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

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

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WORKING PAPER. COMMENTS WELCOME*

Abstract

This paper asks whether bonanzas (surges) in net capital inflows increase the probability of banking crises and whether this is necessarily through a lending boom mechanism. A fixed effects regression analysis indicates that a baseline bonanza, identified as a surge of one s.d. deviation from trend, increases the odds of a banking crisis by three times, even in the absence of a lending boom. Larger windfalls of capital (two s.d. bonanzas) increase these odds by seven times. The joint occurrence of a bonanza and a lending boom raises the odds even more. Decomposing flows in FDI, portfolio-equity and debt indicates that bonanzas in all flows increase the probability of crises when the windfall takes place jointly with a lending boom; but only surges in portfolio-equity flows do so in the absence of a lending boom. Furthermore, emerging economies exhibit greater odds of crises after a windfall of capital.

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1. Introduction

This paper empirically explores whether or not bonanzas (surges) in net capital inflows increase the likelihood of systemic banking crises and whether this association is necessarily through a lending boom mechanism. The paper preforms a multivariate econometric analysis based on fixed effects models and uses data on aggregate and disaggregated flows (FDI, debt and portfolio-equity) for a large number of countries in the period 1973-2008. The methodology focuses on disentangling the effects of windfalls of capital from that of lending booms, and on controlling for potential endogeneity issues. Results indicate that a baseline bonanza, defined as one standard deviation from trend, is associated with odds of a crisis three times greater. Larger bonanzas (two s.d.) increase these odds by seven times. Odds of a crisis are even greater after the joint occurrence of a bonanza and a lending boom. Interestingly, the increased probability of a crisis after a bonanza is significant even in the absence of lending booms. Decomposing the flows indicates that surges in portfolio-equity flows are associated with a higher likelihood of banking crises, even in the absence of excessive lending, while the perverse effects of debt flows operate mainly through lending booms. Overall, the results provide robust evidence that windfalls of international capital increase the likelihood of crises, not only through the traditional mechanisms related to debt flows and "overlending," but also through mechanisms related to portfolio-equity flows and even in the absense of excessive lending.

At least since Díaz-Alejandro (1985), authors have argued that surges in capital inflows heightens macroeconomic and financial risks, particularly after processes of financial liberalization. The argument is that increased international capital inflows, especially in the form of debt, allow the financial sector a larger pool of funds from which to lend, fueling excessive growth in lending. This is problematic because lending booms exacerbate the intrinsic asymmetric information and moral hazard problems of banking, raising the likelihood of bank distress (Gavin and Hausmann (1996), Goldstein and Turner (1996), Mishkin (1996)).[1]. The theoretical literature emphasizes this bonanza-boom-bust cycle narrative (McKinnon and Pill (1996), Giannetti (2007)), and adds to it features such as financial liberalization processes (Daniel and Jones (2007)), bailout guarantees

[1] Macroeconomic concerns also stem from upward pressure on asset prices and increased exposure to currency and maturity mismatches (a fixed exchange regime exacerbates these risks). From a macroeconomic perspective, bonanzas may undermine competitiveness by appreciating the real exchange rate. Sterilization also imposes challenges to monetary authorities. For an early discussion of the policy challenges imposed by bonanzas see Schadler *et al.* (1993), Calvo *et al.* (1993) and Fernández-Arias and Montiel (1996). For a recent treatment and an analysis of regularities around bonanzas see Reinhart and Reinhart (2009), Cardarelli *et al.* (2010), Ostry *et al.* (2010), IMF (2010) and Forbes and Warnock (2011)

and deposit insurance schemes (Corsetti *et al.* (1999)).[2]

The current state of the world economy, with tepid output growth and record-low interest rates in rich countries, has bolstered concerns in high-growth emerging economies about the desirability of windfalls of capital. Similarly, part of the discussion on the recent Global Financial Crisis emphasizes the role of international capital flows as a factor exacerbating the vulnerability of the financial system (Portes (2009), Reinhart and Rogoff (2009, Chp. 13)). However, despite the conventional presumption linking banking crises with lending booms fueled by surges in capital inflows,[3] the empirical literature has provided limited support for such a conclusion.[4]

On one hand, there is no robust evidence on the association between surges in capital inflows and lending booms.[5] This lack of evidence is despite excessive growth in lending before a banking crisis, as shown in the first two panels of Figure 1 and by Schularick and Taylor (Forthcoming), and despite significant growth in net capital inflows before crises (see lower panels of Figure 1). On the other hand, most authors do not find a statistically significant association between the level of capital inflows and banking crises. Despite differing samples and econometric techniques, none of the following empirical papers yields significant results: Sachs *et al.* (1996), Eichengreen and Rose (1998), Radelet and Sachs (1998), Fernández-Arias and Hausmann (2001), Eichengreen and Arteta (2002) and Mendis (2002). Only Bonfiglioli (2008) finds a significant association between banking crises and the stock of foreign liabilities in developed countries, but she does not find any association in developing economies.

Moreover, our understanding of which flows are associated with crises is limited. Joyce (2010) is, to my knowledge, the first to study the association between different types of flows and the

[2]The intrinsic illiquidity of banks' assets and the asymmetric information in the banking industry are microeconomic characteristics making banks prone to crises. Bailout guarantees exacerbate risks stemmed from moral hazard and incentives to too much risk-taking, while liberalization raises the likelihood of crises because it underpins competition among banks and decreases franchise values, providing conditions for excessive risk taking by bankers (Aizenman (2004)). Furthermore, windfalls of capital may be the outcome of processes of financial liberalization as argued by Daniel and Jones (2007).

[3]This conventional perspective is 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". Similarly, Reinhart and Rogoff (2009, p.157) assert that "one common feature of the run-up to banking crises is a sustained surge in capital inflows."

[4]I refer specifically to the literature on banking crises. For studies exploring the effects of capital inflows on currency crises see Eichengreen (2003) and on sudden stops see Edwards (2007), Calvo *et al.* (2008) and Agosín and Huaita (Forthcoming).

[5]For example, Sachs *et al.* (1996) find no association between lending booms and surges in capital inflows during crises in the nineties. Gourinchas *et al.* (2001), using data up to 1999, report only a small increase in capital inflows during lending booms. Similarly, Mendoza and Terrones (2008), using data spanning 1960-2006, report only a weak association between lending booms and surges in capital inflows.

probability of banking crises. Joyce (2010) estimates a multivariate binary outcome model, using data up to 2002 for twenty emerging economies on the stock of foreign liabilities decomposed in FDI, portfolio-equity and portfolio-debt. He reports a robust positive association between the stock of debt liabilities and the likelihood of banking crises, and weak evidence of a negative correlation between crises and the stock of equity liabilities (FDI and portfolio).

The literature's most serious limitation is the focus on measures of the *level* of inflows (or stock) and the lack of attempts to identify surges in international capital. Given this focus on proxies for levels, these studies are not informative about the theoretical mechanism linking banking crises and *surges* in capital inflows suggested in the literature. As with openness in trade, different countries can have different levels of capital inflows or foreign liabilities, and those differences do not have to be related to a greater likelihood of crises. Similarly, a limitation of Bonfiglioli (2008), Joyce (2010) and other papers based on the stock of foreign liabilities, is the valuation effects embedded in those measures, which render them less than a good proxy for capital inflows.

Reinhart and Reinhart (2009) are, to my knowledge, the first authors to systematically identify episodes of unusual growth in capital inflows, and to study their relationship with banking crises. They ask how economies perform in and around "capital flow bonanzas," defined as periods when current account deficits deteriorate beyond a threshold. They find that bonanzas are associated with a greater incidence of banking, currency, sovereign and inflation crises in developing countries. Their analysis is limited to aggregate data, with the results based on comparing conditional and unconditional probabilities of each type of crisis. A limitation of this methodology, however, is that it does not control for other country-specific factors that may be associated with the onset of the crisis, the bonanza, or both.

In this paper I explore these issues. The contribution is along three dimensions. Quantifying the effect of bonanzas in net capital inflows on the probability of banking crises. Identifying bonanzas in the aggregate and by type of flow (FDI, portfolio-equity and debt) using country-specific trends.[6] Performing a multivariate fixed-effects regression analysis, focused on disentangling the effects of surges in international capital from the effects of lending booms. The analysis controls

[6] A bonanza is defined as a significant deviation from the business cycle trend. Baseline bonanzas are defined as deviations of one s.d., intense bonanzas as deviations of two s.d. and mild bonanzas as deviations of 0.5 s.d. Similar methods are employed by Gourinchas *et al.* (2001) and Mendoza and Terrones (2008) for lending booms, and by Cardarelli *et al.* (2010) and Forbes and Warnock (2011) for capital flows. Agosín and Huaita (Forthcoming) and Reinhart and Reinhart (2009) also use a threshold method, but do not include in the definition of bonanzas information from the country business cycle.

for mechanisms triggering a banking crisis and other relevant covariates, including the presence and severity of lending booms, recent domestic and international financial liberalization processes, the quality of banking supervision, the presence of an explicit deposit insurance scheme, the quality of institutions, currency crises,[7] the level of reserves, and domestic and international interest rates.[8]

The results indicate that bonanzas in net capital inflows are associated with an increased likelihood of systemic banking crises. Interestingly, this association is present even in the absence of a lending boom. This suggests that large surges in inflows increase the probability of crises not only through overlending, as traditionally believed, but also through other mechanisms. Moreover, the larger the windfall, the greater the probability of a crisis the following year. If no lending boom has taken place, a crisis becomes seven times more likely after an intense bonanza (2 s.d). If this large surge takes place jointly with a lending boom, a crisis becomes sixteen times more likely –this effect is even larger in emerging economies (defined as middle and upper middle countries). These effects are economically significant. An intense bonanza increases the probability of a crisis to 17 percent in the absence of a lending boom and to 32 percent if a lending boom is underway (from an unconditional probability of 3 percent). For emerging economies the probability increases to 20 percent and 47 percent. Decomposing flows in FDI, portfolio-equity and debt flows shows that bonanzas in all types of flows are associated with future crises if a simultaneous lending boom is underway. However, only portfolio flows have a robust independent association with crises beyond the presence of a lending boom. As in the case of aggregate inflows, the odds of a crisis after a large surge in portfolio-equity inflows are even greater in emerging countries. This is important because traditionally only debt flows have been associated with an increased probability of distress in the financial system.

