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Cross-Country Evidence on Bonanzas in Capital Inflows and Bonanza-Boom-Bust Cycles

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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 standard deviation from trend, increases the odds of a banking crisis by three times, even in the absence of a lending boom. Thus, a bonanza raises the likelihood of a crisis from an unconditional probability of 4.4 percent to 12 percent. Larger windfalls of capital (two-s.d. bonanzas) increase the odds of a crisis by eight times. The joint occurrence of a bonanza and a lending boom raises these odds even more. Decomposing flows into 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. Thus, windfalls in all types of flows exacerbate the deleterious effects of credit. However, surges in portfolio-equity flows seem to have an independent effect, even in the absence of a lending boom. Furthermore, emerging economies exhibit greater odds of crises after a windfall of capital.

Keywords: Banking crises, Financial crises, Capital flows, Credit booms, Lending booms

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

1 Introduction

This paper empirically explores whether 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 performs 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. The 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 eight 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 absence of excessive lending.

The current state of the world economy, with tepid output growth and record-low interest rates in high-income countries, has created perfect conditions for a wave of capital inflows seeking higher yields in emerging economies. In turn, this has bolstered concerns in the receiving countries about the desirability of windfalls of capital, and policymakers have responded with a battery of macro and micro prudential policies that, in some cases, go as far as restricting the free flow of capital across borders. To formulate appropriate policies over the long term, however, it is necessary to determine the macroeconomic and financial effects of windfalls of international capital.

Concerns in emerging economies about the macroeconomic and financial imbalances stemming from surges in inflows are hardly new. At least since Díaz-Alejandro (1985) it has been argued that surges in capital inflows are associated with macroeconomic and financial risks, particularly after processes of financial liberalization.[1] More recently, some authors argue that current

[1] From a macroeconomic perspective, the literature has also emphasized that surges in inflows are associated with appreciation of the real exchange rate. Monetary authorities often intervene to dampen the appreciation, but the sterilization of large inflows imposes challenges to monetary policy and seems to be ineffective and often costly. From a financial perspective, the main concerns stem from upward pressure on asset prices and increased exposure to currency and maturity mismatches (a fixed exchange regime exacerbates these risks). The temporary nature of the flows and a sudden reversal has also been a big concern. 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).

account deficits, and the concomitant net capital inflows, were at the roots of the financial crisis of 2007-2008 in the United States (see, e.g., Portes, 2009; Reinhart and Rogoff, 2009, Chap. 13).The argument is that increased international capital inflows, especially in the form of debt, amplify financial risks because the greater availability of capital increases the funds intermediated by the financial sector, fueling excessive growth in lending and magnifying the intrinsic asymmetric information and moral hazard problems of banking (Gavin and Hausmann, 1996; Goldstein and Turner, 1996; Mishkin, 1996). 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, and deposit insurance schemes (Corsetti et al., 1999).[2]

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 the one hand, there is no robust evidence on the association between surges in capital inflows and lending booms.[5] A recent analysis by Calderón and Servén (2012) using quarterly data spanning 1970-2010 finds "few asset price booms and capital flow bonanzas end up in a lending boom, even though lending booms are often preceded by these other kinds of booms." Their results indicate that it is true that there is an association between bonanzas and lending booms, but this is not because most bonanzas become or are accompanied by lending booms, as most lending booms take place without a previous or contemporaneous bonanza. However, most bonanzas do take place after lending booms, suggesting that the conventional wisdom mistook the direction of causality.

On the other hand, most studies have failed to find a robust statistical association between capital inflows and the likelihood of banking crises, including the studies by Sachs et al. (1996),

[2] The intrinsic illiquidity of banks' assets and asymmetric information in the banking industry are microeconomic characteristics making banks prone to crises (Allen and Gale, 2007). Bailout guarantees exacerbate risks stemming from moral hazard and incentives to excessive 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.

[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 on the effects of capital inflows on currency crises see Eichengreen (2003). On sudden stops see Edwards (2007), Calvo et al. (2008), and Agosín and Huaita (2012).

[5] For example, Sachs et al. (1996) find no association between lending booms and surges in capital inflows during crises in the 1990s. Gourinchas et al. (2001), using data up to 1999, report only a small increase in capital inflows during lending booms. Still, Mendoza and Terrones (2008) find that half of the lending booms in a sample spanning 1960-2006 were accompanied by large gross capital inflows. Similarly, Furceri et al. (2011a) report a positive response of credit to the private sector after the start of a capital inflow bonanza after computing impulse responsive functions; however, their method does not permit the discernment of contemporaneous causal relations (see Jorda, 2005, p. 163).

Eichengreen and Rose (1998), Radelet and Sachs (1998), Fernández-Arias and Hausmann (2001), Eichengreen and Arteta (2002), and Mendis (2002). The evidence on the current account balance is also mixed: although Barrell and Davis (2010) find a significant effect of the current account balance in a regression of banking crises in the period 1980-2008 for OECD countries, Jorda et al. (2011) find the opposite once they control for credit growth in a much larger sample of 14 developed economies in the period 1870-2008.

The literature has had a bit more success at linking banking crises and the stock of foreign liabilities, especially debt, but it is still far from conclusive. Bonfiglioli (2008) reports a positive result focusing on aggregate liabilities, but only in developed countries. Joyce (2010) and Ahrend and Goujard (2011) find a robust association between the likelihood of banking crises and the stock of foreign debt liabilities in emerging economies, with the latter study also reporting a greater probability of crises the larger the share of debt in foreign liabilities. However, Gourinchas and Obstfeld (2012) fail to find any association between the share of external debt in total external liabilities and the probability of banking crises in emerging markets (although they do find a robust association in high-income countries).

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, current account balance, or foreign liabilities, and those differences do not have to be related to a greater likelihood of crises. Similarly, a limitation of the studies 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 given threshold.[6] 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: i) quantifying the effect of bonanzas in net capital inflows on the probability of banking crises; ii) identifying

[6] The term "bonanza" was first used in this regard by Calvo et al. (1992) but went out of use until Reinhart and Reinhart (2009) reintroduced it.

bonanzas in the aggregate and by type of flow (FDI, portfolio-equity, and debt) using country-specific trends; and iii) performing a multivariate regression analysis focused on disentangling the effects of surges in international capital from the effects of lending booms. The regression analysis is based on random-intercept models that are robust to endogeneity of time-invariant country characteristics, and that allow the use of information from countries which did not suffer a crisis in the period of analysis. Thus, this paper goes beyond the usual fixed effects (conditional logit) analysis typical of the literature, which has the disadvantage of limiting the analysis to crisis-stricken countries.[7]

The paper studies a total of 113 crisis events from 141 countries in the period 1973-2008. When including all controls, the regression analysis uses information from 60 countries and 53 crisis events. The analysis controls for mechanisms triggering a banking crisis and most 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,[8] the level of reserves, and domestic and international interest rates.[9]

The results indicate that bonanzas in net capital inflows are associated with an increased likelihood of systemic banking crises.[10] 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 eight times more likely after an intense bonanza (2 s.d). If this large surge takes place jointly with a lending boom, a crisis becomes 16 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 16 percent in the absence of a lending boom and to 42 percent if a lending boom is underway (from an unconditional probability of 4.4 percent). Decomposing flows into FDI, portfolio-equity and

[7] Since the publication of a preliminary version of this study (Caballero, 2010), a new paper by Furceri et al. (2011b) has appeared following the typical logistic methodology. Their findings largely support the results of this paper. However, they do not attempt to disentangle the effects of credit booms from that of bonanzas in different types of inflows, which is the main contribution of this paper.

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

[9] An extensive study of determinants of banking crises is beyond the scope of this paper. I follow the literature to include relevant controls. In addition to those already mentioned, I 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.

[10] 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.

debt flows shows that bonanzas in all types of flows exacerbate the deleterious effects of lending booms. However, portfolio-equity flows are the only type of flow that exhibits a robust independent association with crises in the absence of a lending boom. 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 than during a typical business cycle.[11] The focus is on *net* capital inflows, as opposed to total gross flows. Baseline results are obtained with flows deflated and normalized in per capita terms, but similar results are obtained in robustness checks using flows as a percentage of GDP.[12]

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.[13] 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.[14] 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 1 exemplifies the method for the case of South Korea.

