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Do surges in international capital flows influence the likelihood of banking crises?

Cross-country evidence on capital flows bonanzas and bonanza-boom-bust cycles

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DRAFT. COMMENTS WELCOME

Abstract

This paper asks if bonanzas (i.e. surges) in net capital flows are associated with a higher likelihood of banking crises and whether this association is necessarily through a lending boom mechanism. Using a new database covering over one hundred countries during 1973-2008, the paper shows that previous-year bonanzas in net capital flows are associated with systemic banking crises, even in the absence of a lending boom. Given a baseline bonanza, the odds of a crisis the following year are up to three times higher. The more extreme is the windfall of capital relative to trend (i.e. an *intense* bonanza), the larger is this risk and a crisis becomes seven times more likely. The correlation of mild bonanzas with crises is found to be necessarily associated with a lending boom; this is not the case for *intense* bonanzas, suggesting the existence of a different mechanism when the windfall of capital is too large. For developing countries it is found that intense bonanzas are associated with even higher odds of future crises. When decomposing flows in FDI, portfolio-equity and debt, it is found that bonanzas in both debt and portfolio-equity flows are correlated with future crises; however, portfolio flows are the ones associated with the largest increase in the likelihood of a crisis.

Key words: Banking crises, Financial crises, Capital flows, Credit booms, Lending booms

JEL classification: E44, E51, F21, F32, F34, G01

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1. Introduction

The recent global financial crisis has underpinned a new interest on studying financial crises. The recent discussion in the academia, policy circles and in non-academic outlets has emphasized the role of international capital flows as a factor exacerbating the vulnerability of the financial system.¹ The conventional perception is that surges or bonanzas in capital inflows (or its counterpart in current account deficits) exacerbate the intrinsic fragility of the financial system because the ensuing extra liquidity enables the conditions for lending booms.

Understanding the macroeconomic and financial effects of bonanzas in capital flows is of importance because this is of key policy relevance. As highlighted by [Ostry et al. \[2010\]](#) and [IMF \[April, 2010\]](#), if surges in capital inflows exacerbate macroeconomic imbalances or the risk of financial distress, countries may be inclined to establish administrative controls to certain types of inflows or outflows. However, if the mechanisms through which surges in capital flows exacerbate financial risk are properly identified, countries would have more policy options to prevent crises.

At least since [Díaz-Alejandro \[1985\]](#), it has been argued that surges (i.e. bonanzas) in capital inflows are associated with macroeconomic and financial risks, specially after a financial liberalization process. The literature has studied different risks from accelerated growth in capital inflows. From a macroeconomic management perspective, bonanzas in capital inflows may be associated with appreciation of the real exchange rate, which undermines competitiveness of the tradable sector and may end up inducing lasting damage to the real economy when flows reverse or suddenly stop, specially in the presence of a fixed exchange regime. Also, sterilization may impose challenges to monetary authorities. From a financial perspective, the main concerns stem from upward pressure in asset prices, the possibility of lending booms caused by the larger funds in the domestic economy, increased exposure of the economy to foreign currency liabilities, and from the temporal nature of these surges, that may end up in a sudden stop.² For the banking system, lending booms

¹In the academic literature see the model by [Giannetti \[2007\]](#) and empirical studies by [Reinhart and Rogoff \[2009\]](#) and [Reinhart and Reinhart \[2009\]](#). Some argue that current account deficits are at the roots of the financial crisis of 2007-2008; see for example [Portes \[2009\]](#).

²Of course, the macroeconomic effects of surges in capital inflows and the accompanying policies implemented by fiscal and monetary authorities are intimately associated with the financial risks associated with surges in capital inflows. In particular, sterilization policies aimed to dampen the appreciation effects of capital flows may lead to excessively loose monetary policy that, in turn, create the environment for boom-bust cycles. For an early discussion of the policy challenges imposed by surges or bonanzas in capital inflows see [Schadler et al. \[1993\]](#), [Calvo et al. \[1993\]](#), and [Fernández-Arias and Montiel \[1996\]](#). A more recent treatment is found in [Cardarelli et al. \[2010\]](#), [Ostry et al. \[2010\]](#) and [IMF \[April, 2010\]](#). For an analysis of macroeconomic regularities associated with surges or bonanzas in capital flows see [Cardarelli et al. \[2010\]](#) and [Reinhart and Reinhart \[2009\]](#).

fueled by international capital certainly increase the likelihood of distress. Risk is also increased by foreign currency mismatches, since in case of a currency crisis the event most likely will end up in a banking crisis (a twin crises).

Given the policy concerns and the real effects of financial crises, there is a large literature studying the effects of capital flows and financial crises. However, this literature focuses on studying episodes of currency crises or episodes of sudden stops, as opposed to banking crises.³ To our knowledge, only one paper ([Reinhart and Reinhart \[2009\]](#)) studies the relationship between banking crises and surges or bonanzas in international capital flows. The authors find a positive association, but limit the analysis only to non-parametric methods. The few studies that investigate the association between banking crises and the *level* of capital flows, or their composition, yield mixed results.⁴ The distinction between bonanzas of international capital, as opposed to the level of flows, is important because the theoretical mechanism linking capital flows and financial crises relates to excessive windfalls of capital, not to its level.

The purpose of this paper is to shed light on the systematic relationship between bonanzas in net capital flows and the likelihood of systemic banking crises.⁵ The empirical analysis is aimed at answering two questions (i) whether surges in capital flows are associated with an increase in the likelihood of a systemic banking crisis, and (ii) if so, whether this association is exclusively through a lending boom. The paper goes beyond [Reinhart and Reinhart \[2009\]](#) and performs a multivariate econometric analysis, focusing on disentangling the effects of surges in capital from the effect of lending booms. This is important because identifying the mechanisms at play is useful to guide future theoretical research and because its different policy implications. If surges in capital flows are associated with banking crises only through their correlation with lending booms, prudential regulation and limits to excessive credit growth may be enough to reduce the risks stemmed from unusually large windfalls of capital. However, this is not the case if bonanzas of capital are associated with crises through other not so well understood mechanisms.

³See [Eichengreen \[2003\]](#) for a collection of recent essays on international capital flows and currency crises. For the case of sudden stops see [Edwards \[2007a\]](#), [Calvo et al. \[2008\]](#) and [Agosin and Huaita \[Forthcoming\]](#).

⁴This literature is reviewed in section 2.

⁵This paper defines bonanzas as significant deviations from the business cycle trend, following the literature that uses threshold methods to identify behavior in a variable that is beyond the variation implied by the business cycle. The method uses country-specific thresholds to identify bonanzas and uses net capital flows computed using data from the Balance of Payments. Baseline bonanzas are defined as deviations of one s.d. from trend, intense bonanzas as deviations of 2 s.d. and mild bonanzas as deviations of 0.5 s.d. Similar methods have been employed by [Gourinchas et al. \[2001\]](#) and [Mendoza and Terrones \[2008\]](#) for lending booms, and for [Cardarelli et al. \[2010\]](#) for capital flows. [Agosin and Huaita \[Forthcoming\]](#) and [Reinhart and Reinhart \[2009\]](#) also define capital flows bonanzas with a threshold method, but disregard information from the country business cycle.

The empirical analysis below is done using both aggregate flows and decomposing flows in FDI, portfolio-equity and debt. The analysis focuses on the period 1973-2008 and uses a new database on systemic banking crises from [Laeven and Valencia \[2010\]](#). The database identifies 121 episodes of systemic banking crises in 149 countries (including 23 systemic crises in years 2007-2008). The multivariate econometric analysis uses information from over sixty countries and more than fifty crises episodes, which is an improvement on the existing literature.⁶

The paper starts performing a non-parametric analysis and shows that following these methods it cannot be concluded that bonanzas of capital flows are systematically associated with a higher probability of banking crises, as argued by [Reinhart and Reinhart \[2009\]](#).

The paper then performs a multivariate regression analysis using a binary outcome framework in which the dependent variable is a dummy for the *start* of a crisis. The explanatory variables include the variable of interest (bonanzas in net capital flows) and a set of controls that account for the mechanisms triggering a banking crises and other relevant covariates. In particular, the analysis controls for the existence and severity of lending booms, the existence of recent international or domestic financial liberalization processes, the quality of banking supervision, the existence of an explicit deposit insurance scheme, a proxy for moral hazard, the quality of democratic institutions, currency crises, foreign exchange reserves and the level of domestic and international interest rates.⁷

The results of the regression analysis suggest that bonanzas in net capital flows have a strong association with systemic banking crises. However, only large surges in net capital flows (*intense* bonanzas) are found to have an independent association with crises, beyond the presence of a lending boom. Thus, *large* surges in capital inflows don't only have the potential to make a banking system more prone to crises because of 'overlending', as conventionally argued, but through other channels. The results also suggest a strong association between systemic banking crises and lending booms, currency crises and increased competition after liberalization in the banking industry.

It is also found that more intense bonanzas are associated with a larger likelihood of banking crises. A crisis becomes seven times more likely after an intense bonanza, while these odds are only three times higher after a baseline bonanza.⁸ Furthermore, the odds of a crisis significantly

⁶This paper, however, is silent on issues such as the determinants of bonanza episodes. For this, the reader can see the literature cited in footnote 2.

⁷An extensive study of determinants of banking crises is beyond the scope of this paper. We follow the literature to include relevant controls. Additionally to the ones already mentioned, we include as controls openness to trade, depreciation of the nominal exchange rate, a dummy for a fixed exchange rate regime, output growth, and measures of *de facto* and *de jure* capital account openness.

⁸The unconditional probability of a systemic banking crisis is 3.33% in the baseline sample, which includes 121

increase if a large surge takes place at the same time as a lending boom (a crisis is sixteen times more likely after such a year). Moreover, the simultaneous occurrence of a bonanza and a boom is associated with even larger odds of a crisis in developing countries, specially middle and upper income economies.

The paper also decomposes capital flows in FDI, portfolio-equity and debt flows. This is important to understand which type of flows are correlated with an increased likelihood of banking crises. It is found that bonanzas in portfolio and debt flows are robustly associated with systemic banking crises. The joint occurrence of a lending boom and a bonanza of debt or portfolio flows dramatically increase the odds of a banking crisis the following year. However, only portfolio flows have a robust independent association with crises, beyond the presence of a lending boom. The odds of a crisis after a large surge in portfolio flows are even larger in developing countries. The results suggest, then, that there is a Pecking Order when it comes to the riskiness of international flows, being portfolio flows the riskiest.

The evidence presented in this paper suggests that the mechanisms through which *intense* surges in net capital flows exacerbate financial risk are to be found not only in an increased pool of funds that allows for excessive lending, but also through mechanisms associated with increased portfolio-equity flows that may operate even in the absence of excessive growth in credit. This suggest that imposing speed limits to credit growth to curb over-lending may be insufficient to prevent banking system distress if a country is facing a *large* increase in capital flows, specially of portfolio flows. However, the mechanisms that may be behind this are not well understood in the literature, because most of the existing models and theory focus on the lending boom channel.⁹

The remaining of the paper is structured as follows. Section 2 presents a brief discussion of the theories proposing mechanisms through which bonanzas of capital flows may be linked to banking crises and discusses the existing empirical literature. Section 3 presents the method used to identify bonanzas and the data used in the paper. Sections 4, 5 and 6 perform the empirical analysis. Section 7 concludes and briefly discusses the policy implications of the results.

crises in 97 countries in the period 1973-2008.

⁹For example, a recent survey by Kose et al. [2009] only mentions risks from debt flows because their potential underpinning of lending booms when discussing the pros and cons of international flows. The effect of bonanzas on crises, beyond the presence of lending booms, may be due to at least one additional channel: a main determinant of banking crises may be the existence of asset prices bubbles, potentially fueled by surges in equity-type flows. Recent studies by Aizenman and Jinjark [2009] and IMF [April, 2010] provide some evidence in favor of this idea: the first study finds a strong positive association between current account deficits and appreciation of real state prices; the second paper shows that a measure of ‘excess global liquidity’ has a positive impact in domestic asset prices.

2. Theoretical considerations and existing literature

The literature on financial intermediation and banking crises have identified several intrinsic characteristics of the banking system that make it specially prone to crises. The literature has emphasized the intrinsic illiquidity of banking assets, the problem of imperfect information in the banking industry, and the existence of deposit insurance as some of the microeconomic factors that make banks prone to crises.¹⁰ Given the vulnerability of the banking system, and given an institutional and regulatory frameworks, different macroeconomic shocks (domestic and external) can trigger a banking crisis.

The literature offers some guidance on the possible mechanisms through which banking crises may take place after a macro shock. Five mechanisms have captured much of the attention in the literature: (i) the possibility of deposit runs, as in [Diamond and Dybvig \[1983\]](#); (ii) the existence of deposit insurance schemes or bailout guarantees and the consequent problems of moral-hazard and incentives to too much risk-taking in an industry characterized by asymmetric information, as in [Corsetti et al. \[1999\]](#);¹¹ (iii) currency crises;¹² (iv) lending booms or boom-bust cycles, as in [McKinnon and Pill \[1996\]](#) or [Giannetti \[2007\]](#);¹³ and (v) processes of financial liberalization, including liberalization of the current account, as in [Daniel and Jones \[2007\]](#).¹⁴

¹⁰[Allen and Gale \[2007\]](#) present several models formalizing these mechanisms.

¹¹Also see [Gavin and Hausmann \[1996\]](#), [Mishkin \[1996\]](#), [Goldstein and Turner \[1996\]](#) and [Aizenman \[2004\]](#). The argument is that, even though deposit insurance is an optimal policy because it eliminates the possibility of self-fulfilling deposit panics, the existence of bailout guarantees gives incentives to bankers to take risks they would not take in absence of the safety net. The empirical literature has found support for the hypotheses that deposit insurance by itself may end up exacerbating bank's fragility (see studies by [Hutchison and McDill \[1999\]](#), [Demirgüç-Kunt and Detragiache \[1998\]](#), [Demirgüç-Kunt and Detragiache \[2002\]](#)) and that moral hazard is more of a problem in economies with lower quality of institutions (see papers by [Eichengreen and Arteta \[2002\]](#), [Demirgüç-Kunt and Detragiache \[2002\]](#) and [Barth et al. \[2004\]](#)).

¹²The empirical literature has found support for the association between banking and currency crises ([Kaminsky and Reinhart \[1999\]](#) and [Glick and Hutchison \[2001\]](#)). A sudden stop may trigger a banking crises because the associated balance sheet effects highlighted by [Calvo \[1998\]](#), but the mechanism is associated to a currency crises. This may be why [Edwards \[2007a\]](#) does not find any statistical association between sudden stops and banking crises.

¹³Lending booms may be at the roots of banking crises because during booms some of the asymmetric information and moral hazard problems intrinsic to banking get exacerbated ([Gavin and Hausmann \[1996\]](#); [Goldstein and Turner \[1996\]](#)). The empirical evidence is supportive of the link between lending booms and banking crises, see [Gourinchas et al. \[2001\]](#), [Mendoza and Terrones \[2008\]](#), [Tornell and Westermann \[2005, p.36\]](#), [Eichengreen and Arteta \[2002\]](#), [Demirgüç-Kunt and Detragiache \[2005\]](#), [Ottens et al. \[2005\]](#) and [Schularick and Taylor \[2009\]](#).

¹⁴The argument is that liberalization processes may exacerbate the problems of moral hazard and too much risk taking in the banking industry because liberalization may entail increased competition, a fall in bank's franchise value, and the possibility for banks to enter activities that were forbidden before. The empirical literature has found support for the connection between domestic financial liberalization and financial crises ([Demirgüç-Kunt and Detragiache \[1998, 2002\]](#), [Hutchison and McDill \[1999\]](#), [Kaminsky and Reinhart \[1999\]](#), [Glick and Hutchison \[2001\]](#), [Hutchison \[2002\]](#), [Eichengreen and Arteta \[2002\]](#), [Noy \[2004\]](#), and [Angkinand et al. \[2010\]](#)). However, the evidence on international liberalization is less supportive (see [Reinhart and Rogoff \[2009\]](#) and [Bordo et al. \[2001\]](#), who report positive results; and [Eichengreen and Arteta \[2002\]](#) and [Edwards \[2007b\]](#), [Eichengreen and Arteta \[2002\]](#) and for negative results).