2. Definition of bonanzas, crises and data

Surges in net capital inflows are identified using the threshold method proposed by Mendoza and Terrones (2008). A bonanza is defined as an episode in which net inflows to a country grow by more

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

[8] An 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.

than during a typical business cycle. The focus is on *net* capital inflows, as opposed to total gross flows, because we are interested in evaluating the effects of windfalls of capital. Considering total gross flows has the risk of including in the analysis episodes of large net outflows (i.e. sudden stops), which are different phenomena. Baseline results are obtained with flows deflated and normalized in per capita terms.[9]

The method identifies a bonanza using a country-specific threshold as follows: Let f_{it} be the deviation from long-run trend in net inflows into country i in year t, and let $\sigma(f_i)$ be the country-specific standard deviation of this cyclical component.[10] The method identifies a bonanza in country i if $f_{it} \geq \phi\sigma(f_i)$, where ϕ is a threshold factor, and after imposing two additional constraints: a non-negativity in net capital inflows and a negative current account balance, so that a bonanza cannot take place in the presence of a current account surplus or if there are net capital outflows. Baseline bonanzas are identified with a threshold of $\phi = 1$. Further analyses are performed with $\phi = 0.5$ (mild bonanzas) and $\phi = 2$ (intense bonanzas). Figure 2 exemplifies the method for the case of South Korea.

Robustness checks are done identifying bonanzas using flows as percentage of GDP and bonanzas identified by Reinhart and Reinhart (2009), which are based on the current account balance.[11]

2.1. Lending booms

Lending booms are identified employing the threshold method of Mendoza and Terrones (2008) on data of real per capita domestic credit and setting $\phi = 1$ for baseline estimates. Robustness checks are preformed using a threshold of $\phi = 2$ and using lending booms identified by Gourinchas *et al.* (2001), which are based on data on credit as percentage of GDP.

[9] Similar results are obtained for robustness checks using flows as percentage of GDP. However, a per capita normalization is preferred to a 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 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.

[10] Following Ravn and Uhlig (2002), the long-run trend is calculated using the Hodrick-Prescott filter with the smoothing parameter set to 6.25. Other authors suggest different values. As a check, I performed the analysis with bonanzas identified using a smoothing parameter of 100, as proposed by Backus *et al.* (1992). The results are unchanged.

[11] Bonanzas can also be defined adding a constraint for the size or level of flows (e.g. flows being at least 5% of GDP or some regional average). However, it is preferred to use a threshold relative to a country's business cycle, without imposing an arbitrary size not related to specific country characteristics. This is because it is not clear why it cannot be said tha a country faces a bonanza if its net inflows grow rapidly relative to its specific trend, even though flows never get large enough to be above an ad hoc threshold. The country can have structural characteristics, such as regulation or financial development, that make it more vulnerable if its net inflows grow by more than one or two standard deviations, but are still below an arbitrary threshold.

2.2. Banking crises

Systemic banking crises are taken from Laeven and Valencia (2010). In this 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 losses in the banking system. The definition does not include isolated banks in distress.

The year in which a systemic banking crisis *starts* is identified by the two conditions just mentioned 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 event is classified as a crisis if one of the following two conditions has 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. Because the quantitative thresholds used in this definition of systemic banking crises are ad hoc, events that almost meet the thresholds are classified as "borderline." This paper includes in the analysis all crises in the dataset, no distinguishing borderline cases.

With the methodology just described, 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. As noted by Boyd *et al.* (2010), the identification methodology of crises by Laeven and Valencia (2010) 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 crisis. Thus, this paper uses data from Laeven and Valencia, but performs the empirical analysis using lagged explanatory variables.

2.3. *Description of data*

Data on capital flows are taken from the balance of payments statistics of the International Financial Statistics dataset (IFS BoP). The analysis is based on *net* capital inflows. In the case of aggregate flows, net inflows are equal to the balance in the financial account (line *78bjd* in IFS BoP). To study the effects of the composition of flows, the paper uses data from IFS BoP and compute net inflows for each category of interest. Since IFS BoP records outflows as negative numbers, assets and liabilities are added to obtain net inflows. The set of macroeconomic variables and institutional indexes used as controls was obtained from the World Development Indicators database of the World Bank and other standard sources. Table A-1 in the appendix presents summary statistics for the variables used in the empirical analysis, and Table A-3 explains in detail the variables used and their sources.

Data on deposit insurance are taken from Demirgüc-Kunt *et al.* (2005) and indexes of interest rate controls, banking supervision and barriers to entry in the banking industry from Abiad *et al.* (2010). One limitation of these two datasets is that data are available up to 2003 for deposit insurance and up to 2005 for the indexes. In order to complete the sample with data until 2007, I make the assumptions of no change in explicit deposit insurance schemes between 2003-2007 and no change in the indexes between 2005-2007. This has not significant impact in the analysis. Once a country adopts an explicit deposit insurance scheme, it is rarely dropped. Conversely, significant reversals in the indexes from Abiad *et al.* (2010) are rare.[12] As a check, the analysis is performed with samples until 2006 and 2008 and the same results are obtained.

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

3.1. *Empirical strategy*

The empirical strategy is based on a regression analysis of fixed effects models. 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 binary response variable for the start of a crisis. The likelihood of a crisis starting is hypothesized to be a function of a vector of macroeconomic and institutional characteristics of the country. We can

[12] Demirgüc-Kunt *et al.* (2005) document year of adoption or revision of explicit deposit insurance schemes for 88 countries. They document changes in coverage and other details, but report zero drops. The variable used in this paper is based on the existence or not of an explicit scheme. Thus, it is not affected by changes in scheme's details. Abiad *et al.* (2010, p.9) report an incidence of reversals of five percent in their indexes, asserting that "reversals, especially large ones, are relatively rare, suggesting that, once established, financial reforms are unlikely to be undone."

think about the likelihood of the start of a crisis as an underlying continuous latent variable $y^*_{i,t}$. The observed variable is a realization of a crisis when this latent variable takes a value beyond a threshold (say 0) and a systemic banking crisis starts ($y_{i,t} = 1$). The likelihood of a crisis is approximated by the latent variable model:

$$y_{i,t} = \begin{cases} 1 & \text{if } y^*_{i,t} > 0 \\ 0 & \text{if } y^*_{i,t} \leq 0 \end{cases} \tag{1}$$

A linear regression model is specified for the latent response y^*. Specifically, the analysis below estimates variations of the following random-intercept model:

$$y^*_{i,t} = \gamma\kappa_{i,t-1} + \lambda l_{i,t-1} + \delta(\kappa \times l)_{i,t-1} + \beta' X_{i,t-1} + \zeta_i + \xi_{i,t} \tag{2}$$

where it is assumed that $E[\xi|\kappa, l, X, \zeta] = 0$. Equation (2) includes as determinants of banking crises a dummy variable for bonanzas in net capital inflows (κ), a dummy variable for lending booms (l), the interaction of the two, and a vector X of macroeconomic and institutional characteristics. The covariates in equation 2 are lagged one period in order to reduce endogeneity issues and because the year of start of a banking crisis in Laeven and Valencia (2010) may lag the onset of the crisis. Furthermore, the analysis is performed after eliminating the first three years of observations following a crisis in order to reduce the influence of observations affected by the outcome of crises.

The aim of this econometric analysis is to answer two questions: (i) whether surges in net capital inflows are associated with an increase in the likelihood of a systemic banking crisis, which is answered by estimating equation (2) with no interaction term and evaluating the sign and statistical significance of the coefficient for bonanzas $\hat{\gamma}$ ($H_o : \gamma = 0$); and (ii) whether any effect of bonanzas is necessarily through a lending boom, which is answered by estimating the model with the interaction term of bonanzas and booms and evaluating significance and sign of $\hat{\gamma}$ ($H_o : \gamma = 0$). When including the interacting term, $\hat{\gamma}$ will tell us the association between the likelihood of a banking crisis and a previous year bonanza in net capital inflows when setting the lending boom indicator equal to zero. We will also be interested in the linear combination of the two coefficients, $\hat{\gamma} + \hat{\delta}$, which will tell us the association between crises and bonanzas when we set the indicator for lending boom equal to one (this is, after the joint occurrence of a bonanza and a boom).