On the other hand, measuring bonanzas as deviations of net capital inflows from their long-run trend rests on the implicit assumption that net inflows within the trend can be absorbed without causing distress to the banking system. Thus, I perform a robustness check using an indicator

[11] 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 (2012) 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.

[12] 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 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.

[13] 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 similar.

[14] Bonanzas can also be defined adding a constraint for the size or level of flows (e.g., flows being at least 5 percent of GDP or some regional average). However, it is preferable 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 that 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.

of bonanzas identified by Reinhart and Reinhart (2009), which is based on the current account balance and does not rely on a de-trending technique.

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 performed 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.

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 fewer 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 20 percent or bank closures of at least 20 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, not 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, 15 events are classified as borderline. The database identifies 23 crises in the years 2007-2008, of which 10 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 computes 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 1 presents summary statistics for the variables used in the empirical analysis, and Table 22 in the Appendix 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 does not have a significant impact on 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.[15] As a check, the analysis is performed in a sample until 2006 and similar results are obtained.

3 Do Surges in Net Capital Inflows Influence the Likelihood of Banking Crises?

3.1 First Pass on the Data and 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 bonanzas are on the columns. Frequencies and percentages are presented along with statistics and corresponding *p*-values for three independence tests: Pearson

[15] 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 absence of an explicit scheme. Thus, the variable 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."

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 2 reports two-way tabulations and results of independence tests for banking crises and one-period lagged baseline bonanzas using data covering the period 1973-2008. There are a total of 141 countries with available data for banking crises, capital inflows and credit (115 developing and emerging economies). The methodology identifies a total of 426 baseline bonanza episodes in the sample period. The dataset on banking crises identifies 113 episodes of systemic crises. A total of 89 countries (65 percent) experienced a crisis (this proportion is 61 percent for developing countries and 73 percent for high-income countries). Of these, 21 countries endured two crises during the period. Argentina is the only country with more than two crises, with a tally of four events. Table 25 makes explicit which countries and crises are used in the analysis.

In the full sample, three percent (3.39 percent) is the proportion of pair-year observations identified with the start of a banking crisis (this is the unconditional probability of a crisis). On the other hand, 6.57 percent of bonanzas ended up in a banking crisis the following year (this is its conditional probability). The data also reveal that 24.78 percent of banking crises took place after a baseline capital flow bonanza. The independence tests are rejected, indicating that banking crises and previous-year net capital inflow bonanzas are statistically associated. This non-parametric analysis replicates the results of Reinhart and Reinhart (2009), who find a greater conditional probability of crises after bonanzas.

The great majority of crises (91 out of 113) took place in developing countries. The conditional probability of a crisis is smaller for developing countries (6.27 percent vs. 8.00 percent); however, the unconditional probability of a crisis is similar in all country groups.[16] Because most crises in high-income countries in this sample took place in the years 2007-2008 (15 out of 22), I do not want to make much of the results for OECD countries. For the same reason, this paper focuses on the samples including all countries or developing countries, and no attempt is made to study crises in high-income countries.

If bonanzas increase the likelihood of crises, conditioning by intense bonanzas must result in a stronger association and greater conditional probabilities. Indeed, Table 3 shows that this is the case for the full sample (9.79 percent vs. 6.57 percent) and for all country groups.

The frequencies suggest that neither net capital inflow bonanzas nor lending booms are a recipe for disaster: only a small fraction of bonanzas (28 out of 426) or booms (39 out of 456) end up in a crisis the following year.[17] This is in line with the findings of Calderón and Servén (2012). However, the joint occurrence of the two events greatly increases the likelihood of a

[16] These results are in line with Reinhart and Rogoff (2009, Chap. 13), who also report similar incidence rates of banking crises in high-income and developing countries using historical data.

[17] To save space, results of independent tests and conditional probabilities for lending booms are not shown, but they are available upon request.

crisis. For the sample including all countries, the conditional probability of a crisis following a simultaneous baseline bonanzas and a boom is greater than the unconditional probability of a crisis (13.68 percent vs. 3.39 percent) and greater than the conditional probability of a crisis following a 1 s.d. bonanza (9.79 percent) or a 1 s.d. credit boom (8.55 percent). For intense bonanzas taking place at the same time that credit booms, the conditional probability rises to 18.75 percent.[18]

Using the same non-parametric analysis I find a strong statistical association between net capital inflow bonanzas and lending booms (results available upon request). However, the results suggest that the conventional belief that capital inflows fuel or *cause* lending booms is mistaken. The data reveal a strong association between bonanzas and lending booms because most bonanzas are associated with booms, not because most booms are associated with or preceded by bonanzas, not even in developing countries. The data suggest that lending booms attract windfalls of international capital, exactly the opposite of what it is usually believed, and in line with the recent findings of Calderón and Servén (2012). Only 23.7 percent of baseline bonanzas (1 s.d.) took place in a year in which no lending boom was present. Yet, most baseline lending booms (78.7 percent) were not associated with contemporaneous baseline bonanzas, and this proportion is even higher for more intense bonanzas (89.7 percent). Similar proportions are found if we do the analysis for previous-year bonanzas: only 22.2 percent of booms were preceded by a baseline bonanza (10.2 percent for intense bonanzas). These results do not mean that windfalls of international capital do not end up fueling credit in the domestic economy or that the two events of bonanzas and booms are not correlated. It just means that bonanzas are not the same as lending booms, and that these two phenomena do not necessarily take place at the same time or for the same reasons.[19]

This non-parametric approach indicates an association between windfalls of capital and banking crises. However, it 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, as we will see in the next section, the magnitude of the effect of bonanzas is distorted. The conditional probability of a crisis following a baseline or intense bonanza from a multivariate econometric analysis indicates a much larger effect after controlling for macroeconomic and institutional factors.

3.2 Regression Analysis: Empirical Strategy

The empirical strategy is based on a regression analysis of a binary outcome model. In this binary outcome framework a country experiences (does not experience) the *start* of a banking crisis in a

[18] Exercises not shown indicate that all the results hold if the crises of years 2007-2008 are dropped from the sample.

[19] One explanation may be found in the literature exploring the determinants of bonanzas. For example, findings by Calvo et al. (1993) and Forbes and Warnock (2011) indicate that the most robust determinants of surges are related to external factors (i.e., international interest rates and risk aversion of international investors), not domestic conditions, which are the most likely drivers of credit booms.

given year, so that $y_{i,t}$ is a binary response variable for the start of a crisis. We can 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 $y_{i,t} = 1[y^*_{i,t} > 0], t = 1, ..., T$.

The likelihood of a crisis starting is hypothesized to be a function of a vector of macroeconomic and institutional characteristics of the country, and a linear regression model is specified for the latent response y^*. Specifically, the analysis below estimates variations of the following random-intercept model:

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

where it is assumed that $E[\xi|k, l, X, \zeta] = 0$. Equation (1) includes as determinants of banking crises a dummy variable for bonanzas in net capital inflows (k), a dummy variable for lending booms (l), the interaction of the two, and a vector X of macroeconomic and institutional characteristics. The intercept ζ_i captures country time-invariant specific effects associated with the onset of crises.

The covariates in equation (1) 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. The baseline analysis is performed after eliminating the first three years of observations following a crisis. This is in order to reduce the influence of observations affected by the outcome of crises (robustness checks including all observations show that the results do not hinge on this).

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 (1) 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 in two ways: first by estimating the model with no interaction term and alternatively excluding/including the covariate for lending booms and comparing the estimated coefficients for bonanzas $\hat{\gamma}$; and second, by estimating the model with the interaction term and evaluating significance and sign of $\hat{\gamma}$. 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 are also interested in the linear combination of the coefficients for bonanzas and booms, $\hat{\gamma} + \hat{\delta}$, which will tell us the association between crises and bonanzas when we set the indicator for lending boom equal to one. This way we can evaluate whether a bonanza coinciding with a lending boom exacerbates the effect of the boom or not ($H_o : \gamma + \delta = 0$).