Of these mechanisms the last two allow for a direct link between surges in capital inflows and banking crises. Indeed, most of the literature assumes that lending booms are fueled or exacerbated by surges in capital inflows or that lending booms are associated with financial liberalization processes (domestic and international). The logic is that after a liberalization process a surge in capital inflows may take place during these early stages of financial development, allowing banks a bigger pool of funds from which to provide lending, but at the same time magnifying the moral hazard and incentives problems in the banking industry. The conventional view is that lending booms, exacerbated by financial liberalization and capital inflows, are an important driving force of banking crises.¹⁵

These theories that link financial liberalization processes with lending booms fueled by a surge in capital inflows are appealing to explain banking crises. However, the mixed results in the existing empirical studies cast doubt on its validity. On one hand, there is no strong evidence that surges in capital flows are systematically associated with lending booms.¹⁶ On the other hand, the empirical evidence does not suggest a direct link between the capital level of flows and banking crises (see [Eichengreen and Rose \[1998\]](#), [Sachs et al. \[1996\]](#), [Radelet and Sachs \[1998\]](#), [Eichengreen and Arteta \[2002\]](#), and [Mendis \[2002\]](#)). One problem with the existing literature is that these studies use some measure of capital flows, but do not attempt to identify surges or bonanzas of capital. Thus, these studies don't say much about the theoretical mechanism linking banking crises and *surges* in capital flows, which is the theoretical mechanism. Moreover, our understanding of which kind of capital flows are associated with crises, is quite limited as only few studies have attempted to decompose capital flows.¹⁷

This paper attempts to shed light on these issues studying both surges in capital inflows and decomposing the flows into FDI, portfolio-equity and debt flows. To our knowledge only one paper studies the association between surges or bonanzas in capital flows and banking crises. [Reinhart and](#)

¹⁵This conventional perspective is nicely expressed by [Mishkin \[2009, p.156\]](#): “Given a government safety net for financial institutions, particularly banks, liberalization and globalization of the financial system often encourages a lending boom, which is fueled by capital inflows.”. [Reinhart and Rogoff \[2009, p.157\]](#) complement: “One common feature of the run-up to banking crises is a sustained surge in capital inflows.”

¹⁶[Mendoza and Terrones \[2008\]](#) report that most lending booms in their sample are not associated with financial liberalization and somewhat associated with surges in capital inflows. However, [Sachs et al. \[1996\]](#) find that lending booms were not associated with surges in capital inflows, while [Gourinchas et al. \[2001\]](#) report only a proportionally small increase in capital inflows during lending booms.

¹⁷It has been argued that it is the short term capital flows, especially debt, the kind of flows that may be the culprit of exacerbating macroeconomic instability and making countries more prone to suffer financial crises (see surveys by [Agenor \[2003\]](#) and [Kose et al. \[2009\]](#)). However, the evidence is not supportive of this idea, see [Sachs et al. \[1996\]](#), [Radelet and Sachs \[1998\]](#), [Eichengreen and Rose \[1998\]](#), and [Fernández-Arias and Hausmann \[2001\]](#).

Reinhart [2009] ask how economies perform in and around ‘capital flow bonanzas’, defined as periods when current account deficits deteriorate beyond a given threshold, and find that bonanzas are associated with a higher incidence of banking, currency, sovereign and inflation crises in developing countries after comparing conditional and unconditional probabilities of each type of crisis.

The recent studies by Joyce [2010] and Bonfiglioli [2008] are also related with our paper. Both papers estimate a multivariate binary outcome model, focusing on the *stock* of foreign liabilities, scaled by GDP. Bonfiglioli [2008] finds a significant association between the stock of foreign liabilities in developed countries and no association with crises in developing countries. Joyce [2010] decomposes liabilities in FDI, portfolio and debt and finds that only the stock of debt liabilities is robustly associated with a higher likelihood of banking crises in twenty developing countries.¹⁸ A limitation of these papers is that the stock of foreign liabilities is not a perfect proxy for capital flows, given the valuation effects of those measures. As noted before, the theoretical mechanism linking banking crises and capital inflows is related not to the level of flows or stock of liabilities, but to a large growth in flows. As with openness in trade, different countries may have different levels of capital flows or foreign liabilities and those differences do not have to be related with a higher likelihood of crises.

The analysis in this paper improves on the existing literature identifying bonanzas in capital inflows, at the aggregate and by type of flow, and using country-specific trends to pin down excessive windfalls of capital. Following the literature, the analysis controls for increased competition in the banking industry after a liberalization process, the presence of lending booms and currency crises, the existence of bailout guarantees (i.e. explicit deposit insurance schemes) and a measure of moral hazard. Moreover, the empirical analysis focuses on disentangling the effects of bonanzas in capital inflows from that of lending booms.

3. Definition of bonanzas, crises and data

To identify surges in capital flows this paper relies on the threshold method proposed by Mendoza and Terrones [2008]. Using data on real *per capita* flows, a capital flow bonanza is defined as an episode when net flows to a country grow by more than during a typical business cycle expansion. The analysis is done using real per capita flows.¹⁹

¹⁸The paper also finds weak evidence that the stock of FDI and portfolio liabilities are associated with a lower likelihood of crises. The estimated coefficients for these variables are significant only at a 10% level.

¹⁹A per capita normalization is preferred to the usual normalization by GDP because (i) normalizing by GDP does not allow for different trends in capital flows and GDP (i.e. different trends may be the norm for reasons such as

The method identifies a bonanza in net capital flows using a country-specific threshold as follows: Let f_{it} be the deviation from long-run trend in real per capita net flows into country i in year t ; and let $\sigma(f_i)$ be the country-specific standard deviation of this cyclical component. The long-run trend is calculated using the Hodrick-Prescott (HP) filter with the smoothing parameter set to 6.25, as is recommended for annual data.²⁰ The method identifies a bonanza in country i if $f_{it} \geq \phi\sigma(f_i)$, where ϕ is the threshold factor. Bonanzas, then, is a dummy variable that takes value 1 when the method identifies a bonanza and 0 otherwise. Baseline capital flow bonanzas are identified with a threshold of $\phi = 1$ and after imposing two additional constraints: a non-negativity in net capital inflows and a negative current account balance, so that a capital flow bonanza can't take place in the presence of a current account surplus or if there are net capital outflows.

Thus, a baseline capital flow bonanza takes place in a year in which net capital flows to a country are larger than one standard deviation of its business cycle trend, conditional on experiencing a current account deficit and no net outflows. The rationale for the threshold is that if deviations from trend are normally distributed, then observations larger than one s.d. have a probability of 31.7% of being observed. Bonanzas are also identified using $\phi = 0.5$ and $\phi = 2$, which implies milder or more intense events (e.g. given normality of deviations, two s.d. events are observed with probability of 4.6%).²¹

Besides using three different thresholds to identify capital flow bonanzas, as a robustness check for the identification of bonanzas the analysis is also performed using flows as percentage of GDP, which is the usual normalization, and using the definition of capital flow bonanzas by [Reinhart and Reinhart \[2009\]](#), which is based on the current account balance.

a processes of trade or financial integration); and (ii) there may be situations in which both GDP and inflows are falling but the ratio may increase because GDP is falling faster.

²⁰As shown theoretically and numerically by [Ravn and Uhlig \[2002\]](#), the optimal smoothing parameter for annual data is 6.25 when using the Hodrick-Prescott filter. These authors show that this value for annual data produces equivalent business cycles as a quarterly smoothing parameter of 1600, which is widely accepted as optimal. Other authors have suggested different values for the smoothing parameter of 100 or 1000 (e.g. [Backus et al. \[1992\]](#)). As a check, we performed our analysis with bonanzas identified using a smoothing parameter of 100 and the results were qualitatively and quantitatively the same.

²¹Bonanzas may also be defined adding a constraint for the size or level of flows (e.g. flows being at least 5% of GDP or equal to some regional average). However, we prefer to define bonanzas using only a threshold relative to the country-specific deviations from business cycle, without imposing an arbitrary size that is not related to specific country characteristics. This is because it is not clear why a country cannot be said to suffer a bonanza if its flows grow rapidly relative to its specific trend, even though flows never get large enough to be above a certain threshold that is not related to the country's characteristics. Perhaps the country has structural reasons, such as size, institutions or financial development, that make it more vulnerable if its net flows grow by more than one or two standard deviations, but are still below an arbitrary threshold.

3.1. Lending booms

Data on lending booms are constructed following the threshold method proposed by [Mendoza and Terrones \[2008\]](#) and explained above. The paper uses real per capita domestic credit to the private sector (computed from WDI data) and set $\phi = 1$. As robustness checks, we also use a threshold of $\phi = 2$, and use the definition of lending booms by [Gourinchas et al. \[2001\]](#), which is based on data on credit to private sector as percentage of GDP.

3.2. Banking crises

To identify banking crises the paper uses the database of banking crises by [Laeven and Valencia \[2010\]](#), which is an update on the widely used databases on banking crises made by [Caprio and Klingebiel \[1996\]](#) and [Caprio et al. \[2005\]](#). In these dataset a banking crisis is defined as a *systemic banking crisis* when two conditions are met: (i) significant signs of financial distress in the banking system (as indicated by significant bank runs, losses in the banking system, and bank liquidations); and (ii) significant banking policy intervention measures in response to significant losses in the banking system. Their definition does not include isolated banks in distress.

The year in which a systemic banking crisis *starts* is identified by these two conditions and when at least three out of the following five policy interventions have been used ([Laeven and Valencia \[2010, p.8\]](#)): a) extensive liquidity support (ratio of central bank claims on the financial sector to deposits and foreign liabilities exceeds five percent and more than doubles relative to its pre-crisis level), b) large bank restructuring costs (at least three percent of GDP, excluding asset purchases and direct liquidity assistance from the treasury), c) significant asset purchases or bank nationalizations (treasury or central bank asset purchases exceeding five percent of GDP), d) significant guarantees put in place (excluding increases in the level of deposit insurance coverage), or e) deposit freezes and bank holidays. When a country has faced financial distress but less than three of these measures have been used, the authors classify the event as a crises if one of the following two conditions have been met: (i) a country's banking system exhibits significant losses resulting in a share of nonperforming loans above twenty percent or bank closures of at least twenty percent of banking system assets, or (ii) fiscal restructuring costs of the banking sector exceed five percent of GDP. Since the quantitative thresholds used in this definition of systemic banking crises are ad hoc; the authors classify as borderline cases events that almost met the criteria.

With this methodology [Laeven and Valencia \[2010\]](#) identify 144 crises in 114 countries in the period 1973-2008. Of these crises, fifteen events are classified as borderline. The database identifies

23 crises in the years 2007-2008, of which ten cases are considered borderline systemic crises. This paper includes in the analysis all crises in the dataset, no distinguishing borderline cases.

As it has been recently noted by [Boyd et al. \[2010\]](#), the identification methodology of crises by [Laeven and Valencia](#) relies on a broad definition of a systemic banking crisis and combines quantitative data with some subjective assessment of the situation. This methodology may identify with a lag the actual onset of the crises. Notwithstanding, the literature on banking crises has tended to gravitate around the datasets produced by Caprio and coauthors. Thus, this paper uses the data from [Laeven and Valencia](#), but performs the empirical analysis using lagged explanatory variables.

3.3. Description of data

To measure capital flows the paper uses balance of payments data from the International Financial Statistics dataset (IFS BoP). The analysis focuses on *net* capital flows, which for the case of aggregate flows are registered as the balance in the financial account of the balance of payments (line *78bjd* in IFS BoP). To study the effects of the composition of capital flows, the paper uses data from IFS BoP and compute net flows for each category of interest. Since IFS BoP records outflows as negative numbers, to obtain net flows assets and liabilities are added.²²

The analysis disaggregates flows into three categories: foreign direct investment (FDI), portfolio-equity and debt. Net FDI flows are computed adding lines *78bdd* (for assets) and *78bed* (for liabilities). Portfolio-equity, or just portfolio, assets are computed by adding lines of portfolio investments (*78bfd*) and financial derivatives (*78bud*), and subtracting debt securities (*78bld*). Portfolio liabilities are computed in the same fashion (lines $78bgd + 78bxg - 78bnd$). Computed portfolio assets and liabilities are added to obtain net portfolio flows. Finally, debt net flows are obtained as a residual. Since total net capital flows are equal to the balance in the financial account, debt net flows are obtained by subtracting FDI and portfolio net flows from the balance in the financial account.

The set of macroeconomic variables used as controls was obtained from the World Development Indicators database of the World Bank, including GDP, GDP per capita, interest rates, openness in trade, inflation, nominal and real exchange rates, and foreign exchange reserves. To account for *de jure* capital account openness the paper uses the index by [Chinn and Ito \[2008\]](#). *De facto*

²²The analysis focuses on net flows, as opposed to gross flows or outflows or sudden stops, because we are interested in studying the effects of a windfall of capital and in disentangling its effects from that of lending booms. We recognize that there may be other channels operating when outflows or sudden stops take place.

current account openness is proxied by a measure of total foreign assets and liabilities from [Lane and Milesi-Ferretti \[2007\]](#). Similarly, we use the database on exchange rate regimes by [Ilzetzki et al. \[2008\]](#). Proxies for institutional quality were obtained from the Polity IV Project and the International Country Risk Guide (ICRG). Finally, the USA’s Federal Reserve effective discount rate is used as proxy for international interest rates.

Different databases are used to account for institutional variables, including data on deposit insurance from [Demirgüç-Kunt et al. \[2005\]](#) and data on financial reforms by [Abiad et al. \[2010\]](#), who construct indexes of banking supervision and barriers to entry in the banking industry. One limitation of these two datasets is that data is available only until 2003 for deposit insurance and until 2005 for the reform indexes in the banking industry. In order to complete the sample with data until 2007, we made the assumption that no change occurred between 2003-2007 for the explicit deposit insurance scheme dummy and no change occurred in 2005-2007 for the indexes of financial reform. As shown below, this has not a significant impact in the analysis. We perform the analysis with samples until 2006 or until 2008 and obtain the same results (the empirical analysis uses one-period lagged explanatory variables, so that sample until 2008 include variables only until 2007).²³

Table 1 presents summary statistics for the variables used in the empirical analysis.²⁴ Data appendix (Table 17) explains in detail variables used and their sources.

4. Do surges in capital inflows influence the likelihood of banking crises?

4.1. Non-parametric analysis

This subsection explores the relationship between banking crises, capital flow bonanzas and lending booms using a non-parametric analysis based on frequencies, conditional probabilities and chi-squared independence tests.²⁵ The analysis shows that relying on these non-parametric methods

²³Significant changes in deposit insurance schemes are rare. In particular, once a country has adopted an explicit deposit insurance scheme, it is rarely dropped. Changes to some details of the scheme are more common, but our variable only captures the existence or not of an explicit deposit insurance scheme. Conversely, significant changes in the indexes of financial reform from [Abiad et al. \[2010\]](#) are also rare, specially reversals which are our main concern. Thus, our assumption of keeping these variables fixed for the last couple of years does not have a significant impact in the analysis. It is possible that some of these variables will vary greatly after the global financial crisis of 2008, but this does not affect our analysis.

²⁴In the empirical analysis we eliminate the first three years of observations after a crisis in order to reduce endogeneity issues and the influence of observations after a banking crisis. Summary statistics and the empirical analysis are performed in this sample.

²⁵The independence tests are presented using two way tabulations in which banking crises are on the rows and the other variable is on the columns. Frequencies and percentages are presented along with statistics and corresponding

it cannot be argued that surges in capital flows are associated with an increased likelihood of crises, as has been argued by [Reinhart and Reinhart \[2009\]](#).

Table 2 reports the results of performing independence tests for banking crises and one-period lagged capital flow bonanzas (1sd) using data covering the period 1973-2008. In the full sample, three percent (3.33%) is the proportion of pair-year observations that ended up in a banking crisis; this is the unconditional probability of a systemic crisis. On the other hand, 5.29% of capital flow bonanzas (1sd) ended up in a banking crises; this is the conditional probability of a crisis. The data reveal that 28.10% of banking crises took place after a baseline capital flow bonanza (1sd). The independence tests suggest that banking crises and capital flow bonanzas are statistically associated, and these tests have a strong significance. Table 2 also shows that despite the fact that the great majority of crises (98 out of 121) took place in developing countries, the conditional probability of a crisis is basically the same for developing, high income countries, or the full sample (5.11%, 6.09% and 5.29%). The unconditional probability of a crisis is also the same for all country groups (3.48%, 2.82% and 3.33%).

This analysis basically replicates the results obtained by [Reinhart and Reinhart \[2009\]](#) using conditional and unconditional probabilities. Following their argument: if the conditional probability of a crisis is higher, then bonanzas are exacerbating the risks of a crisis; exactly what is found for all country groups.