The identification strategy relies on two assumptions. Bonanzas in a given year are not caused by banking crises the following year; and, bonanzas are orthogonal to lending booms, in the sense that, on average, bonanzas do not cause booms. At first glance, the latter assumption seems heroic, but the empirical evidence by Gourinchas *et al.* (2001), Sachs *et al.* (1996) and Mendoza and Terrones (2008), and the analysis below, support it. Nevertheless, given the potential endogeneity, the model is also estimated on a sample excluding lending booms.

The analysis is performed using an unbalanced panel dataset of a large number of countries for the period 1973-2008. In this setup two problems can arise: within country unobserved heterogeneity (correlation between covariates at the country level) and endogeneity of bonanzas at the country level. For these reasons baseline results are obtained by estimating a fixed effects model (FE). This will take care of all country-specific and time-invariant characteristics that may affect the likelihood of a crisis or the occurrence of bonanzas, or both, such as a weak banking regulation lax capital controls, commodity exporter, offshore financial center, or tax-heaven.

Another way to tackle the endogeneity of country specific time-invariant variables is by estimating a random effects (RE) model including an instrumental variable for the covariate suspected of endogeneity. Following Mundlak (1978), Skrondal and Rabe-Hesketh (2004) suggest that this can be done by including the country (cluster) mean of the covariate we suspect is endogenous. 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 strategy is that it allows for differences in the between and within effects of a covariate without losing the time-invariant observations. Another advantage is that it attends the issue of potential omitted time-invariant variables, while estimating γ without bias as long as the cluster mean is included as covariate, in addition to the country-year variable (see proof and discussion in Skrondal and Rabe-Hesketh (2004, pp.52-53)).[13] Thus, besides the FE model, I also estimate equation (2) using a RE model including country-means.

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 $Pr(y_{it} = 1|Z_{i,t-1}) = Pr(\beta' Z_{i,t-1} + \varepsilon_{i,t} > 0) = F(\beta' Z_{i,t-1})$. Fixed effects restricts the analysis to assume a Logistic distribution for $F(\cdot)$. In this case equation (2) is estimated by the conditional logit estimator. When no constrained by fixed effects, the Gumbel (extreme value) distribution is assumed, and complementary logarithmic regression is used.[14]

[13]Still, for the estimates to be consistent and considered causal, both of the assumptions of the RE model need to be met: $E[\zeta|\kappa, l, X] = E[\xi|\kappa, l, X, \zeta] = 0$.

[14]This is motivated by the fact that logit methods assume a symmetric distribution around zero. However, banking crises are rare events (i.e 97% of observations are zeros). The Gumbel or extreme value distribution accounts for this, and assumes $F(z) = 1 - exp[-exp(z)]$. For completeness, all models were estimated with a Logistic distribution and

The non-linearity of these binary outcome models makes the interpretation of the coefficients not straightforward. While the sign of a coefficient indicates the direction of change in the probability of crises, the magnitude of this effect depends on the slope of the cumulative distribution function at $z = \beta' Z_{i,t-1}$. That is, a marginal change in a covariate has different effects on the probability of a crisis depending on the country's initial crisis probability. Hence, exponentiated coefficients are reported in order to interpret the magnitude of the effects, and we will refer to them as odds ratios.[15]

The vector X of one-period lagged controls in equation (2) is composed of two sets. The first set includes mechanisms through which banking crises may take place, while the second set is composed of relevant controls given by the banking crises literature. The first set of controls include an indicator variable for the existence of competition risk,[16] a dummy for a process of international financial liberalization, an index of banking supervision, 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.[17]

The second set of covariates include a proxy for income, an index of quality of democratic institutions (*Polity2*), a proxy for openness to trade, an indicator dummy for the existence of a fixed 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 a good proxy for inflation,[18] measures of *de facto* and *de jure* current account openness, and

the results are unchanged.

[15] 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 $p = Pr(y = 1|Z)$ –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 $h = Pr(y = 1|Z)/Pr(y = 0|Z)$.

[16] This index aims to capture the degree of competition after a liberalization by measuring liberalization as the change of interest rate controls and adjusting for the barriers to entry in the banking industry. The index 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 took 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 can take a few years. I also experimented with the conventional dummy for financial liberalization (dummy of value 1 if no interest rates controls) and obtained similar results.

[17] Following the literature, this is captured by the interaction of low quality of institutions and a process of liberalization in the presence of an explicit deposit insurance scheme. Financial liberalization is a dummy that takes value 1 if there was an elimination of interest rate controls in any of the previous five years. 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 index, then, is a discrete variable with possible values from -10 to 10, with -10 representing the highest moral hazard.

[18] I 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 0.95 in the sample that uses all covariates.

the annual average of the Federal Funds rate –as a proxy for international monetary conditions.[19] Table (A-3) explains in detail all variables used in the analysis and their sources.[20]

3.2. Baseline Results

Table 1 reports results of estimating equation (2) with fixed effects. These results are based solely on countries that registered a crisis in the sample period, because the FE model excludes time-invariant variables.[21] The table presents estimated coefficients for seven different specifications, 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. The first specification estimates the correlation of bonanzas in net capital inflows and banking crises with no control variables in the estimation. The coefficient is significant and positive. Specification 2 estimates the model including only the first set of covariates, except lending booms. The coefficient for bonanzas is still significant and with a similar magnitude. The third specification adds the indicator for lending booms.[22] Neither significance or magnitude of the coefficient of interest significantly changes. The results indicate, then, that surges in net capital inflows are associated with a greater likelihood of systemic banking crises. The coefficient of bonanzas in the first three specifications is different from zero at the 1% level.

Column 4 adds an interaction term for bonanzas and booms –the simultaneous occurrence of a 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. 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 underway is given by the linear combination of the estimated coefficients for bonanzas and

[19] In order to work with the most parsimonious model I only include robust and relevant variables, as reported in surveys by Eichengreen and Arteta (2002) and Demirgüc-Kunt and Detragiache (2005). Irrelevant variables left out include public debt, tax revenue, and fiscal balance.

[20] The online appendix presents a table of correlations. No serious issues of collinearity arise. 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 with income, banking supervision and quality of institutions. Despite some degree of correlation between these variables, the preference is to keep them in the estimation. I experimented dropping *kaopen*, and results do not change.

[21] The estimation is performed in a sample of 3,632 country-year pairs and uses data from 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. Since the FE model only includes countries with crises, estimations in Table 1 use a subset of 2,363 observation (794 when including all covariates). A total of 97 countries (65%) experienced a crisis (63% for developing countries and 74% for high income countries). 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. Table A-4 makes explicit which countries and crises are used in the estimation.

[22] Baseline model is estimated with lending booms identified using $\phi = 1$.

the interaction with booms. The bottom of the table reports estimated exponentiated coefficient (odds ratio), standard errors, and a Wald test of joint significance ($H_o : \gamma + \delta = 0$). The results indicate that bonanzas are associated with a greater probability of a systemic banking crisis, if a lending boom is absent ($\hat{\gamma} \neq 0$ at the 10% level) or present ($\hat{\gamma} + \hat{\delta} \neq 0$ at 5% level).[23] These results suggest that bonanzas are correlated with banking crises not only through lending booms, but also through some different channels. This is important because overlending is the mechanism that has captured most of the attention in the literature.

Columns 5, 6 and 7 add the second set of controls. After including all covariates the coefficient of bonanzas is significant at the 1% level (column 6), the differential effect of bonanzas given a lending boom is significant at 5% (bottom of column 7), and the magnitude of the coefficients is roughly the same as before. The coefficient of bonanzas in the absence of a lending boom is significant at 10% and has a similar magnitude as before (top of column 7).

Expressing the results as odds ratios gives an idea of the economic significance of these effects. Odds ratios report the marginal effects in multiplicative form and control for differences between the countries baseline odds of a crisis. The odds of a banking crisis are, on average, between two and three times greater if a baseline bonanza in net capital inflows took place the previous year. If a lending boom is underway, a bonanza is associated with odds of a crisis five times greater. The independent effect of a bonanza raises the probability of a crisis from an unconditional probability of 3% to 8%,[24] after controlling for all other factors. A bonanza jointly ocurring with a lending boom increases the probability of a crisis to 13%.

Estimating the RE model including country-means yields results in the same line as the FE model. The first four columns of Table 2 report summarized results of estimating the RE model including country-means of bonanzas and country-means of all covariates. Only specifications 6 and 7 are reported and only for variables of interest. Complete regression output is reported in the online appendix. The results are similar as the ones obtained with the FE model, and most

[23]Note that the interaction term by itself is not statistically significant. This implies that a bonanza has roughly the same effect with a lending boom or without it –once taking into account the other covariates.

[24]The odds are the ratio of the probability of a positive outcome to the probability of no positive outcome: $odds = p/(1-p)$, where $p = Pr(y = 1|Z)$. The estimated odds ratio (OR) of bonanzas is computed as $OR = odds(crisis|bonanza)/odds(crisis|nobonanza)$. Given $odds(crisis|nobonanza) = 0.03$ and with an estimated odds ratio of 3, then, the estimated probability of a crisis conditional on a bonanza, after controlling for other covariates, is $0.08 = [3 \times 0.03]/[1 + (3 \times 0.03)]$.

coefficients of interest are significant at the 1%level.[25]

Estimated coefficients for all other covariates are consistent with the literature. The likelihood of a banking crisis increases by unusually large growth in credit (a lending boom), increased competition in the banking sector after liberalization and by a contemporaneous currency crisis. The proxy for moral hazard has the correct negative sing, which is represented by an odds ratio less than one, but it is statistically significant at 10% only when no including controls. Neither international liberalization nor quality of institutions shows up significant when controlling for all relevant factors, a result consistent with the literature. A greater level of financial integration is associated with a greater likelihood of crises, as indicated by the coefficient of *de facto* openness. The index of banking supervision exhibits the expected negative sign (when including all controls), but it is not statistically different from zero. This may be because its somewhat high correlation with other covariates. Similarly, odds ratio less than one are obtained for quality of institutions, output growth and trade openness, and odds larger than one for fixed exchange rate regimes.