The identification strategy relies on two assumptions: i) bonanzas in a given year are not caused by banking crises the following year and ii) bonanzas are orthogonal to lending booms, in the sense that, on average, bonanzas do not cause booms. This is the "bad control" problem discussed by Angrist and Pischke (2009, p. 64). At first glance, this assumption seems heroic, but the empirical evidence by Gourinchas et al. (2001), Sachs et al. (1996), and Calderón and Servén (2012), and the non-parametric analysis above support it. Nevertheless, given the potential bad control problem, 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. The simplest strategy to estimate equation (1) is to model the country intercept ζ_i as a random effect, assuming a normal distribution $\zeta_i | X_{i,t-1} \sim N(0, \sigma_\zeta^2)$ and a constant exchangeable within-country correlation of the idiosyncratic error $Corr(\xi_{i,t}, \xi_{i,s} = \rho)$. The first assumption implies that the country intercept ζ_i is uncorrelated with the covariates; equivalently, that the covariates are exogenous with respect to the country intercept. This is the usual random effects model. This specification has the advantage of modeling the country intercept as a random variable that represents the unexplained variability between different countries' probability of a crisis and yields consistent and efficient estimates under the stated assumptions.

However, the assumption of no correlation, or exogeneity, between the country intercept and the covariates may be too strong. In the present analysis it is most likely that this assumption is violated, as many of the macroeconomic and institutional controls in equation (1) may well be correlated with the country intercept. Thus, I will employ estimation techniques of random effects (RE) and fixed effects (FE) models that control for the endogeneity of the covariates with respect to ζ_i, the time-invariant country specific intercept capturing omitted country-specific time-invariant characteristics that explain the probability of a banking crisis.

The exogeneity assumption of time-invariant variables can be relaxed following Mundlak's strategy to include in the RE model the country (cluster) mean of the covariates we suspect are endogenous (Mundlak, 1978). To see why this strategy makes sense, let us focus for a moment on an example with only one covariate.[20] Let the true model be $y^*_{i,t} = \varphi_0 + \varphi_1 \omega_i + \beta x_{i,t} + \xi_{i,t}$, where $\xi_{i,t} = \zeta_i + \epsilon_{i,j}$. This reduced form model includes the country-level covariate ω_i that explains the between-country variability in the probability of a crisis. While ζ_i is just a country-level residual lumped with the idiosyncratic error. Now, let the estimated model be $y^*_{i,t} = \varphi_0 + \beta x_{i,t} + \zeta'_i + \epsilon_{i,t}$. That is, the estimated model omits the important country-level covariate ω_i. Assuming correlation between ω_i and $x_{i,t}$, the estimated model will yield biased estimates of β, the coefficient of interest.

The correlation between ω_i and $x_{i,t}$ can be represented by the regression $\omega_i = \phi_0 + \phi_1 x_{i,t} + u_i$. This expression can be rewritten as $\omega_i = \phi_0 + \phi_1 \bar{x}_{i,\cdot} + u_i$, where $\bar{x}_{i,\cdot}$ is the country mean

[20] This example is based on Skrondal and Rabe-Hesketh (2004, p. 52). The general case with many covariates is presented in Snijders and Berkhof (2008) and in Wooldridge (2009).

of the covariate, after we recognize that $x_{i,t} = (x_{i,t} - \bar{x}_{i,.}) + \bar{x}_{i,.}$ and the fact that the regression coefficient of ω_i on $(x_{i,t} - \bar{x}_{i,.})$ is zero. On the other hand, if the country intercept represents the effects of omitted covariates, it should have expectation $\varphi_1\omega_i$ and can be written in the reduced form $\zeta_i' = \varphi_1\omega_i + \zeta_i$.

Thus, the estimated model can be written as $y^*_{i,t} = \varphi_0 + \beta x_{i,t} + \psi_0 + \psi_1\bar{x}_{i,.} + \bar{\omega}_i + \epsilon_{i,t}$, where $\psi_0 = \varphi_1\phi_0$, $\psi_1 = \varphi_1\phi_1$ and $\bar{\omega}_i = \varphi_1 u_{i,t} + \zeta_i$. We see that by including the country mean $\bar{x}_{i,.}$ as a separate covariate in the estimated model, the coefficient of $x_{i,t}$ becomes the required parameter β in the correctly specified model, although we have omitted ω_i. Wooldridge (2009) shows that this equivalence holds for unbalanced panels and for non-linear models.

The model with country means can be written as $y^*_{i,t} = \varphi_0 + \psi_0 + (\psi_1 + \beta)\bar{x}_{i,.} + \beta(x_{i,t} - \bar{x}_{i,.}) + \bar{\omega}_i + \epsilon_{i,t}$. Thus, $\psi_1 + \beta$ represents the between-country effect and β the within-country effect. We see that in essence the RE-Mundlak strategy allows for different within and between-country effects. If the two effects are equal we have that $\psi_1 = \varphi_1\phi_1 = 0$, and the RE model with no country means will yield unbiased estimates. Snijders and Berkhof (2008) and Skrondal and Rabe-Hesketh (2004, p. 52) discuss that a Wald test of the equality of the between and within effects is identical to the Hausman test for the random intercept model. I will present this test and also will estimate a fixed effects model and show that the results are similar. The important point to keep in mind is that even if there is a difference between the within and between country estimated coefficients, unbiased estimates can be obtained with the RE model, provided that the cluster means of the explanatory variables are included.[21]

A limitation of the RE-Mundlak strategy is that the modeling of the country intercept ζ_i still makes some assumptions $\zeta_i | X_{i,t-1} \sim N(0, \sigma^2_\zeta)$, namely zero expectations, homogeneous variances, and normal distribution. An alternative is to completely disregard the randomness of the country intercept and estimate a fixed effects model (FE). An advantage of this approach is that we obtain consistent estimates that are not influenced at all by the specification of the country intercept, while allowing for endogeneity of the covariates with respect to the time-invariant component of the error. In essence, the FE specification controls for all unexplained differences between countries, taking 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 weak banking regulation, lax capital controls, or being a commodity exporter, offshore financial center, or tax haven.

However, a big disadvantage of the FE model is that it drops from the estimation countries that did not face a crisis in the period of analysis (since they do not have variation in the dependent variable). However, the RE-Mundlak estimator can take into account these countries. This is a very desirable feature of this estimator, as it includes all countries with available data. This allows

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

us to go beyond the traditional FE models that base inference in a sample of countries that only includes countries that ended up having a crisis. This way we can be sure that we are including in the estimation countries that have had bonanzas, but not crises, and in this way find if there is a meaningful relationship in the data. Thus, baseline results are obtained by a random effects model including country means of all time-variant covariates (RE-Mundlak). For completeness, I also estimate a fixed effects model (FE-clogit). Both models are estimated using maximum likelihood.

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 (1) is estimated by the conditional logit estimator. When not constrained by fixed effects, the Gumbel (extreme value) distribution is assumed, and complementary logarithmic regression is used.[22]

The non-linearity of these binary outcome models prevents a straightforward interpretation of the coefficients. 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 I will refer to them as odds ratios.[23]

3.2.1 Control Variables

The vector X of one-period lagged controls in equation (1) 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,[24] a dummy for a process of international

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

[23] If it is a logit model, these exponentiated coefficients have a clear-cut form and interpretation in the odds ratio $or = p/(1-p)$, $p = Pr(y = 1|Z)$ being 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 $h = Pr(y = 1|Z)/Pr(y = 0|Z)$.

[24] 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 it 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.

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.[25]

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,[26] measures of *de facto* and *de jure* current account openness, and the annual average of the Federal Funds rate (as a proxy for international monetary conditions).[27] Table (22) explains in detail all variables used in the analysis and their sources.[28]

3.3 Regression Analysis: Results

Table 4 reports the results of estimating the RE model including country-means of all covariates, the RE-Mundlak estimator. The table presents estimated coefficients for seven different specifications, along with some statistics of the regression.[29] The table presents exponentiated coefficients (odds ratios) and z statistics in parentheses. The last lines at the bottom of the table report the estimated area under the Receiver Operating Characteristic curve (AUROC), which is a measure of the predictive ability of the model (a prefect predictor would obtain an area equal to unity).