However, the robustness of this argument –using conditional and unconditional probabilities of bonanzas, is a bit shaky. On one hand, only a small fraction of capital flow bonanzas end up in a crisis: 94.71% of the 643 bonanzas (1sd) episodes did not lead to a crisis the following year (this proportion is basically the same for all country groups). On the other hand, if it is true that banking crises are more likely after a capital flow bonanza, it follows that conditioning by more *intense* bonanzas (2sd) must obtain a stronger association and higher conditional probabilities. Table 3 reports the conditional probability of a crisis after a more intense bonanza (2sd). Opposite of what would be expected, this probability is only marginally higher of that of a 1sd bonanza (5.62% vs. 5.29%). A similar probability for intense bonanzas of that of 1sd bonanzas is also found in developing countries (5.44% vs. 5.11%) and high-income OECD countries (6.45% vs. 6.09%).

p-values for three independence tests: Pearson Chi-squared, Likelihood-ratio, and Fisher’s exact test. The null hypothesis in these tests has the general form: $H_o : P_{ij} = P_{i+} * P_{j+}$. This is, the probability that an observation selected at random will be classified in the *i*-th row and the *j*-th column is equal to the marginal probability that the observation is classified in the *i*-th row times the marginal probability of being classified in the *j*-th column. Thus, the null hypothesis implies that the rows are statistically independent from the columns.

Thus, the conditional probabilities suggest that 1sd and 2sd bonanzas result in fundamentally the same incidence of banking crises, contrary to what is expected from following [Reinhart and Reinhart \[2009\]](#) argument. Moreover, the independent tests suggest no statistical association between crises and intense (2sd) bonanzas with a significance level of 5% when separating the sample in developing and high-income countries.

The frequencies suggest that neither capital flow bonanzas, nor lending booms, are a recipe for disaster: only a small fraction of bonanzas or booms end up in a crisis the following year.²⁶ A low conditional probability of crises is also found for cases of simultaneous bonanza and boom during the previous year.²⁷ Conversely, the frequencies of simultaneous bonanzas and booms is quite low, especially the more intense cases. The methodology employed here only identifies 22 cases of simultaneous 2sd bonanzas and 2sd booms in the period 1973-2008 (of which 8 cases took place in the years 2007-2008). It seems that the bonanza-boom-bust link is not as prevalent in the data as believed, not even in developing countries.

Before continuing analyzing the data, an important caveat is necessary. Most crises in high income countries in this sample took place in the years 2007-2008 (16 out of 23). Thus, we don't want to make much of the results for high income countries until further investigation. For the same reason, the remaining of the empirical analysis will focus in the sample including all countries and in the sample of developing countries (i.e. no attempt is made to study crises in high income countries).

Using the same non-parametric analysis we find a strong statistical association between capital flow bonanzas and lending booms (results reported in online appendix). However, the results suggest that the conventional belief that capital flows fuel lending booms is mistaken. The data reveal a strong association between bonanzas and lending booms because most bonanzas are associated with booms, not because most booms are associated with bonanzas –not even in developing countries. The data suggest that lending booms is what attracts international capital; exactly the opposite of

²⁶To save space, results of independent tests and conditional probabilities for lending booms are reported in an online appendix located at <http://people.ucsc.edu/~jacaball>.

²⁷For the sample including all countries, the conditional probability of a crisis following simultaneous intense bonanzas and booms is quite higher than the unconditional probability of a crisis (22.73% vs. 3.33%) and higher than the conditional probability of a crisis following a 1sd bonanza (5.29%) or a 1sd boom (8.06%). However, this is not the case when the sample only includes developing countries or when the sample includes all countries but data up to 2006. Conversely, the results of the independent tests suggest no statistical association between crises and simultaneous bonanzas and 2sd booms for the sample of developing countries or when including all countries but restricting the sample for period 1973-2006. The large conditional probability of a crisis following a simultaneous intense bonanza and boom is the product of including in the sample the crises in high income countries in 2007-2008.

what it is usually believed.²⁸

The analysis of frequencies, conditional probabilities and independence tests offers a simple and systematic way to study the statistical association between the incidence of two categorical variables. However, the analysis performed here yields different results from that of [Reinhart and Reinhart \[2009\]](#). The data reveals that the vast majority of capital flows bonanzas and lending booms die a natural death, not being the predecessors of a systemic crisis –not even considering only developing countries. Also, no evidence is found suggesting that surges in capital flows fuel lending booms. The bottom line is that relying on a non-parametric analysis it is hard to make a strong case for either the bonanza-bust, the boom-bust or the bonanza-boom-bust links.

4.2. Multivariate Regression analysis

The non-parametric analysis have many limitations. It cannot capture the interactions of the two variables of interest once controlling for other plausible determinants of the likelihood of banking crises, nothing can be said about causality, and we cannot disentangle the effect of capital flow bonanzas from that of lending booms –one cannot tell whether the conditional probability of a crisis is higher following a bonanza because the unusual influx of capital itself or because a lending boom was already underway or it was fueled by the windfall.

To shed light on these issues, this paper performs a regression analysis using a multivariate econometric approach. In this framework a country experiences the *start* of a banking crisis or not in a given year, so that $y_{i,t}$ is a dichotomous response variable for the start of a crisis, and the likelihood of a crisis starting is hypothesized to be a function of a vector of characteristics associated with the country. We can think about the likelihood of the start of a crisis as an underlying continuous latent variable $y_{i,t}^*$. The observable variable is a realization of a crisis when this latent variable has taken a value beyond a threshold (say 0) and a systemic banking crisis starts ($y_{i,t} = 1$). The likelihood of a crisis can be approximated by the latent variable model:

²⁸Less than 16% of (1sd) bonanzas took place in a year in which no lending boom was present. However, most 1sd lending booms (78.82%) are not associated with contemporaneous 1sd bonanzas, and this proportion is similar for more intense bonanzas (78.66%). As a result, the conditional probability of a lending boom is fundamentally the same if 1sd or 2sd bonanzas have taken place (21.18% and 21.34%). Same results obtained for full sample and developing countries when excluding crises of 2007-2008, or when changing the definition of a boom using [Gourinchas et al. \[2001\]](#) booms or when using a two standard deviation threshold for lending booms. Results reported in online appendix.

$$y_{i,t} = \begin{cases} 1 & \text{if } y_{i,t}^* > 0 \\ 0 & \text{if } y_{i,t}^* \leq 0 \end{cases} \quad (1)$$

A linear regression model is specified for the latent response y^* :

$$y_{i,t}^* = \beta' X_{i,t} + \varepsilon_{i,t} \quad (2)$$

where it is assumed that $E[\varepsilon|X] = 0$. The vector X is composed of macroeconomic and institutional variables that the literature has found to be relevant to explain the onset of banking crises, including dummy variables for the existence of a capital flow bonanza and for the presence of a lending boom, among other covariates. In order to reduce endogeneity issues and to attend the concern that the year of start of a banking crisis in [Laeven and Valencia \[2010\]](#) may lag the onset of the crisis, in the following analysis the covariates in X are lagged one period. Furthermore, to reduce the influence of observations affected by the outcome of crises the estimations are performed after eliminating the first three years of observations following a crisis.

Given equations (1) and (2) the probability of the start of a crisis in country i on year t , conditional on country's characteristics lagged one period, is given by:

$$Pr(y_{it} = 1|X_{i,t-1}) = Pr(\beta' X_{i,t-1} + \varepsilon_{i,t} > 0) = F(\beta' X_{i,t-1}) \quad (3)$$

In the literature the cumulative distribution function $F(\cdot)$ in equation (3) is usually assumed to be either the Logistic or the Normal distributions, so that a logit or probit model is estimated. The estimation procedure takes the log-likelihood function of the model and maximizes it with respect to the unknown parameters. One innovation of this paper is the use of complementary logarithmic regression (*cloglog*). In this case the function $F(\cdot)$ is assumed to be the cumulative distribution function (cdf) of the extreme value (Gumbel) distribution, so that $F(z) = 1 - \exp[-\exp(z)]$.²⁹ When the complementary logarithmic regressor is not defined, such as when including fixed effects, we rely on the familiar logit estimator.

In this non-linear framework the interpretation of the coefficients is not straightforward. While the sign of the coefficient does indicate the direction of the change, the magnitude depends on

²⁹This innovation is motivated from the fact that both logit and probit methods assume that the distribution is symmetric around zero. However, banking crises are rare events (i.e 97% of observations are zeros). The *cdf* of the extreme value distribution can take into account this feature of the data.

the slope of the cumulative distribution function at $z = \beta'X_{i,t-1}$. This is, a marginal change in a covariate will have different effects on the probability of a crisis depending on the country's initial crisis probability. Hence, in order to interpret the size of the effect of a given variable in the probability of a banking crisis it is preferred to use exponentiated coefficients. If it is a logit model, these exponentiated coefficients have a clear cut form and interpretation in the odds ratio $or = p/(1 - p)$, being $p = Pr(y = 1|X)$ –the probability of a positive outcome. In the case of the extreme value distribution and for a binary variable, the exponentiated coefficients have a similar interpretation in the hazard ratio $h = Pr(y = 1|X)/Pr(y = 0|X)$ –the probability of a positive outcome relative to the probability of no positive outcome. In what follows exponentiated coefficients will be reported and we will refer to them as odds ratios.

The dataset used in this paper is a panel of a large number of countries for the period 1973-2008. It is important to recognize that there may be within country unobserved heterogeneity (covariates may be correlated at the country-level). The literature usually tackles this problem estimating a random intercept binary outcome model. This strategy also attends the issue of potential omitted country-year specific variables that affect the likelihood of the dependent variable. We start the multivariate regression analysis in this framework and estimate the latent model of equation (2) with one-period lagged covariates assuming that there is a random country-specific component $\zeta_i|X_{i,t-1} \sim N(0, \sigma_\zeta^2)$.

Specifically, the analysis below estimates variations of the following empirical model:

$$y_{i,t}^* = \gamma\kappa_{i,t-1} + \lambda l_{i,t-1} + \delta(\kappa \times l)_{i,t-1} + \beta'X_{i,t-1} + \zeta_i + \xi_{i,t} \quad (4)$$

In this random-intercept model it is assumed that $E[\zeta|\kappa, l, X] = 0$ and $E[\xi|\kappa, l, X, \zeta] = 0$, so that both ζ and ξ are uncorrelated with the covariates.³⁰ Equation (4) separates the covariates for capital flow bonanzas (κ), lending booms (l) and the vector of controls X ; and also includes an interaction term of bonanzas and booms. The aim of this econometric analysis is to answer two questions: (i) whether surges in capital flows are associated with an increase in the likelihood of a systemic banking crisis, which can be answered by estimating equation (4) with no interaction term and evaluating the sign and statistical significance of $\hat{\gamma}$ ($H_o : \hat{\gamma} = 0$); and (ii) whether any effect of bonanzas is necessarily through a lending boom, which can be answered estimating the

³⁰If we further assume that there is a constant within country correlation of the idiosyncratic error, so that $Cor(\xi_{i,t}, \xi_{i,s}) = \rho$ we have the model known as random effects (RE).

model with an interaction term of bonanzas and booms and evaluating significance and sign of the coefficient for bonanzas ($H_o : \hat{\gamma} = 0$) and evaluating the linear combination of the two coefficients ($H_o : \hat{\gamma} + \hat{\delta} = 0$).

The vector X of one-period lagged controls is composed of two sets. The first set includes mechanisms through which banking crises may take place, following the discussion in section 2. The second set is composed of relevant controls normally used in the banking crises literature.

The first set of controls accounts for the mechanisms triggering banking crises, including an indicator variable for the existence of competition risk,³¹ an indicator dummy for a process of international financial liberalization,³² an index of banking supervision,³³ a (contemporaneous) dummy indicator for a currency crisis, a dummy indicator for the existence of an explicit deposit insurance scheme and a proxy for the existence of moral hazard –based on an interaction with deposit insurance.³⁴ Data appendix (Table 17) explains in detail all variables used in the analysis and their sources.

The second set of covariates relates to control variables that are usually included in the banking crises literature (also with a one-period lag), including a proxy for income, an index of institutional quality (*Polity2*),³⁵ a proxy for openness to trade, an indicator dummy for the existence of a fixed

³¹This is an index that takes four discrete values, from 0 to 3, with three representing the highest competition risk. It is computed as the interaction between a dummy variable for ‘financial liberalization’ that takes the value 1 if an elimination of interest rate controls has taken place in *any* of the previous five years, and an index of entry barriers to the banking industry (this index takes discrete values from 0 to 3, and is increasing in the liberalization level of the industry). The five year window is ad hoc, and aims to capture that the realization of financial risk from increased competition may take some years. The preferred specification is one in which competition risk does not come from the *level* of interest rate controls but is due to a liberalization process. In most of the literature it is the level of interest rate controls what proxies for financial liberalization. Here we try to capture the actual process of liberalization by measuring the change of interest rate controls, adjusted by the barriers to entry in the banking industry. We also experimented with the conventional dummy for financial liberalization (dummy of value 1 if no interest rates controls) and obtained similar results.

³²A process of international financial liberalization is proxied by the change in a *de jure* capital account openness index. This dummy variable takes value 1 if an international liberalization process has taken place in *any* of the last five years. An international liberalization process is defined as a positive change in the *de jure* current account openness index of Chinn and Ito [2008]. In the second set of controls we also include the level of the index to control for *de jure* openness.

³³The index takes four discrete values, from 0 to 3, and is increasing in the level of regulation of the industry.

³⁴Following the literature, this is captured by the interaction between increased competition risk and quality of institutions, given the existence or not of an explicit deposit insurance scheme. Competition risk is proxied by the interaction between an indicator dummy for a financial liberalization process in the last five years (elimination of interest rate controls). Quality of institutions is proxied by Polity IV Project discrete variable for quality of democratic institutions (Polity2), which takes discrete values from -10 to 10. The moral hazard variable used here, then, is a discrete variable that may take values from -10 to 10, with -10 representing the highest moral hazard (the combination of low quality of institutions and a process of liberalization in the presence of an explicit deposit insurance scheme).

³⁵In the baseline regressions the index of institutional quality used is the variable Polity2 from the Polity IV Project. This is mainly due to data availability. Nonetheless, we also experimented with the indexes of law and order and corruption from ICRG. The results don’t change.

exchange rate regime, the level of the real interest rate, the level of international reserves and output growth. This set of controls also includes the depreciation of the nominal exchange rate, which is also a good proxy for inflation, which in turn is a good proxy for macroeconomic instability.³⁶ This set of covariates also includes measures for *de facto* and *de jure* current account openness,³⁷ and the annual average of the Federal Funds rate –as a proxy for international monetary conditions.³⁸

Table 4 shows correlations for all variables used in the analysis. There are no serious issues of collinearity between the key variables of interest. As expected, variables related to income are correlated with variables of banking supervision, deposit insurance and quality of institutions. On the other hand, the proxy for current account openness (*kaopen*) is also correlated to income, banking supervision and quality of institutions. Despite some degree of correlation between these variables, the preference is to keep them in the estimation.³⁹

Table 5 reports results of estimating the baseline random intercept model (RE effects) of equation (4) using complementary logarithmic regression.⁴⁰ Six specifications are presented, along with some statistics of the regression and the log-likelihood of the estimation. The table presents exponentiated coefficients (odds ratios) and z statistics in parentheses.⁴¹

The first specification estimates the correlation of capital flows bonanzas and banking crisis with no control variables in the estimation. The coefficient is significant and positive. This essentially replicates the results of the non-parametric analysis above. Specification 2 estimates the model

³⁶We experimented with inflation, but the models with depreciation offered a better fit. The correlation between the two variables is 0.81 in the sample that uses no controls and 0.9531 in the sample that uses all covariates.

³⁷The proxy for *de facto* current account openness is the ratio of total foreign assets and liabilities to GDP, taken from Lane and Milesi-Ferretti [2007]. The proxy for *de jure* openness is the index *kaopen* from Chinn and Ito [2008].

³⁸We follow the literature to include relevant variables. For a detailed discussion of which variables the literature has found to be robust significant determinants of the likelihood of banking crises see Eichengreen and Arteta [2002] and Demirgüç-Kunt and Detragiache [2005]. In order to work with the most parsimonious model we only include robust and relevant variables found in the literature. Variables not found relevant in most of the literature and left out include fiscal indicators, such as public debt, tax revenue, and fiscal balance.

³⁹We experimented dropping *kaopen*, and results don't change. Note that correlations are computed with the same sample used in the empirical analysis; thus, correlations are computed after eliminating first three years following a crisis.

⁴⁰In the case of complementary logarithmic regression the model further assumes that $\xi_i|X_{i,t-1} \sim C(0, \sigma_\xi^2)$, where $C(\cdot)$ stands for the extreme value (Gumbel) distribution and $\sigma_\xi^2 = \pi^2/6$. Logit regressions were also estimated, and the results are basically the same. In the logit regression it is assumed that $\xi_i|X_{i,t-1} \sim \Lambda(0, \pi^2/3)$, where Λ stands for the Logistic distribution.