3.3. Is there a difference between mild or intense bonanzas?

The results above rely on the identification of bonanzas using a threshold of one standard deviation from the smoothed series of aggregate net capital inflows. To investigate if these results are driven by this ad hoc threshold, the model is estimated using two additional thresholds for mild (0.5 s.d) and intense (2 s.d) bonanzas. The last four columns of Table 2 present summarized results for specifications 6 and 7 of the FE model (complete results are reported in the online appendix, including results for the RE model with country-means). As in the baseline case, bonanzas are associated with an increased likelihood of a crisis. Consistent with the hypothesis that windfalls of international capital are associated with mechanisms that increase the probability of crises, this effect is greater the larger is the windfall of capital. An intense bonanza increases the odds of a crisis the following year by seven times when no lending boom is underway. This implies a probability of a crisis of 17%. When a lending boom is present, an intense bonanza increases the odds of a crisis by sixteen times, raising its probability to 32%. The effects of mild bonanzas are much smaller. The effect of bonanzas in the absence of a lending boom is significantly different from zero at least at the 5% level in both cases. However, the effect of mild bonanzas once a boom is underway is not statistically different from zero.

[25] Note that the estimated coefficient for the country-mean (shown in the online appendix) represents the difference in the between and within effects of bonanzas. This difference is not statistically different from zero.

3.4. Endogeneity and Causality

A causal interpretation of the results holds if the assumptions $E[\zeta|\kappa, l, X] = E[\xi|\kappa, l, X, \zeta] = 0$ are met. The FE model and the RE model with country means allow to relax the first assumption. However, we must consider if the results are driven by the association of capital inflows and lending booms (the assumption of orthogonality between bonanzas and booms). If windfalls of capital and lending booms are correlated because bonanzas cause booms, the regression results cannot be considered causal because the covariate of booms would be determined *after* a bonanza has taken place.

This is a valid concern. However, the empirical literature has failed to find a robust significant association between surges in capital inflows and lending booms. Furthermore, in the full sample most baseline lending booms (78.82%) are not associated with contemporaneous bonanzas, not even intense bonanzas (78.66%). As a result, the conditional probability of a lending boom is fundamentally the same if baseline or intense bonanzas take place (21.18% and 21.34%).[26] Bonanzas and booms are associated not because capital inflows cause booms, but because booms attract international capital. For example, less than 16% of baseline bonanzas take place in a year in which no lending boom is present. This implies that lending booms take place *before* a bonanza.

As a check, the model is estimated dropping all observations that exhibit a lending boom in the previous year. The first three columns of Table 3 report the results of specification 5 –including all covariates (online appendix reports all other specifications). If surges in net capital inflows are a robust determinant of banking crises we expect to find a positive, significant $\hat{\gamma}$ coefficient. The estimates indicate that windfalls of international capital increase the probability of a banking crisis and that this is larger for more intense (2 s.d) bonanzas. The estimated odds ratios are quite similar to the ones obtained in the full sample and in all cases significant at the 5% level.

On the other hand, we must consider the exogeneity assumption that the covariates are independent from the idiosyncratic error: $E[\xi|\kappa, l, X, \zeta] = 0$. 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 bonanzas in net capital inflows may be an endogenous variable because there may be country-year unobservables (error $\xi_{i,t}$) that affect both the probability of a crisis at

[26] Same results obtained for full sample and developing countries, when excluding crises of 2007-2008, when using definiton of booms by Gourinchas *et al.* (2001), and when using a two standard deviation threshold for booms. Results reported in online appendix.

t and the occurrence of bonanzas in $t-1$. However, the results are obtained after including in the regression all relevant factors suggested by the theory and empirical literatures, and after dropping three years of observations following a crisis and using one-period lagged explanatory variables.

The regression results obtained under fixed effects may not considered causal if the reader believes that conditional on the covariates, bonanzas in a given year are not orthogonal to the occurrence of a banking crisis the following year. There is not a clear reason why this can be the case. The argument would have to include the unlikely chain of events that investors foresee a crisis and they flood a country with capital. Given the implausibility of this, the analysis above presents evidence that, after controlling for all relevant factors, including the presence or absence of a lending boom, the quality of regulation and institutions, a currency crisis, and a recent process of liberalization, having an unusually *large* influx of capital can in itself cause a greater probability of a systemic banking crisis.

3.5. Developing countries sample

This section explores if the results differ if estimations are performed including only developing countries. The last three columns of Table 3 present the results (results shown for specification 7 of the FE model; complete results reported in online appendix). Most of the coefficients are in the same ballpark as with the full sample. However, an intense bonanza when a lending boom is underway dramatically increases the probability of a crisis. The odds of a crisis becomes twenty five times greater, equivalent to a probability of a crisis of 43%. When including the interacting term of Bonanza×Boom the statistical significance of baseline bonanzas vanishes. Nonetheless, mild and intense bonanzas exhibit coefficients significant at the 5% level. The developing country sample is revisited below, when studying differences between regions and different income groups.

3.6. Robustness and sensitivity checks

To check whether model specification is driving the results, I also estimate equation (2) using a RE model with no country-means, assuming $\zeta_i|X_{i,t-1} \sim N(0, \sigma^2_\zeta)$ and a constant within country correlation of the idiosyncratic error: $Cor(\xi_{i,t}, \xi_{i,s} = \rho)$. I also estimate the model using a pooled specification with clustered standard errors (assuming zero variance of the random effects and $Cor(\xi_{i,t}, \xi_{i,s} = 0)$). Furthermore, I also estimate the model using a simple OLS linear probability specification. The online appendix reports the results. They are in line with the baseline results.

To rule out the possibility that the methodology is capturing the effect of rare events or the results are driven by the definition of bonanzas as per capita net inflows, the regressions are estimated using as covariate the Hodrick-Prescott residuals used to identify bonanzas and with bonanzas identified using flows as percentage of GDP and bonanzas identified by Reinhart and Reinhart (2009). As another check, the regressions are estimated in two different subsamples: 1973-2006 (dropping observations from recent financial crises) and 1985-2006 (because early data may be noisy, especially for developing countries). Summarized results of these robustness exercises for specification 7 of the FE model are reported in Table 4 (online appendix presents complete results). Encouraging, the results of these exercises are in line with the baseline results.

Two checks are employed to explore if the results are driven by the definition of lending booms: 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), who identify booms using data on credit to private sector as percentage of GDP. Results of these robustness checks are reported in the online appendix. Again, the results are in line with the baseline results.

3.7. Non-parametric analysis

This subsection explores the relationship between banking crises and net capital inflow bonanzas using a non-parametric analysis based on frequencies, conditional probabilities and chi-squared independence tests. The independence tests are presented using two way tabulations in which banking crises are on the rows and the bonanzas are on the columns. Frequencies and percentages are presented along with statistics and corresponding p-values for three independence tests: Pearson Chi-squared, Likelihood-ratio, and Fisher's exact test. The null hypothesis in these tests is that banking crises are statistically independent from bonanzas.

Table 5 reports two-way table and results of independence tests for banking crises and one-period lagged baseline bonanzas 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 crisis). On the other hand, 5.29% of bonanzas ended up in a banking crisis (this is its conditional probability). The data reveal that 28.10% of banking crises took place after a baseline capital flow bonanza. The independence tests are rejected, indicating that banking crises and net capital inflow bonanzas are statistically associated. The great majority of crises (98 out of 121) took place in developing countries. Yet, the conditional probability of a crisis is basically the same for developing and high income countries and the full sample (5.11%, 6.09% and 5.29%). The unconditional probability of a crisis is also similar in all country groups.[27]

This non-parametric analysis replicates the results of Reinhart and Reinhart (2009), who also find a greater conditional probability of crises after bonanzas, and the results of Reinhart and Rogoff (2009, Chp. 13), who find similar incidence rates of banking crises in high income and developing country using historical data. However, the robustness of the results following this methodology is shaky. If bonanzas increase the likelihood of crises, conditioning by intense bonanzas must result in a stronger association and greater conditional probabilities. However, this probability is only marginally greater than that of a baseline bonanza (5.62% vs. 5.29%), as reported in Table 6 (results reported in the online appendix show similar low conditional probabilities for cases of simultaneous bonanza and lending boom during the previous year). A similar probability for intense bonanzas of that of baseline bonanzas is obtained for developing countries and high-income OECD countries. Importantly, the independence tests lose significance and cannot reject the null of independence at the 5% level in the two subsamples

This non-parametric approach not only fails at identifying a robust association between windfalls of capital and banking crises, but it also has many limitations. It cannot capture the interactions of the two variables of interest once controlling for other plausible determinants of the likelihood of crises, nothing can be said about causality, and we cannot disentangle the effect of bonanzas from that of lending booms. Furthermore, the magnitude of the effect of bonanzas is distorted. The conditional probability of a crisis following a baseline or intense bonanza is in either case only over five percent, while the multivariate econometric analysis indicates a much larger effect after controlling for macroeconomic and institutional factors. The regression analysis indicates that a baseline bonanza raises the probability of a crisis to 8% in the absence of a lending boom and to 13% if a boom is underway. For intense bonanzas the distortion is larger, with estimated probabilities of 17% and 32% in each case.