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 specifica-

[25] 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 a 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.

[26] I experimented with inflation, but the models with depreciation offered a better fit. The correlation between the two variables is 0.95.

[27] 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.

[28] No serious issues of collinearity arise in this analysis (to save space, correlation tables are not reported). 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 the results are similar.

[29] The estimation sample includes a total of 3,467 country-year pairs, from 141 countries, and a total of 113 systemic banking crises. However, when including all sets of covariates the sample shrinks to 1,208 country-year pairs and uses information from 60 countries and a total of 53 crises (a subset of 39 countries with crises). All the results in the regression analysis are done maintaining this sample fixed. In exceercises not shown, the point estimates are similar when including all available data in each specificaiton.

tion adds the indicator for baseline lending booms. Neither significance nor magnitude of the coefficient of interest changes significantly. The results indicate, then, that surges in net capital inflows are associated with a greater likelihood of systemic banking crises the following year. The coefficient of bonanzas in the first three specifications is different from zero at the 1 percent 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 us to estimate the differential effect of a bonanza, given the presence or absence of a boom. 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 the interaction with booms. The bottom of the table reports estimated exponentiated coefficients (odds ratios), standard errors, and a Wald test of joint significance ($H_o : \gamma + \delta = 0$). The results indicate that previous-year bonanzas are associated with a greater probability of a systemic banking crisis, whether a previous-year lending boom is absent ($\hat{\gamma} \neq 0$ at the 10 percent level) or present ($\hat{\gamma} + \hat{\delta} \neq 0$ at the 1 percent level). The interaction term by itself is not statistically significant. This implies that a bonanza has roughly the same effect either with or without a lending boom once the other covariates are taken into account.

Columns 5, 6, and 7 add the second set of controls. After including all covariates the coefficient of bonanzas is significant at the 1 percent level (column 6), the differential effect of bonanzas given a lending boom is significant at 5 percent (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 the 10 percent and has a similar magnitude as before (top of column 7).[30]

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. However, comparing the coefficients for bonanzas in column 5 (not including the boom covariate) with columns 6 and 7 (including boom covariate) suggests that the presence of a lending boom does account for some of the effect of the bonanza.

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 countries' baseline odds of a crisis. The interpretation of the magnitude of the effect of a variable is straightforward: a variable multiplies the odds of a crisis times the estimated coefficient. Thus, the results indicate that the odds of a banking crisis are, on average, three times greater if a

[30] The estimated coefficients for the country-means represent the difference in the between and within effects, and in large samples is equivalent to the Hausman test. This difference in the between and within effect is not statistically different from zero when including the first set of covariates. However, when including all covariates it is significant, suggesting that the RE-Mundlak model, or a FE model, offers a better fit than a typical RE estimator.

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 four times greater. The independent effect of a bonanza raises the probability of a crisis from an unconditional probability of 4.4 percent to 12 percent[31] after controlling for all other factors. A bonanza jointly occurring with a lending boom increases the probability of a crisis to 16 percent.

Estimating the FE conditional logit model (FE-clogit) yields results in the same line as the RE-Mundlak estimator. Table 5 reports the results. These results are based solely on countries that registered a crisis in the sample period.[32] The results are similar as the ones obtained with the RE-Mundlak model, and most coefficients of interest are significant at the 1 percent level.

Estimated coefficients for all other covariates are consistent with the literature. The likelihood of a banking crisis increases with unusually large growth in credit (a lending boom), increased competition in the banking sector after liberalization, and a contemporaneous currency crisis. The proxy for moral hazard has the correct negative sign, which is represented by an odds ratio less than one, but it is statistically significant only when not including the second set of controls. Neither international liberalization nor quality of institutions appears as significant when controlling for all relevant factors, a result consistent with the literature. A greater level of financial integration, as proxied by the stock of foreign liabilities, is associated with a greater likelihood of crises, a result in line with the existing literature. 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 of its somewhat high correlation with other covariates. Similarly, odds ratios less than one, albeit not significant, are obtained for quality of institutions, output growth and trade openness, and odds greater than one for fixed exchange rate regimes.

3.4 Is There a Difference between Mild and 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 whether 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. Table 6 presents summarized results for specifications 5 and 7 of the RE-Mundlak and FE-clogit models. As in the baseline case, bonanzas are associated with

[31] 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 $OR = odds(crisis|bonanza)/odds(crisis|nobonanza)$. In the sample used in the baseline regressions, the unconditional probability of a crisis is 4.4 percent (53 crises out of 1,208 observations), which implies $odds(crisis|nobonanza) = 0.0459$. Of the 53 crises, 16 took place after a bonanza, which implies $odds(crisis|nobonanza) = 0.0134$. Thus, the odds ratio is $0.2925 = 0.0459/0.0134$. With an estimated odds ratio of 3 from the regression, then, the estimated probability of a crisis conditional on a bonanza, after controlling for other covariates, is $0.12 = [3 \times 0.2925]/[1 + (3 \times 0.2925)]$.

[32] Regressions are estimated in the baseline sample of 1,208 country-year observations. Since the FE model only includes countries with crises, estimations in Table 5 use a subset of 794 observations.

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 the windfall of capital. An intense bonanza increases the odds of a crisis the following year by eight times when no lending boom is underway. This implies a 27 percent probability of a crisis. When a lending boom is present, an intense bonanza increases the odds of a crisis by 16 times, raising the probability to 42 percent. The effects of mild bonanzas are much smaller and similar to those of baseline bonanzas. For this reason, the rest of the analysis will focus only on baseline and intense bonanzas.

The effect of bonanzas in the absence of a lending boom is significantly different from zero at least at the 5 percent level in all cases. As with the baseline case, comparing the coefficients for bonanzas in specifications 5 and 7 suggests that part, but not all, of the bonanza effect is through its correlation with lending booms.

3.5 Endogeneity and Causality

A causal interpretation of the results holds if the assumptions $E[\zeta|k,l,X] = E[\xi|k,l,X,\zeta] = 0$ are met. Both models, RE-Mundlak and FE-clogit, allow us to relax the first assumption. However, we must consider whether 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.[33]

This is a valid concern. However, the empirical literature has failed to find a robust *causal* relationship between surges in capital inflows and lending booms. In the sample used in the regression analysis, most baseline lending booms (79 percent) are not associated with contemporaneous bonanzas, not even intense bonanzas (90 percent).[34] Bonanzas and booms are associated, but not because capital inflows cause booms. This implies that it is sensible to assume in the regression analysis that lending booms take place *before* a bonanza or for a different reason.

As a check, the model is estimated dropping all observations that exhibit a lending boom in the previous year. Table 7 reports summarized results of specification 5, including all covariates. 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 (two s.d.) bonanzas. The

[33] In any case, if bonanzas and booms are correlated, including both variables in the same regression would give their partial coefficients (i.e., estimates of their separate effects controlling one another).

[34] These proportions are remarkably similar, but not identical, to the ones obtained with the much larger sample of 3,338 observations used in the non-parametric analysis of Section 3.1.

estimated odds ratios are quite similar to the ones obtained in the full sample and in all cases significant at least at the 5 percent level.[35]

On the other hand, we must consider the exogeneity assumption that the covariates are independent from the idiosyncratic error: $E[\xi|k, l, X, \zeta] = 0$. 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. Since the results are obtained using one-period lagged explanatory variables, contemporaneous endogeneity is ruled out as an issue.

The regression results obtained here may not be considered causal if the reader believes that, conditional on the covariates, bonanzas in a given year are affected by the expectation of a banking crisis in 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 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.

