NB}) \\ \text{cov}(\tilde{r}_B^* - c_B, \tilde{r}_L) & \text{var}(\tilde{r}_{NB}^* - c_{NB}) & \text{cov}(\tilde{r}_B^* - c_B, \tilde{r}_{NB}^* - c_{NB}) \\ \text{cov}(\tilde{r}_{NB}^* - c_{NB}, \tilde{r}_L) & \text{cov}(\tilde{r}_{NB}^* - c_{NB}, \tilde{r}_B^* - c_B) & \text{var}(\tilde{r}_{NB}^* - c_{NB}) \end{pmatrix}; \\
 \rho &= \begin{pmatrix} \tilde{r}_L - r \\ (\tilde{r}_B^* - c_B) - r \\ (\tilde{r}_{NB}^* - c_{NB}) - r \end{pmatrix}
 \end{aligned}$$

- Then, the optimal international lending is:

$$L^* = \frac{\lambda}{\Delta} [var(\tilde{r}_L)[(\tilde{r}_L^* - c) - r] - cov(\tilde{r}_L, \tilde{r}_L^*)(\tilde{r}_L - r)] \quad (10)$$

which implies that the bank obtains its preferred portfolio by a combination of the riskless asset and risky assets. [Note: The difference in the behavior of investors derives from the coefficient λ , which indicates that a more risk-averse bank will buy more of the riskless asset and less of the risky asset. Since this model uses a representative bank, it does not apply.]

- The interesting part is the comparative statics analysis. I find that the volume of lending is affected by changes in the monitoring costs. Lower c (ie, better IQ) increases the amount of foreign loans.

$$\frac{\partial L^*}{\partial c} = \frac{1}{-\gamma(1 - 2\rho^*)\sigma^2} < 0 \quad (11)$$