4. Do developing countries face greater risks from surges in net capital inflows?

This section explores whether windfalls of capital have a different effect in developing countries or in different regions. These exercises are performed estimating FE and RE models including

[27]Because most crises in high income countries in this sample took place in the years 2007-2008 (16 out of 23), I do not want to make much of the results for high income countries. For the same reason, this paper focuses on the samples including all countries or developing countries (i.e. no attempt is made to study crises in high income countries).

indicators for developing status and for different regional and income groups.[28] Table A-2 in the appendix 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 p-values of a F test for the joint significance of the two coefficients. The results do not suggest the existence of regional effects.[29] Interestingly, the RE specification indicates a statistically significant effect of bonanzas in the group of developing countries (LDC) and in the groups of middle and upper income economies. However, this is not the case for low income countries.

The upper and middle income groups are explored further. These countries enjoy a greater degree of financial development and international financial integration than the average developing country. These emerging markets can exhibit a greater likelihood of crises after a windfall of capital because their institutions and prudential regulation may not be mature yet, but their openness and integration to global markets heightens their vulnerability. Table 7 reports summarized results of the FE model for the sample of upper and middle income countries (complete results reported in online appendix). The results indicate a greater likelihood of crises after a bonanza for this group compared to 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 in net capital inflows in these countries not only has a greater effect in the absence of a lending boom, but also the joint occurrence with a boom is associated with greater odds of a crisis the following year. As before, the effect of intense bonanzas is larger. An intense bonanza in a middle or upper middle income country makes the odds of a banking crisis eight times greater in the absence of a boom and thirty times greater if a boom is underway. That is, the probability of a crisis rises to 20% and 47%, respectively.

5. Does the composition of capital flows matter?

The results so far indicate that surges in *aggregate* net capital inflows increase the likelihood of banking crises and that this effect does not operate necessarily through a lending boom mechanism.

[28]The regional and income classifications are those 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, Czeck Repulic, Estonia, Hungary and Slovakia as upper middle income countries.

[29]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 FE model, the indicator of region or income group is dropped because of no time-variation, and the region or income effect is given by the interacting term.

However, these results open new questions, especially regarding the mechanisms at play. One way to understand better the effect of bonanzas is to look at the composition of flows. This section performs the analysis decomposing flows into FDI, portfolio-equity and debt.

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 types. The conditional probability of a bonanza in FDI, given a debt or portfolio bonanza, is over 30%. The conditional probability of a bonanza in portfolio flows given a bonanza in debt or FDI is, respectively, over 38% and 50%. These large conditional probabilities indicate that all types of flows fly into the country when international capital markets get excited about an economy, making it difficult to disentangle the effect of each type of flow. With this caveat in mind, the model is estimated independently for each type of flow.

Table 8 presents summarized results for the samples of all countries and upper and middle income countries (complete results in online appendix). Results reported only for baseline (1 s.d) and intense (2 s.d) bonanzas. In this table a column does not refer to a single regression, but estimates are from three different regressions –one for each type of flow. The results for the full sample indicate that only bonanzas in portfolio-equity flows are robustly associated with an increased likelihood of systemic banking crises in the absence of a lending boom –results statistically significant at the 1% level for both baseline and intense bonanzas. Intense bonanzas in portfolio flows raise the odds of a crisis even more. These effects are economically significant. An intense bonanza in portfolio flows is associated with a probability of a crisis of 27% in the absence of a lending boom.

The joint occurrence of a lending boom and a large windfall of capital substantially increases the odds of a crisis, even in the case of FDI. The odds of a crisis are ten times greater if a large surge in portfolio-equity flows took place jointly with a lending boom and thirteen times greater for bonanzas in debt flows (both results significant at the 5% level). This implies a probability of crises of 23% and 28%, respectively. The odds of a crisis are eight times greater in the case of a bonanza in FDI, which implies a crisis probability of 19% (significant at the 10%). Robustness checks reported in the online appendix show similar results when the model is estimated restricting the sample to 1973-2006 or 1985-2006.

These results are qualitatively similar when the sample is restricted to only developing countries (not shown) or only upper and middle income countries (shown in last four columns of Table 8). In these emerging economies, the increase in the odds of a crisis is significantly greater for the case of bonanzas in portfolio-equity flows and in the cases of the joint occurrence of a boom and a bonanza. Again, the independent effect of bonanzas is only robust in the case of intense bonanzas in portfolio-equity flows. In the absence of a lending boom, a bonanza in portfolio flows raises the odds of a crisis by twelve times. If a boom is underway, the odds of a crisis are twenty times greater.

As conventionally believed, a windfall of debt flows, coupled with a domestic lending boom, is a recipe for disaster. Odds of a crisis in this case are fifty times greater, which implies a probability of a crisis of over 60%. This story fits well the anecdotal evidence from many developing countries, especially Latin American ones (e.g. Gavin and Hausmann (1996), Gourinchas *et al.* (2001)).

The results for FDI and portfolio-equity flows are puzzling and in contrast with the results reported by Joyce (2010), who finds weak evidence of a negative association between the stock of FDI and portfolio-equity liabilities and the likelihood of banking crises in a sample of twenty emerging economies. The results here for FDI are similarly weak, since the effect of FDI loses statistical significance in the middle and upper middle income group –it still shows up positive, though. The positive association between net FDI inflows and banking crises can be the result of financial sector's practices. Borrowing the argument from Ostry *et al.* (2010), "some items recorded as financial sector FDI may be disguising a buildup in intragroup debt in the financial sector and will thus be more akin to debt in terms of riskiness."

The results indicating that windfalls of portfolio-equity flows increase the likelihood of crises, even in the absence of lending booms, are novel and do not have a good explanation in the literature. For example, a recent survey by Kose *et al.* (2009) on the benefits and drawbacks of financial globalization only mentions risks from debt flows because their potential links with lending booms, not mentioning potential risks from other types of flows or other mechanisms. Surges in net portfolio-equity inflows may increase the likelihood of banking crises because they exacerbate existing upward pressures in asset prices, accelerating the bursting of bubbles. Recent research provides evidence in line with this idea. Aizenman and Jinjarak (2009) and Sá *et al.* (2011) report a positive association between current account deficits (i.e. net capital inflows) and appreciation of real state prices. Similarly, IMF (2010) shows that a measure of "excess global liquidity" has a positive impact on domestic asset prices in emerging economies. However, there is still much room for research in the development of theoretical models for understanding the mechanisms at play beyond overlending, and in empirical research quantifying the effects of potential mechanisms.

6. Concluding remarks

The evidence presented in this paper indicates that bonanzas (surges) in net capital inflows increase the likelihood of a systemic banking crisis through mechanisms other than excessive lending, and that windfalls of portfolio-equity flows increase the probability of crises –a role usually reserved for debt flows. Moreover, emerging economies face greater risks from windfalls of capital.

These results contribute to the debate on the benefits and costs of financial globalization. As argued by Kose *et al.* (2009) and others, there may be sizable benefits from consumption smoothing and risk diversification. Yet, as found by Calvo *et al.* (2008) and Agosín and Huaita (Forthcoming), countries are exposed to sudden stops. And, as shown here, large windfalls of capital increase the likelihood of banking crises. These results suggest that financial globalization imposes risks from both the size of windfalls and their temporal nature. Paraphrasing Dornbusch (2001): *speed kills, not only the sudden stop.*

According to the results above, if a country is facing a *large* increase in net capital inflows, particularly of portfolio-equity, imposing speed limits on credit growth to curb overlending is insufficient to prevent crises. Furthermore, equity type flows may bypass the banking sector, reducing the effectiveness of banking supervision and credit growth indicators. Thus, policymakers are rightly concerned when facing windfalls of international capital. As it has been proposed in several emerging economies, imposing capital controls may be one alternative to reduce the likelihood of banking distress in the face of large inflows. However, controls seem to be ineffective in reducing the volume of flows and may have the effect of bending them towards equity-like instruments (see Ostry *et al.* (2010), IMF (2010) and Binici *et al.* (2010)). Given the results above indicating that not only debt flows are associated with increased financial risk, and given the fact that windfalls often take place simultaneously across all types of flows, the actual implementation of benign controls is a challenge.

Policymakers should also keep in mind that surges in capital inflows, or in lending, may be the natural outcome of financial deepening and financial integration and may be more benign than harmful (Ranciere *et al.* (2008)). Hence, for policymakers interested in reducing the risks of financial meltdown, strengthening prudential regulation and cooling off the economy at early signs of both excessive credit growth and asset price inflation may be the appropriate first response. Nonetheless, capital controls may be the appropriate tool when the windfall of capital is deemed excessively large.

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Figure 1: Seven year window around banking crises. Plots show average across countries for each year. Variables are credit to private sector, net aggregate inflows (FA balance), net debt inflows and net portfolio-equity inflows. All variables as percentage of GDP. Samples of all countries (left) and developing (no OECD) countries (right). For countries in sample see Table A-4.