⁴¹The estimation is performed with a sample of up to 3,632 country-year pairs (number of observations). The regression uses data from up to 149 countries and a total of 121 systemic banking crises. When including both sets of covariates the sample shrinks to 1,214 country-year pairs and uses information from 61 countries and a total of 53 crises. In the sample of specification 1, a total of 97 countries (65%) experienced a crisis (percentage for developing countries is 63%, for high income countries is 74%). Of these, 21 countries endured two crises during the period. Argentina is the only country with more than two crises, and exhibits a tally of four events (note that these are independent events, in the sense that we are dropping observations following three years after a crisis took place). Table 18 makes explicit which countries and crises are used in the estimation.

including only the first set of covariates: lending booms,⁴² competition risk, international liberalization, currency crises and banking supervision. The coefficient for capital flows bonanzas is still significant and with a similar magnitude. The third specification adds the indicator for an explicit deposit insurance scheme and the proxy for moral hazard. Neither significance or magnitude of the coefficient of interest is fundamentally changed. The results suggest, then, that surges in capital inflows are correlated with an increase in the likelihood of systemic banking crises. The coefficient for bonanzas in the first three specifications is statistically different from zero at 1% level.

Column 4 adds an interaction term for bonanzas and booms (the simultaneous occurrence of a capital flow bonanza and a lending boom during the previous year). This allows to estimate the differential effect of a bonanza, given a boom absent or present –so far regressions suggest that there is a correlation between bonanzas and crises, but we cannot tell if this is so because bonanzas are associated with lending booms or if bonanzas have an independent effect. The effect of a bonanza in the absence of a boom is given by the estimated $\hat{\gamma}$ coefficient at the top of column 4, while the effect of bonanzas once a boom is under way is given by the linear combination of the estimated coefficients for bonanzas and the interaction with booms. At the bottom of the table we present the estimated exponentiated coefficient (odds ratio), standard errors, and a Wald test of joint significance ($H_o : \hat{\gamma} + \hat{\delta} = 0$). The results suggest that capital flow bonanzas are associated with a higher probability of a systemic banking crisis, even if a lending boom is absent ($\hat{\gamma} \neq 0$ at 5% level) or if it is present ($\hat{\gamma} + \hat{\delta} \neq 0$ at 1% level). An interpretation of these two results may be as suggesting that bonanzas are correlated with banking crises not only through lending booms, but also through some different channels. This is important because overborrowing is the mechanism that has captured most of the attention in the empirical and theoretical literatures linking capital flows and banking crises (see [Gavin and Hausmann \[1996\]](#); [Giannetti \[2007\]](#); [McKinnon and Pill \[1996\]](#)).

Columns 5 and 6 add to the former two specifications relevant controls that the literature on banking crises has suggested would explain the likelihood of a systemic banking crisis.⁴³ After including all these covariates the coefficient of bonanzas is still statistically significant at 1% (column 5) and the estimated differential effect of bonanzas given a lending boom present is still significant

⁴²Baseline model is estimated with lending booms identified using $\phi = 1$. Robustness checks are performed using intense booms identified with $\phi = 2$ and booms identified by [Gourinchas et al. \[2001\]](#).

⁴³As noted before, we include controls for the level of international reserves, level of the real interest rate, depreciation of the nominal exchange rate, an indicator for a fixed exchange rate regime, a measure of quality of institutions, openness of the current account, output growth and international interest rates

at a 1% level (bottom of column 6). The magnitude of both coefficients is roughly the same as in the other specifications. The estimated coefficient of bonanzas in the absence of a lending boom is significant at the 10% (top of column 6), and also has roughly the same magnitude as the estimate without these controls.

Expressing the results in odds ratios form gives an idea of the size of these effects. These coefficients report the marginal effects in multiplicative form and control for differences between the countries baseline odds of a crisis. The results suggest that, on average, the odds of a banking crisis taking place are between two and three times higher if a baseline (1sd) capital flow bonanza took place during the previous year. If a lending boom is underway, such a bonanza is associated with an increase in the the odds of a crisis by 4 times.

The results also suggest that the likelihood of a systemic crisis is increased by unusually large growth in domestic credit to the private sector (a lending boom), increased competition in the banking sector after a liberalization process and by a currency crisis. The results also suggest that better institutions are correlated with a smaller likelihood of crises. The proxy for moral hazard has the correct negative sign, which is represented by an odds ratio less than one, but it is statistically significant at 5% only when non including controls. Consistent with the existing literature discussed in section 2, international liberalization is found to be no statistically associated with banking crises –although, an increased level of integration to global financial flows seems to be associated with a higher likelihood of crises, as suggested by the significant coefficient of the proxy for *de facto* current account openness. The index of banking supervision exhibits the expected sign (i.e. odds ratios less than one correspond to coefficients with negative sign), but it is not statistically different from zero. This may be because its somewhat high correlation with other variables included in the estimation, such as deposit insurance, income, quality of institutions and current account openness.⁴⁴

Endogeneity

For the estimates of the random intercept model to be consistent and considered causal both of the assumptions $E[\zeta|\kappa, l, X] = E[\xi|\kappa, l, X, \zeta] = 0$ need to be met. However, it may be argued that the effect of a bonanza of capital flows may be endogenous at the country level: a country may have a weak banking regulation or lax capital controls, or some other country-specific factor that

⁴⁴The sign of the coefficients in second set of controls also are the ones one expects: odds ratio less than one (i.e. negative coefficients) for quality of institutions, output growth and trade openness, and odds higher than one for fixed exchange rate regimes. Variables such as current account openness and international interest rates do not have a clear cut expected sign from theory or empirical literatures.

affects both the likelihood of a crisis and the occurrence of surges in capital flows. In this case the covariate of interest κ may be correlated with the random intercept ζ_i and the estimates of the RE model would be inconsistent.

The assumption of exogeneity of a covariate $E(\zeta|\kappa, l, X) = 0$ can be relaxed by estimating a fixed effects model (FE), which is equivalent to estimating the random intercept model from equation (4) subtracting country-means for all variables (including the dependent variable). In essence, the FE model allows to capture unobserved time-invariant differences across countries. As discussed in Cameron and Trivedi [2005, p.727] and Wooldridge [2002, p.265] the FE model yields consistent estimates even if covariates are correlated with the country-specific effect ζ_i . Provided that assumption of independence of covariates relative to the idiosyncratic error is met ($E[\xi|\kappa, l, X, \zeta] = 0$), this regression can be considered causal.

Results of estimating a FE model of equation (4), assuming a Logistic distribution, are shown in Table 6. This is equivalent to a conditional logit estimation. This estimation only includes countries that have suffered a crisis, hence less observations, since the FE model excludes time-invariant variables. Estimated coefficients for capital flow bonanzas exhibit strong statistical significance and have roughly the same magnitude as before.

Another way to relax the exogeneity assumption $E(\zeta|\kappa, l, X = 0) = 0$ is by including an instrumental variable for the covariate that is suspected to be potentially endogenous. Following Mundlak [1978], Skrondal and Rabe-Hesketh [2004, p.52] suggest that this can be done by including the country (cluster) mean of the covariate we suspect is endogenous (see also Wooldridge [2002, p.487]). The country-mean is an instrumental variable for the covariate because it is correlated with the covariate but is uncorrelated with the random intercept ζ_i . An advantage of this procedure is that it allows for differences in the between and within effects of a covariate without losing the time-invariant observations. Table 7 reports the results of estimating the random intercept model of equation (4) including the country-means of capital flow bonanzas and the country-mean of the interaction term of bonanzas and booms, and including country means for all covariates (only specifications 3-6 are reported).⁴⁵ The estimates are in line with the ones obtained with the RE and FE models.⁴⁶

Thus, results from these fixed effects models suggest that the odds of a crisis are between two and three times higher if a baseline bonanza took place the year before (up to five times higher if a

⁴⁵Only results for variables of interest are reported. Complete output regression is presented in online appendix.

⁴⁶The estimated coefficient for the country-mean represents the difference in the between and within effects of capital flow bonanzas. The results suggest that this difference is not statistically different from zero.

lending boom is underway), and estimates are statistically significant at the 1% level. There is only evidence that baseline bonanzas have an independent effect from that of a lending boom ($\hat{\gamma} \neq 0$ at 10% and 1% levels in specifications 6 of FE and RE models). It is important to emphasize that these results can only be considered causal if the assumption of independence $E[\xi|\kappa, l, X, \zeta] = 0$ holds.

Is there a difference between mild or intense bonanzas?

So far the results above rely on the identification of bonanzas using a threshold of one standard deviation (1sd) from the smoothed series of net aggregate capital flows. To investigate if these results are being driven by these ad hoc threshold, the model is estimated using two additional thresholds for mild (0.5sd) and intense (2sd) bonanzas. Table 8 presents the results.⁴⁷ The estimates provide support for the hypothesis that capital flow bonanzas increase the likelihood of a crisis, beyond the association with a lending boom, and that this effect is larger during more extreme events. A 2sd bonanza increases the odds of a crisis the following year by up to seven times when no lending boom is underway. When a lending boom is present, a 2sd bonanza increases the odds of a crisis by up to 16 times. The effects of a mild (0.5sd) bonanza are much smaller, close to the magnitude of 1sd bonanzas. Note that the effect of bonanzas in the absence of a lending boom is significantly different from zero at the 5% level in both cases. However, the effect of mild bonanzas once a boom is underway is not statistically different from zero. Thus, the analysis suggest that only *large* surges in capital flows (intense bonanzas) have an independent association with banking crises.

Causality

It was emphasized that to be able to give a causal interpretation to the results above both assumptions $E[\zeta|\kappa, l, X] = E[\xi|\kappa, l, X, \zeta] = 0$ of the random intercept model must be met. Estimating the FE model allows to relax the first assumption. Encouraging, with the FE model the same results were obtained. However, it is also important to consider if the results may be driven by the association of capital flows and lending booms. If capital flows bonanzas and lending booms are correlated because bonanzas fuel credit as proposed in most of the literature, the results of regression of equation (4) cannot be considered causal because the covariate of booms would be determined *after* a bonanza has taken place. Despite the fact that the non-parametric analysis

⁴⁷The table only reports specifications 5 and 6 of RE and FE models. Complete output regression is presented in the online appendix.

above suggest that this is not the case (i.e. most lending booms are not associated with bonanzas), the model is estimated restricting the sample to only observations that do not exhibit a lending boom in the previous period. This regression can be given a causal interpretation provided that the covariates are independent from the idiosyncratic error (see discussion in [Angrist and Pischke \[2009, p.64\]](#)).

Table 9 reports the results of specification 5 (including all covariates). If surges in capital inflows are a robust determinant of banking crises one expects to find a positive, significant $\hat{\gamma}$ coefficient. The estimates suggest that surges in capital inflows, indeed, have an independent significant impact on the probability of a banking crisis, and that this is larger for more intense (2sd) bonanzas. The estimated odds ratios are quite similar to the ones obtained in the full sample. Note that these estimations use data from the same 61 countries, but only 34 crises. Thus, the majority of the crises used in the estimations so far have not been associated with a previous lending boom. Still, the magnitude of the effect of bonanzas is quite stable and in all cases significant at the 5% level.

As mentioned above, for the results of the multivariate econometric analysis to be considered causal we must consider the exogeneity assumption that the covariates are independent from the idiosyncratic error $E(\varepsilon_{i,t}|X_{i,t-1}) = 0$ in equation (2). This is the conditional independence assumption discussed by [Angrist and Pischke \[2009, p.53\]](#). This assumption holds if conditional on the controls, the covariate of interest is orthogonal to possible outcomes of the dependent variable.

It can be argued that capital flow bonanzas may be an endogenous variable in the model employed so far because there may be country-year unobservables (error $\varepsilon_{i,t}$) that affect both the probability of a crisis at t and the occurrence of capital flows bonanzas in $t - 1$. However, it is highlighted that the results have been obtained after including in the regression all factors that both theory and empirical literatures have proposed as potential links between surges in capital flows and banking crises. Also, the results are obtained after dropping three years of observations following a crisis and using one-period lagged explanatory variables. The regression results obtained under fixed effects and dropping lending booms may be considered causal if one is to believe that the regression actually meets the conditional independence assumption: conditional on covariates, capital flow bonanzas in a given year are orthogonal to the occurrence of a banking crises the following year. If so, the results suggest that conditional on everything else, including the quality of regulation and institutions, the presence or absence of a lending boom, a currency crises, a recent process of liberalization, the level of domestic and international interest rates and the level of international reserves, having an unusually *large* influx of capital can in itself cause a higher

probability of a systemic banking crisis.

Developing countries sample

One may wonder if these results hold if estimations are done only including developing countries. This also allows to ask whether the effect of capital flows bonanzas are larger in these countries. Table 10 presents results of estimating the model dropping high-income countries.⁴⁸ The results are consistent with the previous findings using the full sample: capital flow bonanzas are significant determinants of systemic banking crises, after controlling for lending booms and all relevant factors. Also, the odds of a crisis are higher when the bonanza is more intense. The estimation of this exercise does not suggest that the effect of bonanzas in developing countries on the odds of a crisis is larger than in the full sample, with the magnitude of the estimated effect being in the same ballpark. However, an intense windfall of international capital when a lending boom is underway dramatically increases the probability of a crisis in a developing country, and the odds of a crisis becomes 25 times higher. Note that when including the interacting term of *bonanza+boom* the statistical significance of 1sd bonanzas vanishes, suggesting a muted effect of baseline bonanzas in the absence of a lending boom in developing countries. Nonetheless, 0.5 and 2 s.d. bonanzas exhibit coefficients significant at the 5% level. We revisit the developing country sample below, when we study differences between regions and different income groups.

Robustness/Sensitivity checks

In order to rule out the possibility that the methodology is capturing the effect of rare events, the model is also estimated using as covariate the Hodrick-Prescott residuals used to identify bonanzas.⁴⁹ Table 11 shows results of this exercise. Consistent with what was found for bonanzas identified by 0.5, 1 and 2 standard deviations, the coefficient for capital flows residuals is positive and statistically significant for both country groups.

To explore if these results are being driven by the definition of capital flows we run the same specifications using capital flows defined as percentage of GDP. Furthermore, to rule out the possibility that the results are driven by the use of data from the financial account, the model is also estimated using bonanzas identified by [Reinhart and Reinhart \[2009\]](#), who used the current account balance. We also explore if the results are being driven by the definition of lending booms, using

⁴⁸Results shown only for RE and FE models using specification 6. Complete results reported in online appendix.

⁴⁹The results so far have been based on the deviations of observations of capital flows from a smoothed series (i.e. bonanzas were computed using residuals of Hodrick-Prescott filtered series). These residuals can be used as a proxy for unusually large capital flows.

two checks: first the model is estimated with booms defined as deviations of two or more standard deviations, to control for the size of lending booms; second, the model is estimated using data on lending booms from [Gourinchas et al. \[2001\]](#).⁵⁰ As another check, we run all the regressions using two different subsamples: 1973-2006 (dropping observations from recent financial crises) and 1985-2008 (because early data may be noisy, specially for developing countries).

Results of these robustness checks are reported in the online appendix. Encouraging, the results of these exercises are in line with the baseline results.

5. Do developing countries face higher risks from surges in capital flows?

Another way to check if there are differences for developing countries is estimating the model interacting capital flows bonanzas with an indicator for developing countries. We perform this exercise using indicators for developing status and for different regional and income groups.⁵¹ Table 12 reports summarized results for these exercises. The regressions are performed including an indicator for income or region and its interaction with bonanzas. The table shows the p -value of a F test for the joint significance of the two coefficients. The only difference in the estimated independent effect of bonanzas when including these indicators for developing status, region and income is that the fixed effects model of intense (2sd) bonanzas loses statistical significance when including the dummy for developing countries status (LDC).

The results don't suggest the existence of regional effects. Latin American countries are not more or less affected by bonanzas than Asian countries.⁵² Interestingly, the RE specifications suggest that there is a statistically significant effect of bonanzas in the case of developing countries: p -values of test of joint significance of interacting term and developing country indicator indicate significance at 1%. The same result is found for the groups of middle and upper income countries. This is not the case for low income countries.

⁵⁰In the latter case the lending boom indicator uses data on credit to private sector as percentage of GDP (as opposed to the per capita measure used in our baseline estimations). Data from [Gourinchas et al. \[2001\]](#) are only available up to 1996, which limits the data used in the estimation, but allows us to also check the stability of our results (changing the sample period).

⁵¹For this exercise we consider the regional and income classifications of the World Bank. Regions are Latin America and Caribbean (*Latam*), South Asia (*SouthAsia*), East Asia & Pacific (*EastAsia*), and one region for Middle East & North Africa & Sub-Saharan Africa (*MeAfr*). Income groups are low, middle and upper income. Note that this paper classifies South Korea, Czech Republic, Estonia, Hungary and Slovakia as upper middle income countries.

⁵²All these regressions include the region or income indicator and the interacting term. The income or region effect in the RE model is given by the F test for significance of the linear combination of the indicator and the interacting term with bonanza. The table reports the p -value of each test. In the case of the FE model, the indicator of region or income group is dropped because of no time-variation, and, thus, the region or income effect is given by the interacting term.