3.6 Predictive Ability of Bonanzas in Net Capital Inflows

The results also indicate that bonanzas in net capital inflows are a factor that enhances the fit and predictive ability of a banking crisis model (relative to a model only including lending booms and other relevant covariates). This is important, as it has significant policy implications (e.g., should policymakers interested in financial stability monitor growth in capital inflows, or is focusing on credit growth sufficient?). Table 8 compares models introducing the covariate of bonanzas in an otherwise standard regression of banking crises on lending booms and relevant covariates. The table shows that introducing the covariate of bonanzas in net capital inflows not only improves the fit of the model (estimated log-likelihood gets closer to zero), but it also consistently reduces the magnitude of the coefficient for credit booms. This suggests that the introduction of the bonanza covariate conveys information that the lending boom covariate does not. As discussed below, the results also indicate that it improves the predictive ability of the model.

To compare the predictive ability of the competing models with and without the bonanza covariate, Figure 2 plots the Receiver Operating Characteristic (ROC) curves of the models, for both the RE-Mundlak and FE-clogit estimators. ROC curves are a standard tool used to evaluate binary classification ability in biological sciences, and have been recently used in economics by Schularick and Taylor (2012). The ROC curve plots the true positive rate $TP(c)$, or $sensitivity$, of

[35] Given the earlier finding that few bonanzas take place jointly with a lending boom, it is not surprising to obtain results on a subsample without a lending boom coinciding with a bonanza similar to the results on the full sample.

the model against the false positive rate $FP(c)$, or $1 - specificity$, for all thresholds c on the real line. Figure 2 plots the TP and FP rates for the estimated probabilities of all models (including and not including the covariate for bonanzas), allowing us to evaluate how the models perform as classifiers. The graph is constructed plotting the results of the indicator function $I(\hat{p} - c > 0)$, where $\hat{p}$ is the linear prediction of the model, which forms a continuous signal, and c is a cutoff threshold. When the threshold c is large and negative, the classifier is very aggressive in making crisis calls and almost all signals are above the threshold, and TP and FP converge to unity. When c is large and positive, the classifier is very conservative in making crisis calls and almost all signals are below the threshold, and TP and FP converge to zero. In between, an informative classifier should deliver $TP > FP$. This implies that the ROC curve of an informative classifier lies above the 45-degree line.

Figure 2 shows that for most cutoffs of relevance the predictive ability of the model introducing the covariate of bonanzas is much better than the alternative model including only covariates of credit booms. Nonetheless, the optimal cutoff is not obvious. Schularick and Taylor (2012) make the point that this depends on the costs of the different possible outcomes and on the frequency of crises. They argue that the cutoff should be more aggressive if the cost of an undiagnosed crisis is high, but less so if the cost of a false alarm is higher. If crises are rare, the threshold should also be raised to deflect too-frequent false alarms. However, to compare the predictive ability of two competing models we only need to compare the area under the ROC curve (AUROC), as it is itself independent of the cutoff level. In essence, the AUROC tests whether the distribution of the model's signals is significantly different under crisis and non-crisis states, allowing us to gauge the global performance of the models as classifiers. The results indicate that the predictive ability of the model estimated with the RE-Mundlak estimator is much better than the FE-clogit, with an AUROC of 0.86 when introducing the covariate of bonanzas. It also provides an improvement over the alternative model not including the bonanzas covariate. A test of equality of the two AUROCs for the RE-Mundlak estimator rejects the null hypothesis of equality at the 6 percent level, and for the FE-clogit at the 1 percent level.

3.7 Robustness and Sensitivity Checks

Baseline results were obtained after dropping the first three years of observations after a banking crisis. Tables 9 and 10 replicate baseline results for the RE-Mundlak and FE-clogit estimators, and show that the baseline results do not depend on this.

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 identifying bonanzas using flows asa percentage of GDP.

Similarly, to rule out the possibility that the de-trending of capital inflows is driving the results (dropping the implicit assumption that net inflows within the trend can be absorbed without causing distress to the banking system), a robustness check is performed using as covariate the bonanzas identified by Reinhart and Reinhart (2009), which do not rely on the use of a time series filter.

As another check, the regressions are estimated in the subsample 1973-2006, dropping observations from the recent financial crises.

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.

Summarized results of these robustness exercises for specifications 5 and 7 are reported in Table 11 for the RE-Mundlak estimator and Table 12 for the FE-clogit estimator. Encouragingly, the results of these exercises are in line with the baseline results.

4 Do Developing Countries Face Greater Risks From Surges in Net Capital Inflows?

This section explores whether windfalls of capital have a different effect on developing countries or on different regions. These exercises are performed estimating specification 7 for both RE-Mundlak and FE-clogit models, and including indicators for developing status and for different regional and income groups.[36] Table 13 reports summarized results for these exercises. The regressions are performed including an indicator for income group 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 income or region effect in the RE-Mundlak 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 the test. In the FE-clogit 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 coefficient of the interacting term.

The results suggest that there are no regional effects. Interestingly, the regressions suggest that bonanzas have a differential effect on middle and upper income economies. However, this is not the case for low income countries.

Another way to explore a differential effect of bonanzas in developing countries is to estimate the models for this subsample. Tables 14 and 15 present summarized results for specifications

[36] The regional and income classifications are those of the World Bank. There is an indicator for developing countries (LDC). Income groups are low, middle, and upper income. 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*). This paper classifies South Korea, Czech Republic, Estonia, Hungary and Slovakia as upper-middle income countries.

5 and 7 and for baseline and intense bonanzas for developing countries as a whole, and for the subsample of upper and middle income countries. The upper and middle income groups are explored further because the regressions with interacting terms suggested a differential effect of bonanzas in this group of countries, and because 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.

The results in Tables 14 and 15 show that the estimated coefficients for the subsample of developing countries are higher than for the full sample. Furthermore, an intense bonanza when a lending boom is underway dramatically increases the probability of a crisis, specially in upper and middle income countries (this is in line with the results from the models using interacting terms). However, when including the interacting term of Bonanza$\times$Boom the statistical significance of baseline bonanzas vanishes. Thus, the effect of baseline bonanzas in these countries most likely operates through a lending boom.

Intense bonanzas seem to have an independent effect, even after discounting the presence of lending booms. Intense bonanzas exhibit coefficients significant at the 5 percent level or better. An intense bonanza in net capital inflows in the group of upper and middle income countries has a greater effect than in the full sample or the sample including all developing economies. The estimated coefficients indicate that an intense bonanza in a middle or upper middle income country makes the odds of a banking crisis 10 times greater in the absence of a boom and 30 times greater if a boom is underway. That is, the probability of a crisis rises to 31 percent and 58 percent, respectively.

Interestingly, the coefficient of banking supervision becomes significant at the 10 percent level for intense bonanzas, suggesting that improving the regulation of the banking sector reduces the probability of banking crises in developing countries.[37]

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 only through a lending boom mechanism. However, these results open new questions, especially regarding the mechanisms at work. 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.

[37] As remarked before, the index of banking supervision is quite correlated with income. It also has little variation across high-income countries. It appeared as negative but not significant in regressions with the full sample.

Before presenting the results a caveat is necessary. The data suggest that 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-equity bonanza, is close to 20 percent. The conditional probability of a bonanza in portfolio-equity flows given a bonanza in debt or FDI is also close to 20 percent. These non-negligible conditional probabilities indicate that all types of flows fly into a country when international capital markets get excited about it, making it difficult to separate the effect of each type of flow. With this caveat in mind, the model is first estimated independently for each type of flow.

Tables 16 and 17 present summarized results for the samples of all countries and upper and middle income countries. Results reported only for specifications 5 and 7 of the RE-Mundlak and FE-clogit models. In these tables each cell refers to a single regression.

Specification 5 and the interacting term of specification 7 indicate that bonanzas in all types of flows, even FDI, are associated with an increase likelihood of crises, but this effect is mainly through a simultaneous lending boom. This result is in line with existing empirical evidence, suggesting that excessive credit growth is a key determinant of banking crises, and that some booms take place simultaneously with windfalls of capital. Still, the joint occurrence of a lending boom and an intense bonanza of any type substantially increases the odds of a crisis. 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).