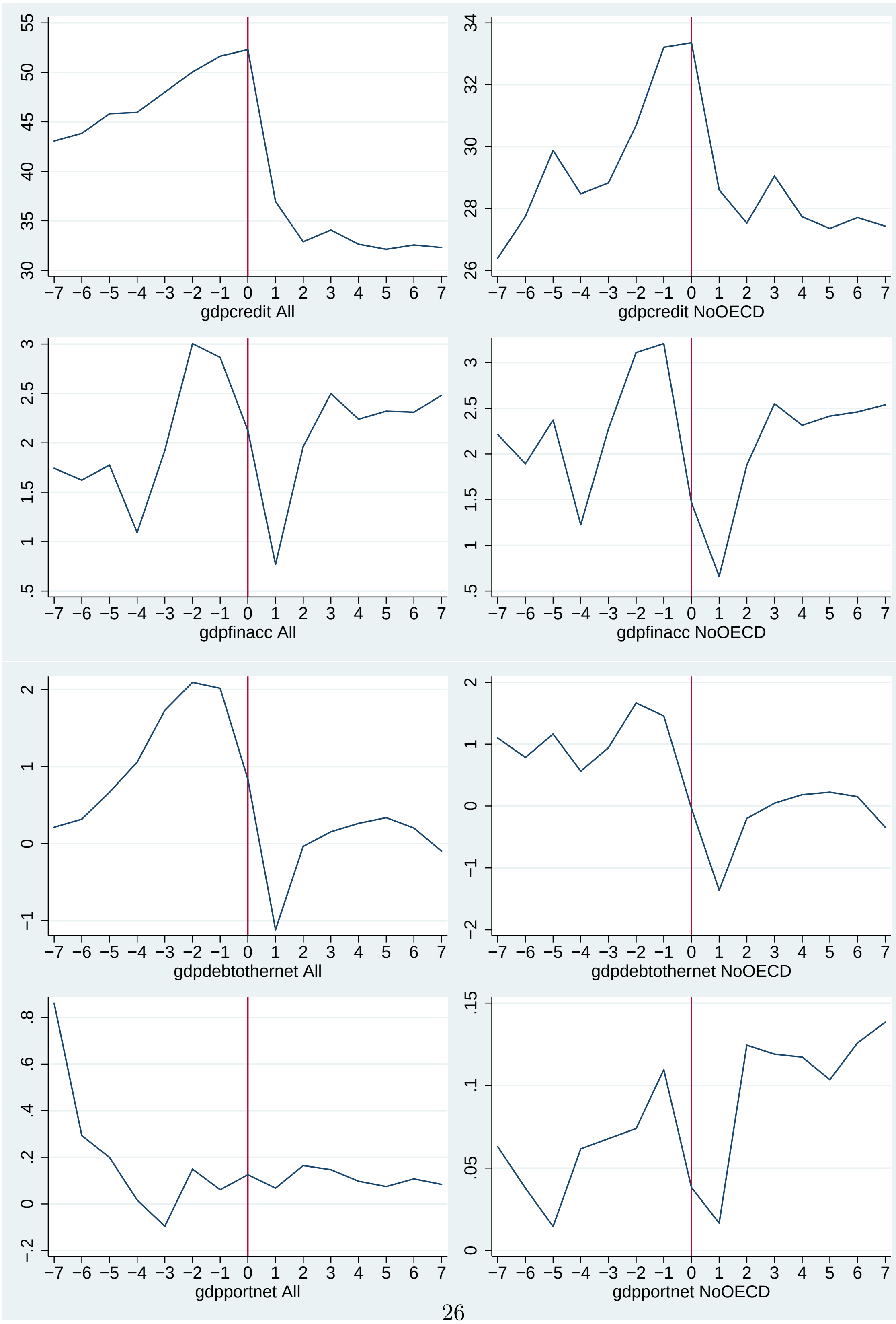

Figure 2: Threshold method to identify bonanzas. Baseline bonanzas are identified as events when per capita net inlfows are greater than one sd of smoothed series; intense bonanzas when flows are greater than 2 sd of smoothed flows; and mild bonanzas when flows are greater than 0.5 sd. Graph shows example of baseline and intense bonanzas for South Korea.

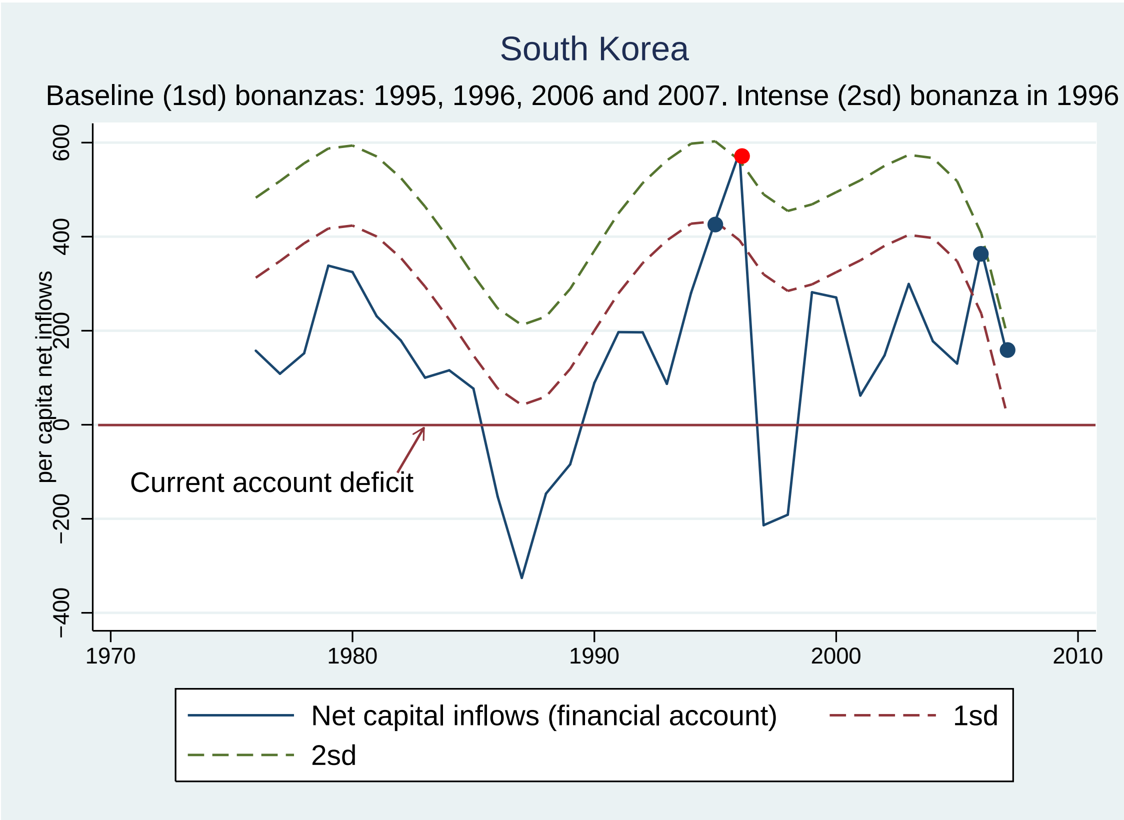

Table 1: FE model. Regression of banking crises on aggregate bonanzas (1 sd). All countries, 1973-2008

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Bonanza	2.121***	3.390***	2.500***	2.106*	4.754***	3.420***	2.771*
	(3.437)	(4.211)	(3.030)	(1.909)	(3.803)	(2.841)	(1.911)
Competition Risk		1.439**	1.502**	1.498**	1.500**	1.583**	1.574**
		(2.329)	(2.553)	(2.530)	(2.013)	(2.264)	(2.229)
Int. Liberalization		0.468**	0.486**	0.489**	0.506	0.503	0.508
		(-2.242)	(-2.139)	(-2.120)	(-1.412)	(-1.397)	(-1.381)
Currency crisis (t)		4.633***	3.606***	3.748***	6.441***	4.403**	4.578**
		(3.350)	(2.793)	(2.862)	(3.112)	(2.424)	(2.493)
Moral Hazard		0.914	0.887*	0.888*	0.974	0.952	0.954
		(-1.495)	(-1.907)	(-1.891)	(-0.340)	(-0.619)	(-0.594)
Banking supervision		1.379	1.322	1.313	0.612	0.577	0.584
		(1.559)	(1.315)	(1.277)	(-1.232)	(-1.369)	(-1.337)
Deposit Insurance		0.509	0.516	0.521	1.016	1.408	1.486
		(-1.567)	(-1.479)	(-1.449)	(0.026)	(0.547)	(0.623)
Lending Boom (1sd)			4.549***	3.910***		4.528***	3.749**
			(4.939)	(3.634)		(3.382)	(2.499)
Bon(1sd)×Boom(1sd)				1.603			1.905
				(0.729)			(0.706)
KA open					0.986	1.032	1.041
					(-0.058)	(0.132)	(0.166)
De facto CA openness					2.519***	2.208**	2.232**
					(2.758)	(2.197)	(2.237)
Polity2					0.958	0.933	0.931
					(-0.741)	(-1.183)	(-1.213)
Reserves					0.998	0.997	0.997
					(-0.489)	(-0.766)	(-0.753)
Interest rate					1.002	1.002	1.001
					(0.786)	(0.644)	(0.708)
GNI per capita					1.000	1.000**	1.000**
					(1.447)	(2.034)	(1.981)
Trade openness					0.991	0.990	0.988
					(-0.519)	(-0.619)	(-0.689)
Depreciation (Nom ER)					1.000	1.000	1.000
					(-0.385)	(-0.136)	(-0.149)
Fixed exch. rate					2.268	2.381	2.419
					(1.524)	(1.583)	(1.607)
GDP Growth					0.967	0.961	0.962
					(-0.631)	(-0.719)	(-0.696)
Fed effective funds rate					1.111	1.097	1.099
					(1.554)	(1.269)	(1.299)
BonIFBoomB				3.3763			5.2774
BonIFBoomSE				1.7232			3.9770
BonIFBoomPval				0.0171			0.0273
Obs	2363	1306	1305	1305	795	794	794
Countries	97	53	53	53	39	39	39
Crises	121	71	71	71	53	53	53
Loglik	-351.4911	-184.9368	-173.6389	-173.3718	-101.8036	-94.1628	-93.9121
Regression	logit	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. Specifications 3 and 4 add dummy for lending boom and the interaction term Bon×Boom. Columns 2-7 include lagged covariates of competition risk (increasing discrete variable), international liberalization (dummy), moral hazard (decreasing discrete variable), banking supervision (increasing discrete variable), dummy for explicit deposit insurance and dummy for (contemporaneous) currency crisis. Specifications 5-7 replicate 2-4 adding 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 asuming a Gumbel distribution. logit refers to the regressor assuming a Logistic distribution.