We explore the upper and middle income groups further. These are the countries that are considered *emerging markets* and enjoy a higher degree of financial development and international financial integration than the average developing country. These countries may exhibit a higher likelihood of crises after a windfall of capital because their institutions and prudential regulation may not be matured yet, but their vulnerability is heightened by their openness and integration to global markets. Table 13 reports the results of running the model restricting the sample only to upper and middle income countries. The results of both RE and FE models suggest a higher likelihood of crises after a bonanza for this group compared with the full sample or the sample including all developing economies (this is in line with the results from RE models using interacting terms). A bonanza of capital flows in these countries not only has a higher effect in the absence of a lending boom, but also the joint occurrence with a boom is associated with higher odds of a crisis the following year. As before, the effect of intense bonanzas seems to be larger. An interpretation of these results may be as evidence suggesting that bonanzas of international capital may have effects in other triggers of banking crises (asset price bubbles?) and it may be possible that characteristics of emerging economies make these countries more vulnerable under intense windfalls.

6. Does the composition of capital flows matter?

So far, there is some evidence indicating that surges in *aggregate* capital flows are associated with an increase in the likelihood of banking crises and that this effect does not operate uniquely through a lending boom mechanism. However, these results open new questions, specially regarding the mechanisms at play. One way to understand better the effect of surges in capital flows on banking crises is to look at the composition of flows.

As described before, the paper uses IFS BoP data to classify capital flows in three categories: FDI, portfolio and debt. Employing the threshold method proposed by [Mendoza and Terrones \[2008\]](#), bonanzas in real per capita capital flows for each category of flows are identified. Then, a similar regression analysis as in section 4.2 is performed, but including as explanatory variable an indicator dummy for a bonanza in each of the three types of flows. As before, estimates are obtained for capital flow bonanzas identified with a threshold of one and two standard deviations from trend.

Before presenting the results a caveat is necessary. The data suggest that most bonanzas in one type of flow are associated with bonanzas in the other categories. The conditional probability of a FDI bonanza, given a debt or a portfolio bonanza, is over 30%. The conditional probability of

a bonanza in portfolio flows given a bonanza in debt or FDI flows is, respectively, over 38% and 50%. When international capital markets get excited about one country, it seems that all types of flows fly into the country to profit from all the enthusiasm. The fact that the windfall seems to be across all types of flows make quite difficult the task of disentangling the effect of each category of flows.

With this caveat in mind, the model is estimated independently for each category of flows. Summarized results are presented in Table 14 for the sample including all countries and Tables 15 and 16 for developing countries.⁵³ Note that in these tables each column does not refer to a single regression, but estimates in each column are actually from three different regressions –one for each category of flows.

The results in the left panel of the table for baseline (1sd) bonanzas suggest that only bonanzas in portfolio and debt flows are positively associated with an increase in the likelihood of a systemic banking crisis. The odds of a banking crises in the current year are three times higher if a surge in debt flows took place the last year, and four times higher if the bonanza was in portfolio flows. Results of specification 6 suggest that surges in both types of flows are associated with an increase likelihood of crises even in the absence of a lending boom. The results for intense (2sd) bonanzas suggest the same. However, only 2sd bonanzas of portfolio flows are found to be correlated with crises in the absence of a lending boom. The increased likelihood of a crisis is also larger in the case of intense bonanzas (nine times in the case of portfolio flows).

On the other hand, the results suggest that in the case of a windfall of international capital, including FDI, at the same time that a lending boom is underway, the odds of a crises the following year increase dramatically (i.e. odds of a crisis are 10 times higher if an intense surge in debt or portfolio flows took place the previous year and a lending boom was underway. In the case FDI flows, these odds are eight times higher).

These results are similar when we restrict the sample to only developing countries, reported in Table 15. However, the increased in odds of a crisis is significantly higher for the case of bonanzas in portfolio flows and in the cases of a simultaneous boom and bonanza of portfolio or debt flows.⁵⁴ In the case of an intense bonanza in portfolio flows to a developing country, odds of a crisis are

⁵³To save space the paper only presents results for variables of interest. Complete regressions output is presented in the online appendix.

⁵⁴Robustness checks (not shown, but reported in online appendix) show that these results don't change when the model is estimated using lending booms defined by two standard deviations of cyclical component, or when restricting the sample up to 2006 or for 1985-2008.

17 times higher in the absence of a lending boom. If a boom is underway, the odds of a crisis are estimated to be 28 times higher.

The results are qualitatively the same if the sample is restricted to upper and middle income developing countries, reported in Table 16. However, in these emerging economies the odds of a crisis are significantly higher following a year in which large flows of debt take place jointly with a lending boom. This story fits the anecdotal evidence from many developing countries (e.g. [Gavin and Hausmann \[1996\]](#)). However, the results suggest that windfalls of portfolio flows are associated with a higher likelihood of future crises, even in the absence of a lending boom. For this, the literature does not have a good explanation.

7. Conclusions

Using a multivariate econometric model this paper shows that the likelihood of a crisis is positively associated with the existence of a previous bonanza in net capital flows, even after controlling for lending booms and other relevant factors. Given a baseline bonanza, the odds of a systemic banking crisis the following year are between two and three times higher. The results also suggest that the more intense is the bonanza (i.e. the more extreme is the windfall relative to business cycle trend) the larger is the ensuing increased risk and a crisis becomes seven times more likely.⁵⁵ The analysis suggest that not all surges in capital flows are independently associated with a higher likelihood of crises, but only *large* fluctuations (i.e. intense bonanzas, defined as growth in flows larger than two s.d. from trend). For mild surges, the evidence suggest that any association with crises operates through an excessive growth in lending. The results also suggest that windfalls of capital to developing countries, especially upper and middle income countries, are associated with a higher likelihood of banking crises in those countries. In the absence of a lending boom, a crisis is up to nine times more likely after an intense bonanza in these countries. Moreover, the joint occurrence of an intense bonanza and a lending boom significantly increases the odds of a crisis in these countries (odds are up to thirty times higher). Finally, the analysis yields results consistent with existing literature and show a strong association between systemic banking crises and lending booms, currency crises and increased competition risk in the financial industry.

When decomposing the capital flows bonanzas in FDI, portfolio and debt flows, the results suggest a strong association between crises and bonanzas in debt and portfolio flows, with the

⁵⁵Note that the unconditional probability of a systemic banking crisis is 3.33% in a baseline sample including crises in 97 countries in the period 1973-2008.

strongest association found for portfolio flows. A crisis is up to ten times more likely after an intense surge in portfolio flows. The results also suggest that the simultaneous occurrence of a windfall of international capital and a lending boom significantly increases the likelihood of a banking crisis. As before, the results suggest that developing countries face higher risks when facing large fluctuations in inflows or when surges occur at the same time as a lending boom. The magnitude of the effects suggest that there is a Pecking Order when it comes to the riskiness of international flows, being portfolio flows the riskiest.

Overall, the data show that most capital flows bonanzas die a natural death. However, the results suggest that when a bonanza is too misaligned with the business cycle, the odds of a crisis significantly increase –even more in the case of developing countries or surges in portfolio flows. It may be argued that imposing some sort of capital flow controls may be an alternative to reduce the likelihood of banking distress, specially controls on portfolio equity flows. However, the evidence suggesting that not only debt flows may be associated with increased financial risk, coupled with the fact that windfalls are often simultaneously across all categories of flows, make the actual implementation of benign capital controls a challenge.⁵⁶ Implementing capital controls may allow countries to temporarily isolate from short term debt flows, but are not a silver bullet to isolate countries from the risks of too much of a good thing. Authorities should also consider that surges in lending or in capital inflows are the natural outcome of financial deepening and financial integration and that these surges may be more benign than harmful. As argued in the model presented by [Ranciere et al. \[2008\]](#) and the empirical evidence shown in [Tornell and Westermann \[2005\]](#), the growth benefits from increased financial intermediation during boom-bust cycles might well surpass the negative effects of increased systemic risk and the occasional crisis. Thus, for countries interested in reducing the risks of financial meltdown, strengthening prudential regulation and cooling off the economy at early signs of both credit growth and asset price inflation may be the appropriate first response.

⁵⁶Most of the recent evidence on the effectiveness of capital controls suggest that controls are not effective in reducing the volume of flows, but are somewhat effective in changing the maturity of flows and may have the effect of bending the flows toward equity-like financial instruments. See surveys by [Ostry et al. \[2010\]](#) and IMF [[April, 2010](#)], and paper by [Binici et al. \[2010\]](#).

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8. Appendix

Table 1: Summary statistics. All countries, 1973-2008

Variable	Mean	Std. Dev.	Min.	Max.	Obs
Banking crisis (dummy)	0.033	0.179	0	1	3632
Agg. Kflow bonanza 1 sd (dummy)	0.177	0.382	0	1	3632
Agg. Kflow bonanza 2 sd (dummy)	0.098	0.297	0	1	3632
Lending boom 1 sd (dummy)	0.136	0.343	0	1	3491
Lending boom 2sd (dummy)	0.037	0.189	0	1	3491
Bon(1sd)+Boom(1sd) (dummy)	0.033	0.179	0	1	3491
Bon(1sd)+Boom(2sd) (dummy)	0.011	0.104	0	1	3491
Competition risk (discrete)	0.378	0.861	0	3	2201
Int. liberalization (dummy)	0.305	0.46	0	1	3430
Currency crisis (dummy)	0.033	0.178	0	1	3632
Banking supervision (discrete)	0.958	1.038	0	3	2201
Moral hazard (discrete)	0.656	2.622	-9	10	1522
(Explicit) Deposit insurance (dummy)	0.604	0.489	0	1	1764
KA Open	0.058	1.522	-1.831	2.5	3430
De facto CA openness	1.485	1.758	0.089	25.731	3498
Polity2 (discrete)	2.412	7.309	-10	10	3357
Reserves (\$ bn)	11.423	53.817	-0.001	1530.28	3513
Interest rate (%)	10.842	112.757	-97.812	5844.983	2970
GNI (\$)	5776.921	9321.460	90	77250	3374
Trade openness (% of GDP)	74.727	43.599	0.309	456.646	3475
Depreciation (%)	100.706	4406.558	-100	262826.844	3582
Fixed exchange rate (dummy)	0.647	0.478	0	1	3315
GDP growth (%)	3.767	4.833	-50.248	35.224	3462
FED effective discount rate(%)	6.347	3.412	1.126	16.386	3632

Table 2: Two way tables and independence tests of banking crises and previous year capital flow bonanzas. 1973-2008

Banking crisis	All countries Bonanzas 1 sd			Developing countries Bonanzas 1 sd			High income countries Bonanzas 1 sd		
	0	1	Total	0	1	Total	0	1	Total
0	2902	609	3511	2217	501	2718	685	108	793
	82.65	17.35	100	81.57	18.43	100	86.38	13.62	100
	97.09	94.71	96.67	96.90	94.89	96.52	97.72	93.12	97.18
1	87	34	121	71	27	98	16	7	23
	71.90	28.10	100	72.45	27.55	100	69.57	30.43	100.00
	2.91	5.29	3.33	3.10	5.11	3.48	2.28	6.09	2.82
Total	2989	643	3632	2288	528	2816	701	115	816
	82.30	17.70	100	81.25	18.75	100	85.91	14.09	100
	100	100	100	100	100	100	100	100	100
Observations		3632			2816			816	
Pearson_coef		9.284			5.162			5.220	
Pearson_sig		0.002			0.023			0.022	
LR_coef		8.228			4.682			4.175	
LR_sig		0.004			0.030			0.041	
Fishers_exact_p		0.004			0.034			0.032	

Notes: Each cell presents frequencies in first row, row percentages in second row and column percentages in third row.

Table 3: Two way tables and independence tests of banking crises and previous year capital flow bonanzas. 1973-2008

Banking crisis	All countries Bonanzas 2 sd			Developing countries Bonanzas 2 sd			High income countries Bonanzas 2 sd		
	0	1	Total	0	1	Total	0	1	Total
0	3175	336	3511	2440	278	2718	735	58	793
	90.43	9.57	100	89.77	10.23	100	92.69	7.31	100
	96.92	94.38	96.67	96.75	94.56	96.52	97.48	93.55	97.18
1	101	20	121	82	16	98	19	4	23
	83.47	16.53	100	83.67	16.33	100	82.61	17.39	100.00
	3.08	5.62	3.33	3.25	5.44	3.48	2.52	6.45	2.82
Total	3276	356	3632	2522	294	2816	754	62	816
	90.20	9.80	100	89.56	10.44	100	92.40	7.60	100
	100	100	100	100	100	100	100	100	100
Observations		3632			2816			816	
Pearson_coef		6.407			3.762			3.233	
Pearson_sig		0.011			0.052			0.072	
LR_coef		5.460			3.290			2.460	
LR_sig		0.019			0.070			0.117	
Fishers_exact_p		0.018			0.063			0.090	

Notes: Each cell presents frequencies in first row, row percentages in second row and column percentages in third row.

Table 4: Cross-correlations table. All countries, 1973-2008

Variables	Banking Crisis	Agg. KFlowBon(1sd)	Lending Boom (1sd)	Lending Boom (2sd)	Bon(1sd)+Boom(1sd)	Bon(1sd)+Boom(2sd)	Competition Risk	Int. Liberalization	Currency crisis (t)	Banking supervision	Deposit Insurance	Moral Hazard	KA open	De facto CA openness	Polity2	Reserves	Interest rate	GNI per capita	Trade openness	Depreciation (Nom ER)	Fixed exch. rate	GDP Growth	Fed effective funds rate
Banking Crisis	1.00																						
Agg. KFlowBon(1sd)	0.10	1.00																					
Lending Boom (1sd)	0.14	0.10	1.00																				
Lending Boom (2sd)	0.16	0.05	0.49	1.00																			
Bon(1sd)+Boom(1sd)	0.15	0.44	0.46	0.23	1.00																		
Bon(1sd)+Boom(2sd)	0.16	0.23	0.23	0.48	0.51	1.00																	
Competition Risk	0.05	-0.04	-0.04	-0.03	-0.03	-0.01	1.00																
Int. Liberalization	-0.04	0.03	0.00	-0.03	-0.02	-0.04	0.10	1.00															
Currency crisis (t)	0.16	-0.01	0.08	0.10	-0.03	-0.02	0.01	-0.05	1.00														
Banking supervision	-0.05	0.04	0.06	0.06	0.09	0.06	-0.21	0.10	-0.13	1.00													
Deposit Insurance	-0.06	0.01	0.05	0.03	0.04	0.04	-0.14	0.04	-0.12	0.57	1.00												
Moral Hazard	-0.04	-0.04	0.02	-0.01	-0.01	-0.02	0.47	0.06	-0.04	-0.06	0.18	1.00											
KA open	-0.07	0.04	0.02	0.05	0.04	0.04	-0.17	0.16	-0.18	0.55	0.41	0.04	1.00										
De facto CA openness	0.05	0.05	0.08	0.10	0.07	0.02	-0.11	-0.04	-0.05	0.46	0.21	-0.07	0.38	1.00									
Polity2	-0.08	-0.02	0.07	0.05	0.02	-0.01	-0.07	-0.00	-0.06	0.32	0.33	0.24	0.36	0.22	1.00								
Reserves	0.01	0.07	0.01	0.04	0.05	0.06	-0.09	-0.01	-0.04	0.19	0.18	-0.01	0.16	0.03	0.14	1.00							
Interest rate	0.14	-0.01	0.07	0.16	-0.01	-0.01	0.02	-0.03	-0.00	-0.06	-0.06	-0.00	-0.08	-0.02	-0.00	-0.01	1.00						
GNI per capita	0.01	0.02	0.08	0.09	0.04	0.02	-0.14	-0.08	-0.11	0.56	0.36	0.04	0.61	0.58	0.45	0.31	-0.04	1.00					
Trade openness	-0.03	0.04	0.04	0.06	0.09	0.08	-0.03	0.08	-0.08	0.32	0.11	-0.14	0.21	0.48	0.09	-0.13	-0.08	0.14	1.00				
Depreciation (Nom ER)	-0.00	0.07	-0.01	-0.01	-0.01	-0.00	-0.01	-0.02	-0.00	-0.03	-0.05	-0.01	-0.05	0.10	-0.04	-0.01	0.13	-0.02	0.01	1.00			
Fixed exch. rate	-0.03	0.10	-0.01	0.01	0.03	0.05	0.00	0.03	-0.11	0.02	-0.01	-0.02	0.18	0.05	0.06	-0.16	-0.06	-0.03	0.28	-0.04	1.00		
GDP Growth	-0.01	0.07	0.07	0.04	0.10	0.06	0.03	0.03	-0.05	0.05	0.04	-0.08	-0.03	-0.06	-0.19	-0.02	-0.04	-0.19	0.14	-0.15	0.12	1.00	
Fed effective funds rate	0.04	0.02	0.00	-0.01	-0.02	-0.01	0.02	-0.18	0.10	-0.51	-0.37	0.09	-0.23	-0.23	-0.11	-0.14	0.04	-0.17	-0.21	0.01	0.00	-0.16	1.00