Interestingly, the results of specification 7 for the bonanza covariate indicate that bonanzas in portfolio-equity flows are robustly associated with an increased likelihood of systemic banking crises in the absence of lending booms –results statistically significant at the 1 percent level for intense bonanzas, and at 5 percent for baseline bonanzas. In line with the hypothesis that it is the windfall of capital by itself that is triggering mechanisms in the economy that end up in a crisis, intense bonanzas of portfolio-equity flows raise the odds of a crisis more than baseline bonanzas. These effects are economically significant. In the full sample, an intense bonanza in portfolio-equity flows is associated with a 30 percent probability of a crisis in the absence of a lending boom; simultaneous occurrence with a lending boom increases the probability to 48 percent.

These results are qualitatively similar when the sample is restricted to only developing countries (not shown) or only upper and middle income countries (Table 17). 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-equity flows raises the odds of a crisis by 10 times, and by 20 times if a boom is underway.

An alternative way to estimate the model is including all the bonanzas in a single regression. This is done for the sample including all countries in Tables 18 and 19, respectively for baseline and intense bonanzas. The tables show summarized results of specifications 5, 6, and 7 of RE-Mundlak and FE-clogit models. As with the regressions including only one bonanza covariate, these regressions indicate that the effects of FDI and debt bonanzas are channeled mainly through their correlation with lending booms, although intense bonanzas in these flows do have a differential effect if jointly occurring with a lending boom.

Bonanzas of portfolio-equity flows are still significant determinants of banking crises on their own (in both cases baseline and intense bonanzas the coefficient is significant at least at the 5 percent level). They magnify the effects of credit, when taking place along lending booms, but they also have an effect in the absence of excessive growth in credit. Tables 20 and 21 show that these results are also obtained when estimating the models restricting the sample to upper and middle income countries.

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 20 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; nonetheless, it still appears as positive. 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 intra-group 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 they 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 of 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 estate prices. Similarly, IMF (2010) shows that a measure of "excess global liquidity" has a positive impact on domestic asset prices in emerging economies. On the other hand, Calvo (2012) offers a model in which the liquidity characteristics of financial assets may be a vehicle that increases financial fragility. His model offers a way to rationalize why windfalls of capital may increase the likelihood of banking crises, even if there is not excessive growth in lending that can be classified as a lending boom. However, there is still much room for research in the development of theoretical models for understanding the mechanisms at work 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 not only related to 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 (2012), countries are exposed to sudden stops. Moreover, 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 temporary 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 may be 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 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; 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 they 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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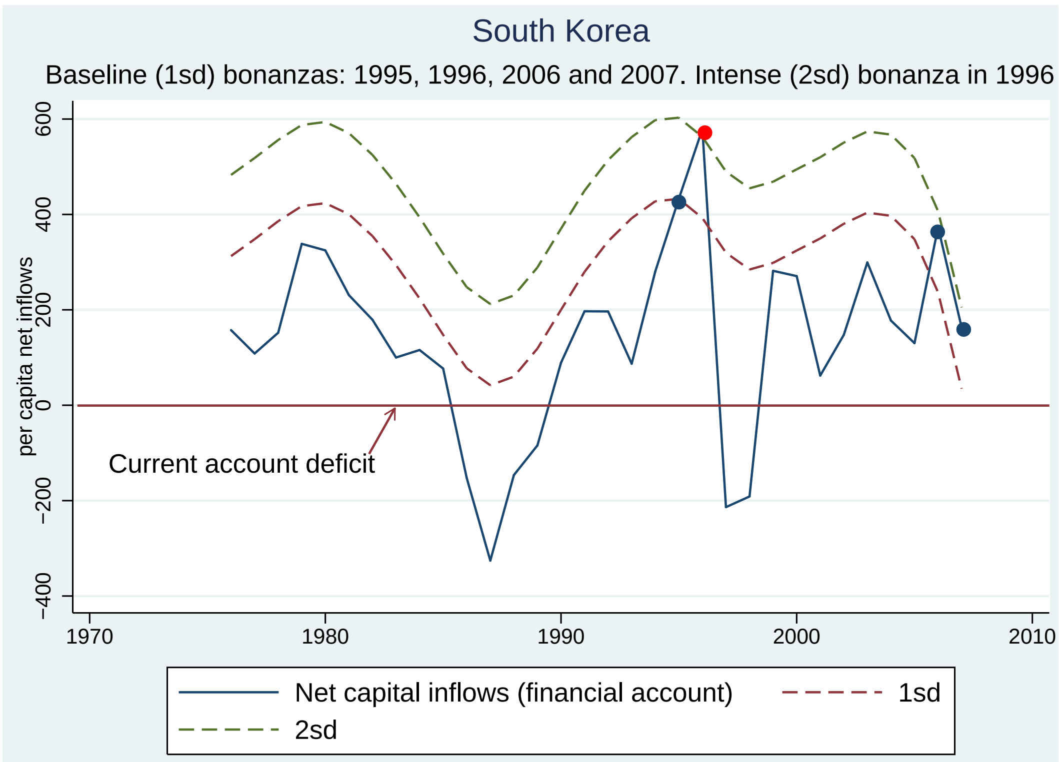
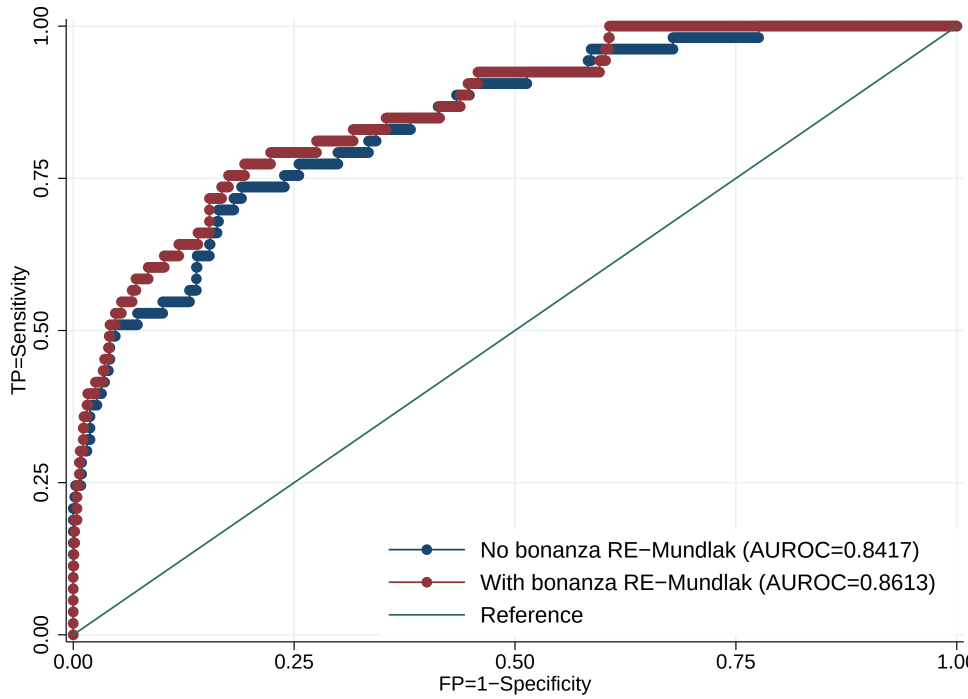
Figure 1. Threshold Method to Identify Bonanzas



Note: Baseline bonanzas are identified as events when per capita net inflows 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

Figure 2. Comparison of Predictive Ability of Model with Bonanza Covariate

Panel A. RE-Mundlak model (includes all-variables means)



Panel B. FE-clogit model (conditional logit)