Table 2: RE model with country means, and FE model with different size of bonanza. All countries, 1973-2008

	RE model including country means				FE model for different bonanza thresholds			
	Including bonanza mean		Including ALL means		Mild (0.5sd) bonanzas		Intense (2sd) bonanzas	
	(6)	(7)	(6)	(7)	(6)	(7)	(6)	(7)
Bonanza	2.945***	2.272*	3.102***	2.312***	3.279***	3.290***	10.403***	7.134**
	(3.179)	(1.831)	(3.170)	(1.813)	(3.302)	(2.934)	(4.203)	(2.500)
Competition Risk	1.453***	1.453***	1.670***	1.683***	1.548**	1.548**	1.582**	1.552**
	(2.375)	(2.385)	(2.904)	(2.941)	(2.197)	(2.196)	(2.256)	(2.133)
Int. Liberalization	0.971	1.004	0.741	0.744	0.522	0.521	0.559	0.555
	(-0.086)	(0.011)	(-0.801)	(-0.785)	(-1.303)	(-1.302)	(-1.180)	(-1.195)
Currency crisis (t)	4.251***	4.540***	3.502**	3.889***	3.314*	3.314*	4.700***	4.701***
	(3.124)	(3.244)	(2.516)	(2.679)	(1.926)	(1.926)	(2.598)	(2.605)
Moral Hazard	0.928	0.929	0.918	0.914	0.941	0.941	0.940	0.946
	(-1.302)	(-1.282)	(-1.231)	(-1.302)	(-0.795)	(-0.794)	(-0.774)	(-0.696)
Banking supervision	0.880	0.875	0.655	0.649	0.590	0.589	0.533	0.537
	(-0.496)	(-0.516)	(-1.251)	(-1.253)	(-1.294)	(-1.293)	(-1.468)	(-1.448)
Lending Boom (1sd)	4.780***	3.875***	5.344***	4.136***	4.294***	4.330**	3.756***	3.210**
	(4.622)	(3.282)	(4.453)	(3.124)	(3.279)	(2.278)	(2.853)	(2.238)
Bonanza×Boom		1.899		2.023		0.985		2.319
		(0.886)		(0.884)		(-0.018)		(0.717)
Controls 1	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls 2	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BonIFBoomB		4.3146		4.6766		3.2413		16.5423
BonIFBoomSE		2.4510		3.0080		2.4042		14.2902
BonIFBoomPval		0.0101		0.0165		0.1129		0.0012
Obs	1214	1214	1214	1214	794	794	794	794
Countries	61	61	61	61	39	39	39	39
Crises	53	53	53	53	53	53	53	53
Loglik	-177.2755	-176.8021	-151.8371	-150.8848	-92.468	-92.468	-90.148	-89.884
Regression	cloglog	cloglog	cloglog	cloglog	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. Specifications 3 and 4 add dummy for lending boom and the interaction term Bon×Boom. Columns 2-7 include lagged covariates of competition risk (increasing discrete variable), international liberalization (dummy), moral hazard (decreasing discrete variable), banking supervision (increasing discrete variable), dummy for explicit deposit insurance and dummy for (contemporaneous) currency crisis. Specifications 5-7 replicate 2-4 adding 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 asuming a Gumbel distribution. logit refers to the regressor assuming a Logistic distribution.

Table 3: No previous lending boom, and developing countris sample. FE model. Sample 1973-2008

	No previous lending boom			Developing countries		
	1sd Bon	0.5sd Bon	2sd Bon	1sd Bon	0.5sd Bon	2sd Bon
	(5)	(5)	(5)	(7)	(7)	(7)
Bonanza	2.959**	3.404***	5.431**	1.711	2.780**	6.560**
	(1.968)	(2.789)	(2.070)	(0.920)	(2.249)	(2.110)
Competition Risk	1.626**	1.586*	1.610*	1.504**	1.523**	1.479*
	(1.972)	(1.891)	(1.934)	(1.973)	(2.020)	(1.835)
Int. Liberalization	0.373	0.353	0.411	0.540	0.545	0.568
	(-1.542)	(-1.603)	(-1.402)	(-1.149)	(-1.077)	(-1.044)
Currency crisis (t)	3.988**	3.362*	4.062**	4.496**	3.542**	4.732***
	(1.990)	(1.702)	(2.053)	(2.525)	(2.024)	(2.633)
Banking supervision	0.731	0.705	0.672	0.534	0.546	0.421*
	(-0.624)	(-0.671)	(-0.762)	(-1.381)	(-1.309)	(-1.737)
Moral Hazard	0.960	0.944	0.946	0.975	0.961	0.980
	(-0.436)	(-0.636)	(-0.596)	(-0.294)	(-0.473)	(-0.231)
Lending Boom (1sd)				2.386	2.043	1.978
				(1.380)	(0.830)	(1.084)
Bonanza×Boom				2.988	1.644	3.589
				(1.038)	(0.465)	(0.918)
Controls 1	Yes	Yes	Yes	Yes	Yes	Yes
Controls 2	Yes	Yes	Yes	Yes	Yes	Yes
BonIFBoomB				5.1104	4.5698	23.5444
BonIFBoomSE				4.5661	4.4632	24.9830
BonIFBoomPval				0.0679	0.1198	0.0029
Obs	463	463	463	523	523	523
Countries	26	26	26	29	29	29
Crises	34	34	34	42	42	42
Loglik	-67.019	-64.900	-67.029	-78.961	-77.132	-74.401
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. Specifications 3 and 4 add dummy for lending boom and the interaction term Bon×Boom. Columns 2-7 include lagged covariates of competition risk (increasing discrete variable), international liberalization (dummy), moral hazard (decreasing discrete variable), banking supervision (increasing discrete variable), dummy for explicit deposit insurance and dummy for (contemporaneous) currency crisis. Specifications 5-7 replicate 2-4 adding 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 asuming a Gumbel distribution. logit refers to the regressor assuming a Logistic distribution.

Table 4: Robustness checks. FE model. All countries.

	Residuals	GDP (1sd) Bon	RR Bon	1973-2006	1985-2006
	(7)	(7)	(7)	(7)	(7)
Bonanza	1.002**	4.183***	2.703**	2.709*	3.149*
	(2.109)	(3.100)	(2.325)	(1.782)	(1.898)
Competition Risk	1.557**	1.503*	1.459**	1.519**	1.318
	(2.210)	(1.931)	(2.000)	(2.077)	(1.102)
Int. Liberalization	0.512	0.473	0.647	0.543	0.893
	(-1.376)	(-1.501)	(-0.944)	(-1.217)	(-0.189)
Currency crisis (t)	3.649**	4.214**	3.220**	4.550***	4.869**
	(2.190)	(2.267)	(1.968)	(2.619)	(2.433)
Banking supervision	0.614	0.525	0.610	0.580	0.617
	(-1.208)	(-1.556)	(-1.212)	(-1.200)	(-1.001)
Moral Hazard	0.943	0.958	0.952	0.930	0.947
	(-0.726)	(-0.529)	(-0.663)	(-0.906)	(-0.577)
Lending Boom (1sd)	4.644***	3.849**	4.693***	3.078*	2.383
	(3.313)	(2.501)	(3.010)	(1.919)	(1.265)
Bonanza×Boom	1.000	1.902	0.927	2.158	4.529
	(-0.250)	(0.722)	(-0.091)	(0.764)	(1.237)
Controls 1	Yes	Yes	Yes	Yes	Yes
Controls 2	Yes	Yes	Yes	Yes	Yes
BonIFBoomB	1.0020	7.9554	2.5057	5.8455	14.2637
BonIFBoomSE	0.0011	6.2783	1.8344	4.8993	15.0945
BonIFBoomPval	0.0722	0.0086	0.2096	0.0351	0.0120
Obs	780	794	807	598	451
Countries	39	39	38	33	32
Crises	53	53	52	43	36
Loglik	-93.382	-90.174	-98.156	-85.499	-65.971
Regression	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. Specifications 3 and 4 add dummy for lending boom and the interaction term Bon×Boom. Columns 2-7 include lagged covariates of competition risk (increasing discrete variable), international liberalization (dummy), moral hazard (decreasing discrete variable), banking supervision (increasing discrete variable), dummy for explicit deposit insurance and dummy for (contemporaneous) currency crisis. Specifications 5-7 replicate 2-4 adding 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 asuming a Gumbel distribution. logit refers to the regressor assuming a Logistic distribution.