Table 5: RE model. Regression of banking crises on aggregate bonanzas (1 sd). All countries, 1973-2008

	(1)	(2)	(3)	(4)	(5)	(6)
Agg. Bonanza (1sd)	1.839*** (3.012)	2.070*** (3.076)	2.623*** (3.701)	2.119** (2.152)	2.866*** (3.167)	2.187* (1.799)
Lending Boom (1sd)		3.607*** (5.673)	3.513*** (4.882)	2.878*** (3.158)	4.019*** (4.251)	3.167*** (2.821)
Competition Risk		1.190 (1.574)	1.430*** (2.838)	1.412*** (2.735)	1.464** (2.439)	1.458** (2.422)
Int. Liberalization		0.680 (-1.581)	0.611* (-1.782)	0.618* (-1.741)	0.909 (-0.279)	0.943 (-0.170)
Currency crisis (t)		2.973*** (3.122)	4.074*** (3.687)	4.318*** (3.798)	4.926*** (3.409)	5.297*** (3.551)
Banking supervision		0.907 (-0.888)	1.105 (0.682)	1.089 (0.578)	0.825 (-0.734)	0.810 (-0.805)
Deposit Insurance			0.787 (-0.747)	0.788 (-0.749)	0.828 (-0.473)	0.835 (-0.459)
Moral Hazard			0.904** (-2.074)	0.909** (-1.973)	0.927 (-1.299)	0.927 (-1.304)
Bon(1sd)+Boom(1sd)				1.716 (0.986)		2.026 (1.035)
KA open					0.812 (-1.269)	0.817 (-1.236)
De facto CA openness					1.186* (1.946)	1.192** (2.006)
Polity2					0.937** (-2.138)	0.939** (-2.083)
Reserves					1.001 (0.381)	1.001 (0.370)
Interest rate					1.001 (0.699)	1.001 (0.737)
GNI per capita					1.000** (1.988)	1.000** (2.023)
Trade openness					0.992 (-1.202)	0.992 (-1.308)
Depreciation (Nom ER)					1.000 (-0.578)	1.000 (-0.552)
Fixed exch. rate					1.334 (0.780)	1.343 (0.805)
GDP Growth					0.978 (-0.483)	0.976 (-0.525)
Fed effective funds rate					1.005 (0.083)	1.007 (0.124)
BonIFBoomB				3.6352		4.4303
BonIFBoomSE				1.5236		2.3510
BonIFBoomPval				0.0021		0.0050
Obs	3632	2108	1466	1466	1214	1214
Countries	149	89	62	62	61	61
Crises	121	89	71	71	53	53
Loglik	-526.459	-341.018	-254.083	-253.592	-180.592	-180.055
Regression	cloglog	cloglog	cloglog	cloglog	cloglog	cloglog

Exponentiated coefficients; z statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Dependent variable is dummy for start of banking crisis. All specifications include lagged dummy for capital flow bonanza. Columns 2-6 include lagged covariates of lending boom (dummy), competition risk (increasing discrete variable), international liberalization (dummy), banking supervision (increasing discrete variable) and dummy for (contemporaneous) currency crisis. Specifications 3-6 include lagged covariates for moral hazard (decreasing discrete variable) and dummy for explicit deposit insurance. Specifications 5 and 6 add lagged covariates for *de jure* and *de facto* current account openness, quality of institutions, reserves, domestic interest rate, income, trade openness, depreciation, dummy for fixed exchange rate regime, output growth, and international interest rate. cloglog refers to the regressor assuming a Gumbel distribution. logit refers to the regressor assuming a Logist distribution.

Table 6: FE model. Regression of banking crises on aggregate bonanzas (1 sd). All countries, 1973-2008

	(1)	(2)	(3)	(4)	(5)	(6)
Agg. Bonanza (1sd)	2.121*** (3.437)	2.080*** (2.750)	2.500*** (3.030)	2.106* (1.909)	3.420*** (2.841)	2.771* (1.911)
Lending Boom (1sd)		4.179*** (5.511)	4.549*** (4.939)	3.910*** (3.634)	4.528*** (3.382)	3.749** (2.499)
Competition Risk		1.192 (1.332)	1.502** (2.553)	1.498** (2.530)	1.583** (2.264)	1.574** (2.229)
Int. Liberalization		0.572* (-1.937)	0.486** (-2.139)	0.489** (-2.120)	0.503 (-1.397)	0.508 (-1.381)
Currency crisis (t)		2.471** (2.272)	3.606*** (2.793)	3.748*** (2.862)	4.403** (2.424)	4.578** (2.493)
Banking supervision		0.920 (-0.558)	1.322 (1.315)	1.313 (1.277)	0.577 (-1.369)	0.584 (-1.337)
Deposit Insurance			0.516 (-1.479)	0.521 (-1.449)	1.408 (0.547)	1.486 (0.623)
Moral Hazard			0.887* (-1.907)	0.888* (-1.891)	0.952 (-0.619)	0.954 (-0.594)
Bon(1sd)+Boom(1sd)				1.603 (0.729)		1.905 (0.706)
KA open					1.032 (0.132)	1.041 (0.166)
De facto CA openness					2.208** (2.197)	2.232** (2.237)
Polity2					0.933 (-1.183)	0.931 (-1.213)
Reserves					0.997 (-0.766)	0.997 (-0.753)
Interest rate					1.002 (0.644)	1.001 (0.708)
GNI per capita					1.000** (2.034)	1.000** (1.981)
Trade openness					0.990 (-0.619)	0.988 (-0.689)
Depreciation (Nom ER)					1.000 (-0.136)	1.000 (-0.149)
Fixed exch. rate					2.381 (1.583)	2.419 (1.607)
GDP Growth					0.961 (-0.719)	0.962 (-0.696)
Fed effective funds rate					1.097 (1.269)	1.099 (1.299)
BonIFBoomB				3.3763		5.2774
BonIFBoomSE				1.7232		3.9770
BonIFBoomPval				0.0171		0.0273
Obs	2363	1650	1305	1305	794	794
Countries	97	67	53	53	39	39
Crises	121	89	71	71	53	53
Loglik	-351.491	-230.626	-173.639	-173.372	-94.163	-93.912
Regression	logit	logit	logit	logit	logit	logit

Exponentiated coefficients; z statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Dependent variable is dummy for start of banking crisis. All specifications include lagged dummy for capital flow bonanza. Columns 2-6 include lagged covariates of lending boom (dummy), competition risk (increasing discrete variable), international liberalization (dummy), banking supervision (increasing discrete variable) and dummy for (contemporaneous) currency crisis. Specifications 3-6 include lagged covariates for moral hazard (decreasing discrete variable) and dummy for explicit deposit insurance. Specifications 5 and 6 add lagged covariates for *de jure* and *de facto* current account openness, quality of institutions, reserves, domestic interest rate, income, trade openness, depreciation, dummy for fixed exchange rate regime, output growth, and international interest rate. cloglog refers to the regressor assuming a Gumbel distribution. logit refers to the regressor assuming a Logist distribution.

Table 7: RE model with country means. Regression of banking crises on aggregate bonanzas (1 sd). All countries, 1973-2008

	Including only bonanza mean			Including ALL means				
	(3)	(4)	(5)	(6)	(7)	(8)		
Agg. Bonanza (1sd)	2.850*** (3.902)	2.918*** (3.120)	3.857*** (4.195)	3.460*** (3.096)	2.842*** (3.904)	2.874*** (3.089)	4.375*** (4.270)	3.530*** (3.029)
Lending Boom (1sd)	3.870*** (5.119)	3.957*** (4.145)	5.028*** (4.773)	4.473*** (3.532)	3.905*** (5.109)	3.947*** (4.114)	5.896*** (4.639)	4.596*** (3.248)
Competition Risk	1.389** (2.564)	1.392** (2.574)	1.412** (2.169)	1.412** (2.168)	1.550*** (2.987)	1.552*** (2.999)	1.613*** (2.652)	1.622*** (2.692)
Int. Liberalization	0.636 (-1.624)	0.634 (-1.636)	0.930 (-0.211)	0.945 (-0.165)	0.537** (-2.077)	0.535** (-2.089)	0.737 (-0.805)	0.729 (-0.832)
Currency crisis (t)	4.065*** (3.674)	4.012*** (3.575)	4.340*** (3.148)	4.483*** (3.184)	3.685*** (3.249)	3.663*** (3.184)	3.377** (2.295)	3.664** (2.425)
Banking supervision	1.124 (0.792)	1.128 (0.810)	0.844 (-0.659)	0.845 (-0.652)	1.272 (1.263)	1.274 (1.272)	0.629 (-1.366)	0.620 (-1.390)
Moral Hazard	0.911* (-1.928)	0.909* (-1.928)	0.933 (-1.182)	0.935 (-1.150)	0.874** (-2.295)	0.873** (-2.296)	0.920 (-1.189)	0.919 (-1.215)
Bon(1sd)+Boom(1sd)	0.981 (-0.033)	0.981 (-0.033)	1.300 (0.379)	1.300 (0.379)	1.014 (0.024)	1.014 (0.024)	1.833 (0.772)	1.833 (0.772)
mm_lagkflowbon	0.387 (-0.727)	0.400 (-0.694)	0.237 (-0.813)	0.235 (-0.788)	0.385 (-0.682)	0.408 (-0.633)	2.816 (0.423)	1.186 (0.061)
Controls Deplns	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls 2	No	No	Yes	Yes	No	No	Yes	Yes
BonIFBoomB		2.8617		4.4989		2.9149		6.4711
BonIFBoomSE		1.3498		2.5498		1.3850		4.3409
BonIFBoomPval		0.0258		0.0080		0.0243		0.0054
Obs	1455	1455	1214	1214	1455	1455	1214	1214
Countries	62	62	61	61	62	62	61	61
Crises	70	70	53	53	70	70	53	53
Loglik	-247.878	-247.834	-174.005	-173.842	-245.002	-244.962	-147.300	-146.571
WaldTestChi2	2.3751	2.4669	4.9111	4.7487	8.0031	8.1314	46.9552	46.6003
WaldTestPval	0.3050	0.4813	0.0858	0.1911	0.4332	0.5210	0.0002	0.0004
Regression	cloglog	cloglog	cloglog	cloglog	cloglog	cloglog	cloglog	cloglog

Exponentiated coefficients; z statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: See Table 5.

Table 8: RE and FE models. Regression of banking crises on mild (0.5sd) and intense (2sd) aggregate bonanzas. All countries, 1973-2008

	Mild (0.5sd) bonanzas			Intense (2sd) bonanzas		
	(5) RE	(6) RE	(5) FE	(6) RE	(5) RE	(6) FE
Agg. Bonanza	3.212*** (3.979)	3.044*** (3.120)	3.279*** (3.302)	3.290*** (2.934)	6.353*** (4.370)	7.134*** (2.500)
Lending Boom (1sd)	3.792*** (4.030)	3.430** (2.430)	4.294*** (3.279)	4.330** (2.278)	3.620*** (3.847)	3.210** (2.238)
Competition Risk	1.435** (2.321)	1.435** (2.322)	1.548** (2.197)	1.548** (2.196)	1.439** (2.314)	1.552** (2.133)
Int. Liberalization	0.917 (-0.253)	0.920 (-0.243)	0.522 (-1.303)	0.521 (-1.302)	0.952 (-0.142)	0.555 (-1.195)
Currency crisis (t)	4.313*** (3.107)	4.304*** (3.101)	3.314* (1.926)	3.314* (1.926)	5.492*** (3.654)	4.701*** (2.605)
Moral Hazard	0.924 (-1.367)	0.925 (-1.367)	0.941 (-0.795)	0.941 (-0.794)	0.922 (-1.368)	0.946 (-0.696)
Bon()+Boom(1sd)		1.186 (0.265)		0.985 (-0.018)	3.296 (1.411)	2.319 (0.717)
Controls Deplns	Yes	Yes	Yes	Yes	Yes	Yes
Controls 2	Yes	Yes	Yes	Yes	Yes	Yes
BonIFBoomB		3.6083		3.2413	10.9387	16.5423
BonIFBoomSE		1.9147		2.4042	6.1547	14.2902
BonIFBoomPval		0.0156		0.1129	0.0000	0.0012
Obs	1214	1214	794	794	1214	794
Countries	61	61	39	39	61	39
Crises	53	53	53	53	53	53
Loglik	-177.278	-177.243	-92.468	-92.468	-177.027	-89.884
Regression	cloglog	cloglog	logit	logit	cloglog	logit

Exponentiated coefficients; z statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: See Table 5.

Table 9: RE and FE models. Regression of banking crises on aggregate bonanzas. No previous lending boom. All countries, 1973-2008

	1sd bonanzas		Mild (0.5sd) bonanzas		Intense (2sd) bonanzas	
	(5) RE	(5) FE	(5) RE	(5) FE	(5) RE	(5) FE
Agg. Bonanza	2.318* (1.925)	2.959** (1.968)	3.265*** (3.257)	3.404*** (2.789)	4.415** (2.213)	5.431** (2.070)
Competition Risk	1.327 (1.643)	1.626** (1.972)	1.309 (1.573)	1.586* (1.891)	1.318 (1.634)	1.610* (1.934)
Int. Liberalization	0.646 (-1.035)	0.373 (-1.542)	0.658 (-0.984)	0.353 (-1.603)	0.658 (-0.996)	0.411 (-1.402)
Currency crisis (t)	5.022*** (3.084)	3.988** (1.990)	4.999*** (3.141)	3.362* (1.702)	5.473*** (3.332)	4.062** (2.053)
Banking supervision	0.746 (-0.921)	0.731 (-0.624)	0.763 (-0.852)	0.705 (-0.671)	0.749 (-0.933)	0.672 (-0.762)
Deposit Insurance	1.151 (0.324)	2.028 (0.882)	1.025 (0.057)	1.809 (0.728)	1.221 (0.464)	2.582 (1.230)
Moral Hazard	0.966 (-0.538)	0.960 (-0.436)	0.950 (-0.791)	0.944 (-0.636)	0.965 (-0.571)	0.946 (-0.596)
KA open	1.011 (0.065)	1.181 (0.608)	0.974 (-0.153)	1.176 (0.603)	1.027 (0.162)	1.161 (0.548)
De facto CA openness	1.246* (1.933)	2.926* (1.931)	1.226* (1.827)	2.736* (1.909)	1.232* (1.881)	2.600* (1.771)
Polity2	0.949 (-1.565)	0.908 (-1.332)	0.947 (-1.644)	0.904 (-1.404)	0.944* (-1.743)	0.901 (-1.442)
Reserves	1.001 (0.431)	0.993 (-0.794)	1.002 (0.526)	0.996 (-0.555)	1.001 (0.478)	0.994 (-0.738)
Interest rate	1.003 (1.040)	1.002 (0.451)	1.003 (1.152)	1.001 (0.396)	1.003 (1.086)	1.001 (0.282)
GNI per capita	1.000 (-0.649)	1.000 (1.620)	1.000 (-0.634)	1.000 (1.555)	1.000 (-0.788)	1.000 (1.638)
Trade openness	0.989 (-1.331)	0.977 (-1.057)	0.989 (-1.273)	0.976 (-1.111)	0.988 (-1.442)	0.978 (-1.066)
Depreciation (Nom ER)	1.000 (-0.687)	1.000 (-0.214)	1.000 (-0.727)	1.000 (-0.169)	1.000 (-0.577)	1.000 (-0.168)
Fixed exch. rate	0.874 (-0.322)	1.043 (0.060)	0.931 (-0.173)	1.160 (0.208)	0.903 (-0.246)	1.119 (0.163)
GDP Growth	0.986 (-0.281)	1.005 (0.086)	0.999 (-0.018)	1.015 (0.252)	0.979 (-0.434)	0.997 (-0.052)
Fed effective funds rate	0.972 (-0.434)	1.113 (1.251)	0.969 (-0.482)	1.104 (1.138)	0.984 (-0.257)	1.105 (1.194)
Obs	1057	463	1057	463	1057	463
Countries	61	26	61	26	61	26
Crises	34	34	34	34	34	34
Loglik	-131.067	-67.019	-127.597	-64.900	-130.888	-67.029
Regression	cloglog	logit	cloglog	logit	cloglog	logit

Exponentiated coefficients; z statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: See Table 5.