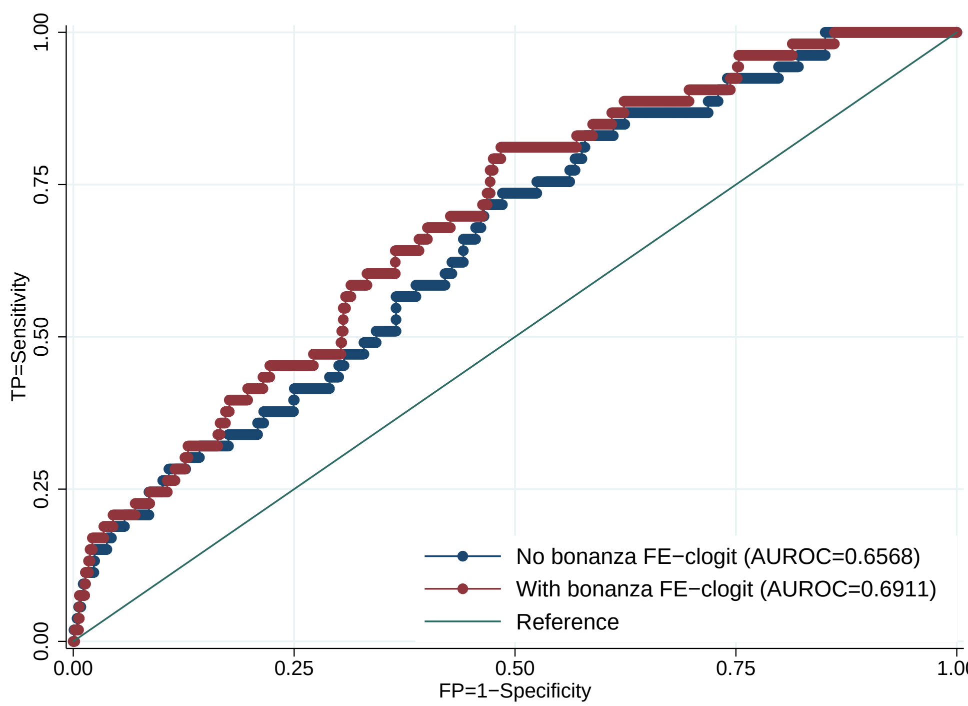


Table 1. Summary Statistics. All Countries, 1973-2008

Variable	Obs	Mean	Std. Dev.	Min	Max
Banking crisis (dummy)	1208	0.0439	0.2049	0.0000	1.0000
Agg. Kflow bonanza 1 sd (dummy)	1208	0.1250	0.3309	0.0000	1.0000
Lending Boom 1 sd (dummy)	1208	0.1316	0.3382	0.0000	1.0000
Lending Boom 2 sd (dummy)	1208	0.0339	0.1812	0.0000	1.0000
Bon(1 sd)$\times$Boom(1 sd)	1208	0.0290	0.1678	0.0000	1.0000
Bon(1 sd)$\times$Boom(2 sd)	1208	0.0075	0.0860	0.0000	1.0000
Competition risk (discrete)	1208	0.4611	0.9399	0.0000	3.0000
Int. liberalization (dummy)	1208	0.3949	0.4890	0.0000	1.0000
Currency crisis (dummy)	1208	0.0281	0.1655	0.0000	1.0000
Moral hazard (discrete)	1208	0.8444	2.8434	-9.0000	10.0000
Banking supervision (discrete)	1208	1.1167	1.0963	0.0000	3.0000
(Explicit) Deposit insurance (dummy)	1208	0.6978	0.4594	0.0000	1.0000
KA Open	1208	0.6210	1.5719	-1.8312	2.5000
De facto CA openness	1208	1.5489	1.8809	0.1491	19.8512
Polity2 (discrete)	1208	6.5778	5.2586	-9.0000	10.0000
Reserves ($ bn)	1208	21.1526	63.2677	0.0141	952.7840
Interest rate (%)	1208	15.9498	174.2845	-86.3178	5844.9834
Trade openness (% of GDP)	1208	64.8745	33.6076	9.1024	184.3178
Depreciation (%)	1208	241.7072	7566.0721	-100.0000	262826.8438
Fixed exchange rate (dummy)	1208	0.6101	0.4879	0.0000	1.0000
GDP growth (%)	1208	3.7772	3.2795	-13.1279	18.2863
FED effective discount rate(%)	1208	6.1630	3.3453	1.1265	16.3864

Table 2. Two-way Tabulations and Independence Tests of Banking Crises and Previous Year Capital Flow Bonanzas. Baseline (1 sd) Bonanzas. 1973-2008

	All countries			Developing countries			High income countries		
	Bonanzas 1 sd			Bonanzas 1 sd			Bonanzas 1 sd		
Banking crisis	0	1	Total	0	1	Total	0	1	Total
0	2827	398	3225	2139	329	2468	688	69	757
	87.66	12.34	100	86.67	13.33	100	90.89	9.11	100
	97.08	93.43	96.61	96.88	93.73	96.44	97.73	92.00	97.18
1	85	28	113	69	22	91	16	6	22
	75.22	24.78	100	75.82	24.18	100	72.73	27.27	100
	2.92	6.57	3.39	3.13	6.27	3.56	2.27	8.00	2.82
Total	2912	426	3338	2208	351	2559	704	75	779
	87.24	12.76	100	86.28	13.72	100	90.37	9.63	100
	100	100	100	100	100	100	100	100	100
Observations	3338			2559			779		
Pearson_coef	15.170			8.722			8.101		
Pearson_sig	0.000			0.003			0.004		
LR_coef	12.480			7.418			5.776		
LR_sig	0.000			0.006			0.016		
Fishers_exact_p	0.000			0.007			0.014		

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

Table 3. Two-way Tabulations and Independence Tests of Banking Crises and Previous Year Capital Flow Bonanzas. Intense (2 sd) Bonanzas. 1973-2008

	All countries			Developing countries			High income countries		
	Bonanzas 2 sd			Bonanzas 2 sd			Bonanzas 2 sd		
Banking crisis	0	1	Total	0	1	Total	0	1	Total
0	3096	129	3225	2399	69	2468	738	19	757
	96.00	4.00	100	97.20	2.80	100	97.49	2.51	100.00
	96.90	90.21	96.61	96.66	89.61	96.44	97.49	86.36	97.18
1	99	14	113	83	8	91	19	3	22
	87.61	12.39	100	91.21	8.79	100	86.36	13.64	100
	3.10	9.79	3.39	3.34	10.39	3.56	2.51	13.64	2.82
Total	3195	143	3338	2482	77	2559	757	22	779
	95.72	4.28	100	96.99	3.01	100	97.18	2.82	100
	100	100	100	100	100	100	100	100	100
Observations	3338			2559			779		
Pearson_coef	18.739			10.809			9.644		
Pearson_sig	0.000			0.018			0.002		
LR_coef	12.863			7.344			5.248		
LR_sig	0.000			0.007			0.022		
Fishers_exact_p	0.000			0.005			0.021		

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

Table 4. RE-Mundlak Model (RE with all-variables means). Regression of Banking Crises on Aggregate Bonanzas (1 sd). Odds Ratios. All Countries, 1973-2008