Table 5: Two way tables and independence tests of banking crises and previous year capital flow bonanzas. 1973-2008

	All countries Bonanzas 1 sd			Developing countries Bonanzas 1 sd			High income countries Bonanzas 1 sd		
Banking crisis	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 6: Two way tables and independence tests of banking crises and previous year capital flow bonanzas. 1973-2008

	All countries Bonanzas 2 sd			Developing countries Bonanzas 2 sd			High income countries Bonanzas 2 sd		
Banking crisis	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 7: FE models. Regression of banking crises on aggregate bonanzas. Upper and middle income developing countries, 1973-2008.

	Baseline (1sd) bonanzas		Mild (0.5sd) bonanzas		Intense (2sd) bonanzas	
	(6)	(7)	(6)	(7)	(6)	(7)
Bonanza	3.804**	2.358	4.613***	4.364***	14.655***	8.571**
	(2.527)	(1.361)	(3.193)	(2.799)	(3.613)	(2.173)
Lending Boom (1sd)	3.842**	2.234	3.347**	2.779	2.315	1.817
	(2.238)	(1.093)	(1.961)	(1.057)	(1.294)	(0.815)
Competition Risk	0.986	0.964	0.971	0.973	1.057	1.009
	(-0.054)	(-0.136)	(-0.103)	(-0.097)	(0.207)	(0.033)
Int. Liberalization	0.448	0.463	0.452	0.462	0.549	0.523
	(-1.306)	(-1.258)	(-1.218)	(-1.175)	(-0.979)	(-1.053)
Currency crisis (t)	7.254***	9.248***	4.757**	4.819**	9.237***	9.230***
	(2.829)	(3.011)	(2.194)	(2.193)	(3.077)	(3.062)
Banking supervision	0.428*	0.421*	0.451	0.460	0.393*	0.377*
	(-1.651)	(-1.661)	(-1.497)	(-1.445)	(-1.676)	(-1.725)
Moral Hazard	1.113	1.129	1.088	1.090	1.086	1.099
	(1.057)	(1.193)	(0.840)	(0.855)	(0.808)	(0.916)
Bonanza×Boom		6.153		1.354		3.517
		(1.530)		(0.255)		(0.828)
Controls 1	Yes	Yes	Yes	Yes	Yes	Yes
Controls 2	Yes	Yes	Yes	Yes	Yes	Yes
BonIFBoomB		14.5078		5.9076		30.1421
BonIFBoomSE		15.0125		6.4346		35.1283
BonIFBoomPval		0.0097		0.1029		0.0035
Obs	440	440	440	440	440	440
Countries	25	25	25	25	25	25
Crises	37	37	37	37	37	37
Loglik	-61.678	-60.485	-59.284	-59.251	-58.131	-57.778
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. Specifications 3 and 4 add dummy for lending boom and the interaction term Bon×Boom. Columns 2-7 include lagged covariates of competition risk (increasing discrete variable), international liberalization (dummy), moral hazard (decreasing discrete variable), banking supervision (increasing discrete variable), dummy for explicit deposit insurance and dummy for (contemporaneous) currency crisis. Specifications 5-7 replicate 2-4 adding 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 asuming a Gumbel distribution. logit refers to the regressor assuming a Logistic distribution.

Table 8: FE models. Regression of banking crises on bonanzas decomposing flows (per capita). Sample 1973-2008

	All countries				Upper and Middle income countries			
	Baseline (1sd) Bonanzas		Intense (2sd) Bonanzas		Baseline (1sd) Bonanzas		Intense (2sd) Bonanzas	
	(6)	(7)	(6)	(7)	(6)	(7)	(6)	(7)
FDI Bonanza	1.279	1.542	2.744	1.843	1.385	1.619	2.761	1.861
	(0.445)	(0.649)	(1.606)	(0.789)	(0.468)	(0.596)	(1.346)	(0.686)
FDI Bonanza×Boom		0.597		4.437		0.604		5.459
		(-0.460)		(1.059)		(-0.348)		(0.991)
BonIFBoomB		0.9208		8.1785		0.9786		10.1592
BonIFBoomPval		0.9279		0.0794		0.9860		0.1262
Obs	794	794	794	794	440	440	440	440
Countries	39	39	39	39	25	25	25	25
Crises	53	53	53	53	37	37	37	37
Portfolio Bonanza	3.907***	4.074***	9.622***	9.602***	4.700***	4.745**	13.937***	12.573***
	(2.823)	(2.644)	(3.822)	(3.551)	(2.687)	(2.417)	(3.543)	(3.163)
Portfolio Bonanza×Boom		0.832		1.010		0.964		1.615
		(-0.185)		(0.008)		(-0.033)		(0.373)
BonIFBoomB		3.3886		9.6946		4.5722		20.3088
BonIFBoomPval		0.1793		0.0340		0.1371		0.0166
Obs	794	794	794	794	440	440	440	440
Countries	39	39	39	39	25	25	25	25
Crises	53	53	53	53	37	37	37	37
Debt Bonanza	2.667**	2.747**	4.348**	1.254	5.590***	5.380***	7.256**	1.115
	(2.278)	(2.038)	(2.302)	(0.195)	(3.029)	(2.730)	(2.052)	(0.079)
Debt Bonanza×Boom		0.903		10.492		1.213		49.247**
		(-0.118)		(1.559)		(0.165)		(2.019)
BonIFBoomB		2.4803		13.1542		6.5273		54.9058
BonIFBoomPval		0.2261		0.0070		0.0882		0.0040
Obs	794	794	794	794	440	440	440	440
Countries	39	39	39	39	25	25	25	25
Crises	53	53	53	53	37	37	37	37

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 bonanza in net capital inflow. 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 asuming a Gumbel distribution. logit refers to the regressor assuming a Logistic distribution.

7. Appendix (Not to Print)

Table A-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 1sd (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 A-2: RE and FE models. Regression of banking crises on aggregate bonanzas. All countries, 1973-2008

	Baseline (1sd) bonanzas		Mild (0.5sd) bonanzas		Intense (2sd) bonanzas	
	(7) RE	(7) FE	(7) RE	(7) FE	(7) RE	(7) FE
Developing country indicator (LDC)						
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	
Regional groups						
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	
Income groups						
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 1	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: Dependent variable is dummy for start of banking crisis. Specifications 3 and 4 add dummy for lending boom and the interaction term Bon×Boom. Columns 2-7 include lagged covariates of competition risk (increasing discrete variable), international liberalization (dummy), moral hazard (decreasing discrete variable), banking supervision (increasing discrete variable), dummy for explicit deposit insurance and dummy for (contemporaneous) currency crisis. Specifications 5-7 replicate 2-4 adding 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 asuming a Gumbel distribution. logit refers to the regressor assuming a Logistic distribution. 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 A-3: Data description

Variable	**Definition**	**Source**
Banking crises	Dummy variable that takes value 1 if a crisis starts in that year. Definition of a systemic banking crisis is found in the text in section 2.	Laeven and Valencia (2010)
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. Please see description of threshold method in section 2.	Computed using data from IFS database,
Net capital inflows	Capital flows data from Balance of Payments statistics IFS dataset. Net capital inflows are computed adding reported assets and liabilities in IFS data. Aggregate net inflows are equal to the balance in the financial account (line *78bjd*). Flows are disagregated into three categories: (i) FDI, (ii) portfolio-equity, and (iii) debt.	International Monetary Fund
Net capital inflows by type	Net FDI inflows are computed adding lines *78bdd* (for assets) and *78bed* (for liabilities). Portfolio-equity assets are computed by adding lines of portfolio investments (*78bfd*) and financial derivatives (*78bwd*), and subtracting debt securities (*78bld*). Portfolio-equity liabilities are computed in the same fashion (lines *78bgd* + *78bxd* − *78bnd*). Obtained portfolio-equity assets and liabilities are added to compute net portfolio-equity inflows. Finally, net debt inflows are obtanied as a residual. Since total net capital inflows are equal to the balance in the financial account, net debt inflows are computed by subtracting net FDI and net portfolio-equity inflows from the balance in the financial account.	
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. Please see description of threshold method in 2.	Computed using data from WDI database. World
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).	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 rats 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 A-3 – 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.	Demirgüc-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.	Ilzetzki *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 (2010)
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 interst 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
De facto CA openness	*De facto* current account openness is proxied by the ratio of total foreign assets and liabilities to GDP.	Lane and Milesi-Ferretti (2007)

Table A-4: Sample of countries. Year of systemic banking crises in parenthesis

High income countries			
Used in specification 6 of multivariate econometric analysis			
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)	
Used only in specification 1 and non-parametric analysis			
Australia (none)	Iceland (2008)	Kuwait (none)	Singapore (none)
Hong Kong (none)	Israel (1977)	New Zealand (none)	Slovenia (2008*)
Developing countries			
Used in specification 6 of multivariate econometric analysis			
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)	
Used only in specification 1 and non-parametric analysis			
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)