Table 10: RE and FE models. Regression of banking crises on aggregate bonanzas. Developing countries, 1973-2008

	1sd bonanzas		Mild (0.5sd) bonanzas		Intense (2sd) bonanzas	
	(6) RE	(6) FE	(6) RE	(6) FE	(6) RE	(6) FE
Agg. Bonanza	1.887 (1.336)	1.711 (0.920)	2.651** (2.528)	2.780** (2.249)	7.258*** (3.018)	6.560** (2.110)
Lending Boom (1sd)	1.544 (0.818)	2.386 (1.380)	1.191 (0.226)	2.043 (0.830)	1.387 (0.628)	1.978 (1.084)
Bon()+Boom(1sd)	2.722 (1.183)	2.988 (1.038)	2.010 (0.764)	1.644 (0.465)	2.206 (0.827)	3.589 (0.918)
Competition Risk	1.556*** (2.645)	1.504** (1.973)	1.483** (2.340)	1.523** (2.020)	1.484** (2.382)	1.479* (1.835)
Int. Liberalization	0.731 (-0.811)	0.540 (-1.149)	0.762 (-0.693)	0.545 (-1.077)	0.735 (-0.785)	0.568 (-1.044)
Currency crisis (t)	4.974*** (3.428)	4.496** (2.525)	3.694*** (2.781)	3.542** (2.024)	5.156*** (3.534)	4.732*** (2.633)
Banking supervision	0.698 (-1.174)	0.534 (-1.381)	0.721 (-1.079)	0.546 (-1.309)	0.616 (-1.495)	0.421* (-1.737)
Deposit Insurance	1.006 (0.016)	1.447 (0.526)	1.030 (0.072)	1.342 (0.423)	1.146 (0.349)	1.605 (0.680)
Moral Hazard	0.961 (-0.572)	0.975 (-0.294)	0.963 (-0.537)	0.961 (-0.473)	0.965 (-0.487)	0.980 (-0.231)
KA open	1.004 (0.022)	0.999 (-0.003)	0.960 (-0.250)	0.979 (-0.082)	1.016 (0.093)	0.996 (-0.014)
De facto CA openness	1.784*** (2.697)	1.963 (1.342)	1.950*** (3.102)	2.439* (1.688)	1.847** (2.553)	1.689 (1.059)
Polity2	0.986 (-0.431)	0.898* (-1.717)	0.973 (-0.861)	0.904 (-1.631)	0.971 (-0.892)	0.879** (-1.964)
Reserves	1.000 (0.131)	0.991 (-1.577)	1.001 (0.209)	0.992 (-1.400)	0.998 (-0.448)	0.988* (-1.742)
Interest rate	1.001 (0.518)	1.003 (0.765)	1.002 (0.802)	1.003 (0.887)	1.001 (0.516)	1.003 (0.791)
GNI per capita	1.000** (2.079)	1.000** (2.368)	1.000** (2.070)	1.000** (2.202)	1.000** (2.527)	1.000** (2.468)
Trade openness	0.988 (-1.639)	0.982 (-0.973)	0.989 (-1.622)	0.979 (-1.167)	0.988* (-1.717)	0.985 (-0.822)
Depreciation (Nom ER)	1.000 (-0.468)	1.000 (-0.342)	1.000 (-0.585)	1.000 (-0.356)	1.000 (-0.205)	1.000 (-0.309)
Fixed exch. rate	1.857 (1.561)	2.419 (1.521)	1.834 (1.518)	1.962 (1.105)	1.645 (1.240)	2.161 (1.315)
GDP Growth	0.966 (-0.785)	0.991 (-0.147)	0.979 (-0.461)	1.004 (0.069)	0.957 (-1.010)	0.997 (-0.058)
Fed effective funds rate	1.075 (1.195)	1.066 (0.819)	1.064 (1.014)	1.061 (0.749)	1.088 (1.404)	1.068 (0.828)
BonIFBoomB	5.1361	5.1104	5.3287	4.5698	16.0139	23.5444
BonIFBoomSE	3.7043	4.5661	4.4427	4.4632	11.9526	24.9830
Obs	697	523	697	523	697	523
Countries	42	29	42	29	42	29
Crises	42	42	42	42	42	42
Loglik	-130.674	-78.961	-128.355	-77.132	-124.854	-74.401
Regression	cloglog	logit	cloglog	logit	cloglog	logit

Exponentiated coefficients; z statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: See Table 5.

Table 11: RE and FE models. Regression of banking crises on deviations (HP residulas) of aggregate capital flows (per capita). All and developing countries, 1973-2008

	All countries				Developing countries			
	(5) RE	(6) RE	(5) FE	(6) FE	(5) RE	(6) RE	(5) FE	(6) FE
Agg. Bonanza (hpres)	1.001*** (2.704)	1.001 (1.435)	1.002** (2.368)	1.002** (2.109)	1.005*** (3.243)	1.006*** (2.617)	1.004** (2.143)	1.004* (1.682)
Lending Boom (1sd)	4.056*** (4.182)	3.485*** (3.505)	4.513*** (3.358)	4.644*** (3.313)	1.766 (1.307)	1.906 (1.373)	3.169** (2.192)	2.847* (1.777)
Competition Risk	1.434** (2.295)	1.405** (2.148)	1.554** (2.201)	1.557** (2.210)	1.506** (2.470)	1.502** (2.455)	1.489* (1.934)	1.466* (1.841)
Int. Liberalization	0.932 (-0.206)	0.924 (-0.232)	0.515 (-1.364)	0.512 (-1.376)	0.684 (-0.979)	0.677 (-1.000)	0.559 (-1.056)	0.582 (-0.974)
Currency crisis (t)	4.665*** (3.345)	4.715*** (3.376)	3.658** (2.195)	3.649** (2.190)	3.994*** (3.055)	3.932*** (3.000)	3.507** (2.098)	3.492** (2.087)
Moral Hazard	0.927 (-1.282)	0.923 (-1.340)	0.941 (-0.746)	0.943 (-0.726)	0.955 (-0.672)	0.953 (-0.704)	0.964 (-0.427)	0.965 (-0.419)
Bon(hpres)+Boom(1sd)		1.001 (1.527)		1.000 (-0.250)		0.999 (-0.399)		1.002 (0.452)
Controls Deplns	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls 2	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BonIFBoomB		1.0017		1.0020		1.0046		1.0063
BonIFBoomSE		0.0006		0.0011		0.0019		0.0047
BonIFBoomPval		0.0056		0.0722		0.0134		0.1783
Obs	1171	1171	780	780	697	697	523	523
Countries	61	61	39	39	42	42	29	29
Crises	53	53	53	53	42	42	42	42
Loglik	-178.383	-177.222	-93.412	-93.382	-128.629	-128.551	-78.518	-78.413
Regression	cloglog	cloglog	logit	logit	cloglog	cloglog	logit	logit

Exponentiated coefficients; z statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: See Table 5.

Table 12: RE and FE models. Regression of banking crises on aggregate bonanzas. All countries, 1973-2008

	1sd bonanzas		Mild (0.5sd) bonanzas		Intense (2sd) bonanzas	
	(6) RE	(6) FE	(6) RE	(6) FE	(6) RE	(6) FE
<i>Developing country indicator (LDC)</i>						
Agg. Bonanza	4.766*	17.015**	5.517**	6.263*	4.446*	7.149
	(1.942)	(2.298)	(2.402)	(1.876)	(1.685)	(1.503)
Bon+LDC	0.385	0.127	0.471	0.469	1.299	0.997
	(-1.136)	(-1.609)	(-0.972)	(-0.740)	(0.285)	(-0.002)
BonLDCPval	0.0000		0.0000		0.0000	
<i>Regional indicators</i>						
Agg. Bonanza	1.973	3.953*	3.095**	3.948**	3.138	6.837*
	(1.112)	(1.651)	(2.171)	(2.186)	(1.575)	(1.864)
Bon+Latam	0.840	0.442	1.151	0.951	0.934	0.191
	(-0.221)	(-0.769)	(0.199)	(-0.057)	(-0.054)	(-1.034)
Bon+SouthAsia	0.000	0.000	0.000	0.000	0.000	0.000
	(-0.002)	(-0.007)	(-0.003)	(-0.015)	(-0.001)	(-0.013)
Bon+EastAsia	8.446*	5.049	3.799	4.292	7.642*	8.249
	(1.715)	(1.118)	(1.098)	(1.101)	(1.757)	(1.354)
Bon+MeAfr	0.000	0.000	0.164	0.115	0.000	0.000
	(-0.003)	(-0.014)	(-1.480)	(-1.638)	(-0.001)	(-0.016)
BonLatamPval	0.4798		0.1949		0.5705	
BonSouthasiaPval	0.9983		0.9979		0.9991	
BonEastasiaPval	0.1614		0.2707		0.1095	
BonMeafrPval	0.9974		0.2430		0.9991	
<i>Income indicators</i>						
Agg. Bonanza	4.730*	18.272**	5.405**	6.063*	5.414*	10.666*
	(1.863)	(2.319)	(2.350)	(1.815)	(1.915)	(1.882)
Bon+Low	0.000	0.000	0.000	0.000	0.000	0.000
	(-0.005)	(-0.014)	(-0.003)	(-0.020)	(-0.000)	(-0.011)
Bon+Middle	0.788	0.395	0.964	1.116	2.299	1.960
	(-0.261)	(-0.673)	(-0.042)	(0.096)	(0.823)	(0.477)
Bon+Upper	0.281	0.082*	0.476	0.526	0.986	0.531
	(-1.306)	(-1.757)	(-0.852)	(-0.573)	(-0.013)	(-0.390)
BonLowincomePval	0.9970		0.9980		0.9998	
BonMiddleincomePval	0.0000		0.0000		0.0000	
BonUpperincomePval	0.0004		0.0000		0.0001	
Controls DepIns	Yes	Yes	Yes	Yes	Yes	Yes
Controls 2	Yes	Yes	Yes	Yes	Yes	Yes
Obs	1214	794	1214	794	1214	794
Countries	61	39	61	39	61	39
Crises	53	53	53	53	53	53
Regression	cloglog	logit	cloglog	logit	cloglog	logit

Exponentiated coefficients; z statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: See Table 5. Regions are Latin America and Caribbean (*Latam*), South Asia (*SouthAsia*), East Asia & Pacific (*EastAsia*), and one region for Middle East & North Africa & Sub-Saharan Africa (*MeAfr*).

Table 13: RE and FE models. Regression of banking crises on aggregate bonanzas. Upper and middle income developing countries, 1973-2008

	1sd bonanzas		Mild (0.5sd) bonanzas		Intense (2sd) bonanzas	
	(6) RE	(6) FE	(6) RE	(6) FE	(6) RE	(6) FE
Agg. Bonanza	2.296*	2.358	3.651***	4.364***	8.981***	8.571**
	(1.661)	(1.361)	(3.028)	(2.799)	(3.241)	(2.173)
Credit Boom (1sd)	1.877	2.234	1.689	2.779	1.690	1.817
	(1.133)	(1.093)	(0.660)	(1.057)	(0.966)	(0.815)
Bon()+Boom(1sd)	2.480	6.153	1.543	1.354	1.661	3.517
	(1.026)	(1.530)	(0.460)	(0.255)	(0.528)	(0.828)
Competition Risk	1.415	0.964	1.327	0.973	1.419*	1.009
	(1.618)	(-0.136)	(1.290)	(-0.097)	(1.734)	(0.033)
Int. Liberalization	0.729	0.463	0.752	0.462	0.734	0.523
	(-0.760)	(-1.258)	(-0.665)	(-1.175)	(-0.740)	(-1.053)
Currency crisis (t)	6.406***	9.248***	4.238***	4.819**	6.931***	9.230***
	(3.560)	(3.011)	(2.795)	(2.193)	(3.938)	(3.062)
Banking supervision	0.726	0.421*	0.776	0.460	0.656	0.377*
	(-0.981)	(-1.661)	(-0.795)	(-1.445)	(-1.236)	(-1.725)
Deposit Insurance	1.098	0.925	1.118	0.989	1.395	1.093
	(0.198)	(-0.094)	(0.229)	(-0.013)	(0.758)	(0.106)
Moral Hazard	0.983	1.129	0.985	1.090	0.959	1.099
	(-0.201)	(1.193)	(-0.184)	(0.855)	(-0.481)	(0.916)
KA open	0.987	0.929	0.943	0.993	1.020	0.903
	(-0.072)	(-0.244)	(-0.340)	(-0.024)	(0.116)	(-0.343)
De facto CA openness	1.741**	1.376	1.939***	2.054	1.817**	1.184
	(2.321)	(0.577)	(2.745)	(1.240)	(2.137)	(0.311)
Polity2	0.978	0.857**	0.962	0.883*	0.962	0.851**
	(-0.571)	(-2.195)	(-1.007)	(-1.749)	(-1.053)	(-2.307)
Reserves	1.000	0.988*	1.001	0.991	0.999	0.989
	(0.065)	(-1.700)	(0.190)	(-1.445)	(-0.416)	(-1.490)
Interest rate	1.001	1.002	1.001	1.002	1.001	1.002
	(1.045)	(0.802)	(0.455)	(0.649)	(0.876)	(0.749)
GNI per capita	1.000*	1.001***	1.000	1.000**	1.000**	1.001***
	(1.665)	(2.599)	(1.551)	(2.191)	(2.052)	(2.579)
Trade openness	0.988	0.989	0.987*	0.979	0.988	0.988
	(-1.622)	(-0.561)	(-1.650)	(-0.980)	(-1.615)	(-0.594)
Depreciation (Nom ER)	1.000	1.000	1.000	1.000	1.000	1.000
	(-0.465)	(-0.224)	(-0.577)	(-0.354)	(-0.151)	(-0.243)
Fixed exch. rate	2.429*	6.242**	2.265*	4.009*	1.994	4.896**
	(1.959)	(2.448)	(1.765)	(1.736)	(1.574)	(2.174)
GDP Growth	0.951	0.960	0.957	0.967	0.943	0.962
	(-1.065)	(-0.639)	(-0.885)	(-0.489)	(-1.243)	(-0.578)
Fed effective funds rate	1.072	1.084	1.061	1.079	1.090	1.090
	(1.061)	(0.934)	(0.885)	(0.842)	(1.382)	(1.000)
BonIFBoomB	5.6944	14.5078	5.6319	5.9076	14.9210	30.1421
BonIFBoomSE	4.2563	15.0125	4.7307	6.4346	11.1052	35.1283
BonIFBoomPval	0.0200	0.0097	0.0396	0.1029	0.0003	0.0035
Obs	577	440	577	440	577	440
Countries	35	25	35	25	35	25
Crises	37	37	37	37	37	37
Loglik	-108.702	-60.485	-105.332	-59.251	-103.444	-57.778
Regression	cloglog	logit	cloglog	logit	cloglog	logit

Exponentiated coefficients; z statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: See Table 5.

Table 14: RE and FE models. Regression of banking crises on bonanzas decomposing flows (per capita). All countries, 1973-2008

	1sd Bonanzas			Intense 2sd Bonanzas		
	(5)	(6)	(5)	(6)	(5)	(6)
FDI bonanza	RE cloglog 1.764 (1.322)	RE cloglog 1.945 (1.196)	FE logit 1.279 (0.445)	FE logit 1.542 (0.649)	RE cloglog 3.297** (2.339)	FE logit 2.744 (1.606)
FDI bonanza+Boom(1sd)		0.801 (-0.263)	0.597 (-0.460)	0.597 (-0.460)	1.191 (0.183)	4.437 (1.059)
BonIFBoomB		1.5567	0.9208	0.9208	3.6669	8.1785
BonIFBoomPval		0.4939	0.9279	0.9279	0.0902	0.0794
Obs	1214	1214	794	794	1214	794
Countries	61	61	39	39	61	39
Crises	53	53	53	53	53	53
Portfolio bonanza	3.135*** (3.017)	3.719*** (3.047)	3.907*** (2.823)	4.074*** (2.644)	4.124*** (2.996)	9.622*** (3.822)
Portfolio bonanza+Boom(1sd)		0.577 (-0.764)	0.832 (-0.185)	0.832 (-0.185)	0.591 (-0.634)	1.010 (0.008)
BonIFBoomB		2.1448	3.3886	3.3886	2.8778	9.6946
BonIFBoomPval		0.2301	0.1793	0.1793	0.1589	0.0340
Obs	1187	1187	794	794	1187	794
Countries	60	60	39	39	60	39
Crises	53	53	53	53	53	53
Debt bonanza	2.660*** (2.943)	2.460** (2.095)	2.667** (2.278)	2.747** (2.038)	4.602*** (3.264)	1.254 (0.195)
Debt bonanza+Boom(1sd)		1.225 (0.295)	0.903 (-0.118)	0.903 (-0.118)	6.468 (1.480)	10.492 (1.559)
BonIFBoomB		3.0137	2.4803	2.4803	8.4222	13.1542
BonIFBoomPval		0.0394	0.2261	0.2261	0.0003	0.0070
Obs	1187	1187	794	794	1187	794
Countries	60	60	39	39	60	39
Crises	53	53	53	53	53	53

Exponentiated coefficients; z statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: See Table 5.

Table 15: RE and FE models. Regression of banking crises on bonanzas decomposing flows (per capita). Developing countries, 1973-2008

	1sd Bonanzas				Intense 2sd Bonanzas			
	(5)	(6)	(5)	(6)	(5)	(6)	(5)	(6)
	RE cloglog	RE cloglog	FE logit	FE logit	RE cloglog	RE cloglog	FE logit	FE logit
FDI bonanza	1.118 (0.223)	1.073 (0.111)	1.058 (0.087)	1.297 (0.347)	3.148** (1.978)	1.986 (0.887)	2.994 (1.525)	2.088 (0.852)
FDI bonanza+Boom(1sd)		1.117 (0.105)		0.540 (-0.461)		3.897 (1.217)		5.175 (0.964)
BonIF'BoomB		1.1991		0.7009		7.7401		10.8066
BonIF'BoomPval		0.8262		0.7512		0.0177		0.1165
Obs	697	697	523	523	697	697	523	523
Countries	42	42	29	29	42	42	29	29
Crises	42	42	42	42	42	42	42	42
Portfolio bonanza	3.118*** (2.698)	3.300*** (2.585)	5.125*** (3.031)	4.963*** (2.713)	5.473*** (2.923)	5.522*** (2.716)	18.930*** (4.140)	17.173*** (3.778)
Portfolio bonanza+Boom(1sd)		0.777 (-0.288)		1.155 (0.136)		0.967 (-0.037)		1.674 (0.428)
BonIF'BoomB		2.5629		5.7313		5.3374		28.7491
BonIF'BoomPval		0.2419		0.0754		0.0604		0.0055
Obs	691	691	523	523	691	691	523	523
Countries	41	41	29	29	41	41	29	29
Crises	42	42	42	42	42	42	42	42
Debt bonanza	2.580** (2.440)	2.472** (1.997)	2.774** (2.041)	3.033** (2.021)	5.032*** (2.682)	1.544 (0.380)	5.014* (1.859)	1.023 (0.018)
Debt bonanza+Boom(1sd)		1.175 (0.186)		0.673 (-0.368)		7.851 (1.551)		32.499* (1.913)
BonIF'BoomB		2.9040		2.0423		12.1189		33.2554
BonIF'BoomPval		0.1512		0.4625		0.0013		0.0068
Obs	691	691	523	523	691	691	523	523
Countries	41	41	29	29	41	41	29	29
Crises	42	42	42	42	42	42	42	42

Exponentiated coefficients; z statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: See Table 5.

Table 16: RE and FE models. Regression of banking crises on bonanzas decomposing flows (per capita). Upper and middle income developing countries, 1973-2008

	1sd Bonanzas			Intense 2sd Bonanzas		
	(5)	(6)	(5)	(6)	(5)	(6)
FDI bonanza	1.296 (0.494)	1.323 (0.419)	1.385 (0.468)	1.619 (0.596)	3.525** (2.119)	2.761 (1.346)
FDI bonanza+Boom(1sd)		0.947 (-0.050)		0.604 (-0.348)		5.459 (0.991)
BonIF'BoomB		1.2534		0.9786		10.1592
BonIF'BoomPval		0.7895		0.9860		0.1262
Obs	577	577	440	440	577	440
Countries	35	35	25	25	35	25
Crises	37	37	37	37	37	37
Portfolio bonanza	2.910** (2.328)	3.202** (2.307)	4.700*** (2.687)	4.745** (2.417)	4.847** (2.420)	13.937*** (3.543)
Portfolio bonanza+Boom(1sd)		0.675 (-0.432)		0.964 (-0.033)		1.615 (0.373)
BonIF'BoomB		2.1612		4.5722		20.3088
BonIF'BoomPval		0.3552		0.1371		0.0166
[0.5em] Obs	577	577	440	440	577	440
Countries	35	35	25	25	35	25
Crises	37	37	37	37	37	37
Debt bonanza	3.232*** (2.830)	3.218** (2.412)	5.590*** (3.029)	5.380*** (2.730)	5.434*** (2.747)	7.256** (2.052)
Debt bonanza+Boom(1sd)		1.016 (0.018)		1.213 (0.165)		49.247** (2.019)
BonIF'BoomB		3.2704		6.5273		54.9058
BonIF'BoomPval		0.1221		0.0882		0.0040
Obs	577	577	440	440	577	440
Countries	35	35	25	25	35	25
Crises	37	37	37	37	37	37

Exponentiated coefficients; z statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: See Table 5.

Table 17: Data description

Variable	Definition	Source
Banking crises	Dummy variable that takes value 1 if a crisis starts in that year. A crisis is defined as a systemic banking crisis, as explained in the text.	Laeven and Valencia [2008]
Capital flows bonanzas	Bonanzas are defined as an episode in which real per capita net capital flows grow more than during a typical business cycle expansion. We use a country specific measure of the business cycle. Please see description of threshold method in the paper.	Computed using data from IFS database, International Monetary Fund
Aggregate net capital flows	Capital flows data from Balance of Payments statistics IFS dataset. Net capital flows are equal to balance in financial account (line 78bjd in IFS BoP data). To obtain net capital flows by category, we add reported assets and liabilities in IFS BoP data. We disaggregate flows into three categories: (i) FDI, (ii) portfolio, and (iii) debt.	IFS database, International Monetary Fund
FDI net flows	Net FDI flows are obtained adding lines 78bdd (for assets) and 78bed (for liabilities).	IFS database, International Monetary Fund
Portfolio net flows	Portfolio flows are defined as the sum of lines for portfolio investments and financial derivatives, minus debt securities. To obtain portfolio assets we add lines 78bfd + 78bwd - 78bld. To compute portfolio liabilities we add lines 78bgd + 78bxd - 78bnd. To obtain net portfolio flows we add computed portfolio assets and liabilities.	IFS database, International Monetary Fund
Debt net flows	Net debt flows are obtained as a residual. Since total net capital flows are equal to the balance in the financial account, we compute debt net flows by subtracting FDI and portfolio net flows from the balance in the financial account.	IFS database, International Monetary Fund
Lending booms	Booms are defined as an episode in which real credit per capita to the private sector grows more than during a typical business cycle expansion. We use a country specific measure of the business cycle. Please see description of threshold method in the paper.	Computed using data from WDI database. World Bank
Domestic credit to private sector	Variable FS.AST.PRVT.GD.ZS in WDI database. Original data is as percentage of GDP. Using GDP per capita in constant prices (US dollars, 2000=100) (series NY.GDP.PCAP.KD), a series of per capita real credit to private sector is obtained. For countries with missing GDP data, GDP per capita in US dollars was used (NY.GDP.PCAP.CD).	WDI database. World Bank
Competition risk	Variable that takes discrete values from 0 to 3, with three representing the highest competition risk. It is computed as the interaction between a dummy that takes the value 1 if an elimination of interest rate controls has taken place in any of the previous five years and an index of entry barriers to the banking industry.	Computed using data from Abiad et al. [2010]
Financial liberalization	Dummy variable that takes the value of one if an elimination of interest rate controls has taken place in any of the previous five years. Elimination of interest rate controls is proxied as a positive change in an index of interest rate controls.	Computed using data from Abiad et al. [2010]
Interest rate controls	Index of interest rate controls, considering both deposit and lending rates. Index is based in regulation of rates, considering if rates are set by the government or subject to a binding ceilings or bands, or if rates are freely floating. Index takes discrete values from 0 to 4, with 4 being fully liberalized.	Abiad et al. [2010]
Entry barriers to banking industry	Index of barrier to entry in the banking industry. Index evaluates how easy is for foreign banks to enter the domestic market, restrictions for new domestic banks, restrictions on branching and restrictions on universal banking. Index takes discrete values from 0 to 5, and is increasing in the liberalization level of the banking industry.	Abiad et al. [2010]
International liberalization	Dummy variable that takes value 1 if an international liberalization process has taken place in the last five years. This is proxied by a positive change in the capital account openness index (kaopen).	Computed using data from Chinn and Ito [2008]
KA open	Index that measures the extent of openness in capital account transactions (it tries to capture the extent and intensity of capital controls). It is built based on the binary dummy variables that codify the tabulation of restrictions on cross-border financial transactions reported in the IMF's Annual Report on Exchange Arrangements and Exchange Restrictions (AREAER). The index is continuous and increasing in the openness of the capital account transactions. For the available sample it ranges in the interval [-1.8, 2.5].	Chinn and Ito [2008]

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Table 17 – Continued

Variable	Definition	Source
Moral hazard	Discrete variable that may take values from -10 to 10, with -10 representing the highest moral hazard (the combination of low quality of institutions and a process of financial liberalization in the presence of an explicit deposit insurance scheme). This variable is computed as the interaction between a dummy for the existence of an explicit deposit insurance scheme, a variable for competition, and a proxy for quality of institutions. Competition is proxied by the interaction between an indicator dummy for a financial liberalization process (elimination of interest rate controls) with and indicator dummy for the elimination of barriers to entry in the banking industry. Quality of institutions is proxied by Polity IV project discrete variable for strength of democratic institutions (Polity2),	Computed using data from Abiad et al. [2010] and Polity IV project
Deposit insurance	Dummy variable that takes value of 1 if an explicit deposit insurance scheme is in place.	Demirgüç-Kunt et al. [2005]
Banking supervision Index	Banking supervision index. It is increasing in the level of regulation of the banking system. The index is built using four dimensions: (i) adoption of Basle standards on capital adequacy, (ii) independence of banking supervisory agency from executive's influence, (iii) existence and effectiveness of on-site and off-site examinations by the supervisory agency, and (iv) spectrum of financial institutions covered by the supervisory agency. Index goes from 0 to 6 and is increasing in the level of regulation (however, the highest index awarded in the database is 3).	Abiad et al. [2010]
GDP growth	Annual percentage change in real GDP (US dollars, 2000=100). Variable FS.AST.PRVT.GD.ZS in WDI database.	WDI database. World Bank
Income Dummy	Dummy variable that takes value 1 if country is high income country. Income group is that of World Bank. High income countries include all OECD countries, plus Hong Kong, Israel, Kuwait and Slovenia. However, some OECD members are classified as developing countries: Chile, Czech Republic, Hungary, Korea, Mexico, Poland, and Slovak Republic, and Turkey.	World Bank, OECD
GNI per capita	GNI per capita, Atlas method (current US\$) Variable NY.GNP.PCAP.CD in WDI.	WDI database. World Bank
Polity2	Combined polity score (index) of strength of democratic institutions designed by Polity IV Project. The index is discrete and ranges from -10 to +10 and is increasing in the strength/quality of democratic institutions.	Polity IV Project
Trade Openness	Total trade (sum of exports and imports of goods and services) as a percentage of GDP. Variable NE.TRD.GNFS.ZS in WDI.	WDI database. World Bank
Terms of trade change	Annual percentage change in terms of trade index (2000=100). Terms of trade index is variable TT.PRI.MRCH.XD in WDI.	WDI database. World Bank
Depreciation	Annual percentage change in official nominal exchange rate (LCU per US\$, period average). Variable PA.NUS.FCRF in WDI database.	WDI database. World Bank
Exchange rate regime	"Coarse" classification of exchange rate regimes. The index goes from 1 to 6 and is increasing in the flexibility of the regime. 1 is for pegs, 2 is for narrow bands and crawling pegs; 3 is for managed floats and wider bands; 4 is for flexible regimes, and 5 refers to what the authors call "rely falling". When there is a dual market, the index is 6.	Iizetzki et al. [2008]
Currency crises	Dummy variable that takes value 1 if a crisis starts in that year; zero otherwise. A currency crisis is defined as a nominal depreciation of the currency of at least 30% that is also at least a 10% increase in the rate of depreciation compared to the year before.	Laeven and Valencia [2008]
Reserves	Total reserves minus gold. Comprises special drawing rights, reserves of IMF members held by the IMF, and holdings of foreign exchange under the control of monetary authorities. Gold holdings are excluded. Data are in current U.S. dollars. Variable FI.RES.XGLD.CD in WDI.	WDI database. World Bank
Real interest rate	Real interest rate is variable FR.INR.RINR from WDI, which is the lending interest rate adjusted for inflation as measured by the GDP deflator. For countries with no real interest rate available, we used either the lending rate or the deposit rate and adjust for GDP deflator.	WDI database. World Bank
Fed Effective Funds Rate	This is the annual average of the daily effective funds rate reported by the FRED database of the Federal Reserve Bank of St. Louis.	Federal Reserve Bank of St. Louis

Table 18: Sample of countries. Year of systemic banking crises in parenthesis

High income countries			
<i>Used in specification 6 of multivariate econometric analysis</i>			
Austria (2008)	Germany (2008)	Norway (1991)	United States (1988*, 2007)
Belgium (2008)	Greece (2008*)	Portugal (2008*)	
Canada (none)	Ireland (2008)	Spain (1976, 2008*)	
Denmark (2008)	Italy (none)	Sweden (1974, 2008*)	
Finland (1991)	Japan (1997)	Switzerland (2008*)	
France (2008*)	Netherlands (2008)	United Kingdom (2007)	
<i>Used only in specification 1 and non-parametric analysis</i>			
Australia (none)	Iceland (2008)	Kuwait (none)	Singapore (none)
Hong Kong (none)	Israel (1977)	New Zealand (none)	Slovenia (2008*)
Developing countries			
<i>Used in specification 6 of multivariate econometric analysis</i>			
Albania (1994)	Estonia (none)	Nigeria (1991)	Venezuela (1994)
Algeria (1990)	Guatemala (none)	Paraguay (1995)	Vietnam (1997)
Argentina (1980, 1989, 1995*, 2001)	Hungary (1991, 2008*)	Peru (1983)	Zimbabwe (1995)
Bangladesh (1987)	India (1993)	Philippines (1983, 1997*)	
Belarus (1995)	Indonesia (1997)	Poland (1992)	
Brazil (1990*)	Jamaica (1996)	Romania (1990)	
Bulgaria (1996)	Jordan (1989)	Russia (1998, 2008*)	
Chile (1976, 1981)	Kenya (1985, 1992)	Sri Lanka (1989)	
Colombia (1982, 1998)	Korea (1997)	Tanzania (1987)	
Czech Republic (1996*)	Latvia (1995, 2008)	Thailand (1997, 1983)	
Dominican Republic (2003)	Lithuania (1995)	Turkey (1982, 2000)	
Ecuador (1982, 1998)	Mexico (1981, 1994)	Uganda (1994)	
El Salvador (1989)	Nicaragua (1990, 2000)	Ukraine (1995)	
<i>Used only in specification 1 and non-parametric analysis</i>			
Angola (none)	Cote d'Ivoire (none)	Kyrgyz Republic (1995)	Pakistan (none)
Armenia (1994)	Croatia (1998)	Laos (none)	Panama (1988)
Azerbaijan (none)	Djibouti (none)	Lesotho (none)	Papua New Guinea (none)
Barbados (none)	Dominica (none)	Libya (none)	Rwanda (none)
Belize (none)	Egypt (1980)	Macedonia (none)	Sao Tome and Principe (none)
Benin (1988)	Equatorial Guinea (none)	Madagascar (1988)	Saudi Arabia (none)
Bolivia (1986, 1994)	Ethiopia (none)	Malawi (none)	Senegal (1988)
Bosnia and Herzegovina (none)	Fiji (none)	Malaysia (1997)	Sierra Leone (1990)
Botswana (none)	Gabon (none)	Maldives (none)	Slovakia (1998)
Burkina Faso (1990)	Gambia (none)	Mali (1987)	South Africa (none)
Burundi (1994)	Georgia (none)	Mauritania (1984)	Sudan (none)
Cambodia (none)	Ghana (1982)	Mauritius (none)	Suriname (none)
Cameroon (1987, 1995)	Grenada (none)	Moldova (none)	Swaziland (1995)
Cape Verde (1993)	Guinea (1993)	Mongolia (none)	Syria (none)
Central African Republic (1995)	Guinea-Bissau (none)	Morocco (1980)	Togo (1993)
Chad (1983, 1992)	Guyana (1993)	Mozambique (1987)	Trinidad and Tobago (none)
China (1998)	Haiti (1994)	Myanmar (none)	Tunisia (1991)
Comoros (none)	Honduras (none)	Namibia (none)	Uruguay (1981, 2002)
Congo, Republic of (1992)	Iran (none)	Nepal (1988)	Yemen (1996)
Costa Rica (1987, 1994)	Kazakhstan (2008*)	Niger (1983)	Zambia (none)

Notes: Borderline systemic banking crises are denoted with *. Source [Laeven and Valencia \[2010\]](#)