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Bonanza	3.008***	3.167***	2.855***	2.250*	3.616***	3.089***	2.484*
	(3.607)	(3.705)	(3.332)	(1.928)	(3.684)	(3.132)	(1.955)
Lending Boom (1 sd)			3.745***	3.113***		3.969***	3.219***
			(4.328)	(2.949)		(3.870)	(2.670)
Bon(1 sd)×Boom(1 sd)				2.004			1.700
				(0.988)			(0.680)
Competition Risk		1.595***	1.690***	1.680***	1.599***	1.716***	1.725***
		(3.016)	(3.382)	(3.329)	(2.693)	(3.108)	(3.132)
Int. Liberalization		0.525*	0.542*	0.550*	0.675	0.699	0.711
		(-1.931)	(-1.844)	(-1.792)	(-1.028)	(-0.941)	(-0.888)
Currency crisis (t)		4.646***	3.763***	4.069***	4.694***	3.795***	4.148***
		(3.459)	(2.957)	(3.074)	(3.087)	(2.642)	(2.781)
Moral Hazard		0.885**	0.863**	0.865**	0.942	0.907	0.902
		(-1.978)	(-2.384)	(-2.334)	(-0.877)	(-1.421)	(-1.492)
Banking supervision		1.227	1.151	1.135	0.605	0.635	0.621
		(0.912)	(0.615)	(0.552)	(-1.451)	(-1.302)	(-1.325)
KA open					0.823	0.840	0.839
					(-0.998)	(-0.903)	(-0.908)
De facto CA openness					1.338*	1.342*	1.336*
					(1.695)	(1.673)	(1.653)
Polity2					1.008	0.993	0.993
					(0.198)	(-0.183)	(-0.180)
Reserves					0.998	0.997	0.997
					(-0.734)	(-0.934)	(-0.945)
Interest rate					1.002	1.001	1.001
					(0.937)	(0.354)	(0.374)
Trade openness					1.003	0.999	1.001
					(0.232)	(-0.042)	(0.057)
Depreciation (Nom ER)					1.000	1.000	1.000
					(-0.616)	(-0.522)	(-0.504)
Fixed exch. rate					2.517*	2.864**	2.976**
					(1.956)	(2.153)	(2.220)
GDP Growth					1.024	0.993	0.989
					(0.531)	(-0.166)	(-0.247)
Fed effective funds rate					1.113*	1.095	1.095
					(1.750)	(1.445)	(1.450)
Bon+BoomB				4.5100***			4.2236**
Bon+BoomSE				2.4584			2.6272
Obs	1208	1208	1208	1208	1208	1208	1208
Countries	60	60	60	60	60	60	60
Crises	53	53	53	53	53	53	53
Loglik	-211.1647	-193.6157	-185.3774	-184.8439	-162.0725	-155.0612	-154.6240
WaldTestChi2	0.5135	8.6173	8.6048	9.3158	37.8349	37.6653	37.3822
WaldTestPval	0.4736	0.2813	0.2823	0.3164	0.0026	0.0027	0.0047
AUROC	0.6062	0.7559	0.7927	0.7963	0.8543	0.8608	0.8613
AUROCse	0.0464	0.0351	0.0319	0.0317	0.0250	0.0254	0.0260
Regression	cloglog	cloglog	cloglog	cloglog	cloglog	cloglog	cloglog

Note: Exponentiated coefficients; z statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Dependent variable is dummy for start of banking crisis. cloglog refers to the regressor assuming a Gumbel distribution.

Table 5. FE-clogit Model (conditional logit). Regression of Banking Crises on Aggregate Bonanzas (1 sd). Odds Ratios. All Countries, 1973-2008

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Bonanza	3.077***	3.667***	2.670***	2.336*	4.722***	3.420***	2.771*
	(3.361)	(3.667)	(2.627)	(1.791)	(3.740)	(2.841)	(1.911)
Lending Boom (1 sd)			5.821***	5.234***		4.528***	3.749**
			(4.560)	(3.681)		(3.382)	(2.499)
Bon(1 sd)×Boom(1 sd)				1.450			1.905
				(0.476)			(0.706)
Competition Risk		1.539**	1.669***	1.665***	1.497**	1.583**	1.574**
		(2.475)	(2.877)	(2.857)	(1.985)	(2.264)	(2.229)
Int. Liberalization		0.467*	0.486*	0.491*	0.505	0.503	0.508
		(-1.922)	(-1.844)	(-1.815)	(-1.403)	(-1.397)	(-1.381)
Currency crisis (t)		4.951***	3.508**	3.606**	6.460***	4.403**	4.578**
		(2.990)	(2.345)	(2.390)	(3.097)	(2.424)	(2.493)
Moral Hazard		0.894*	0.864**	0.865**	0.980	0.952	0.954
		(-1.652)	(-2.060)	(-2.052)	(-0.259)	(-0.619)	(-0.594)
Banking supervision		1.092	1.027	1.025	0.557	0.577	0.584
		(0.370)	(0.105)	(0.099)	(-1.438)	(-1.369)	(-1.337)
KA open					0.974	1.032	1.041
					(-0.109)	(0.132)	(0.166)
De facto CA openness					2.389**	2.208**	2.232**
					(2.537)	(2.197)	(2.237)
Polity2					0.957	0.933	0.931
					(-0.760)	(-1.183)	(-1.213)
Reserves					0.998	0.997	0.997
					(-0.618)	(-0.766)	(-0.753)
Interest rate					1.002	1.002	1.001
					(0.768)	(0.644)	(0.708)
Trade openness					0.992	0.990	0.988
					(-0.438)	(-0.619)	(-0.689)
Depreciation (Nom ER)					1.000	1.000	1.000
					(-0.366)	(-0.136)	(-0.149)
Fixed exch. rate					2.447	2.381	2.419
					(1.637)	(1.583)	(1.607)
GDP Growth					0.969	0.961	0.962
					(-0.573)	(-0.719)	(-0.696)
Fed effective funds rate					1.122*	1.097	1.099
					(1.676)	(1.269)	(1.299)
Bon+BoomB				3.3873**			5.2774**
Bon+BoomSE				2.1104			3.9770
Obs	794	794	794	794	794	794	794
Countries	39	39	39	39	39	39	39
Crises	53	53	53	53	53	53	53
Loglik	-136.7318	-124.9934	-114.8909	-114.7776	-99.7021	-94.1628	-93.9121
AUROC	0.5925	0.7269	0.7556	0.7560	0.6694	0.6905	0.6911
AUROCse	0.0322	0.0378	0.0382	0.0382	0.0338	0.0345	0.0346
Regression	logit	logit	logit	logit	logit	logit	logit

Note: Exponentiated coefficients; z statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Dependent variable is dummy for start of banking crisis. logit refers to the regressor assuming a Logistic distribution.

Table 6. RE-Mundlak and FE-clogit Models. Mild and Intense Bonanzas. Regression of Banking Crises on Aggregate Bonanzas. Odds Ratios. All Countries, 1973-2008

	Mild (0.5 sd) Bonanzas				Intense (2 sd) Bonanzas			
	RE-Mundlak (5)	RE-Mundlak (7)	FE-clogit (5)	FE-clogit (7)	RE-Mundlak (5)	RE-Mundlak (7)	FE-clogit (5)	FE-clogit (7)
Bonanza	4.030***	3.649***	4.757***	3.730***	15.340***	8.351***	16.430***	7.338**
	(4.471)	(3.411)	(4.245)	(3.095)	(6.192)	(3.069)	(5.256)	(2.513)
Lending Boom (1 sd)		4.062***		4.359**		2.732**		3.211**
		(2.768)		(2.324)		(2.345)		(2.239)
Bon()×Boom(1 sd)		0.895		0.891		1.964		2.263
		(-0.160)		(-0.138)		(0.679)		(0.695)
Competition Risk	1.580**	1.698***	1.435*	1.518**	1.700***	1.703***	1.505**	1.550**
	(2.540)	(2.939)	(1.793)	(2.079)	(3.044)	(3.084)	(2.026)	(2.125)
Int. Liberalization	0.734	0.758	0.519	0.507	0.748	0.714	0.607	0.561
	(-0.798)	(-0.708)	(-1.316)	(-1.344)	(-0.746)	(-0.844)	(-1.022)	(-1.172)
Currency crisis (t)	3.638**	2.830*	4.312**	3.208*	5.706***	4.437***	6.366***	4.717***
	(2.499)	(1.944)	(2.314)	(1.853)	(3.536)	(2.980)	(3.169)	(2.610)
Moral Hazard	0.924	0.900	0.955	0.938	0.905	0.880*	0.957	0.947
	(-1.174)	(-1.539)	(-0.596)	(-0.826)	(-1.398)	(-1.793)	(-0.558)	(-0.680)
Banking supervision	0.606	0.639	0.565	0.575	0.652	0.667	0.503	0.538
	(-1.432)	(-1.267)	(-1.373)	(-1.355)	(-1.218)	(-1.094)	(-1.582)	(-1.443)
Controls 1	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls 2	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bon+BoomB		3.2652**		3.3218		16.4027***		16.6033***
Bon+BoomSE		1.9126		2.4609		12.1061		14.3394
Obs	1208	1208	794	794	1208	1208	794	794
Countries	60	60	39	39	60	60	39	39
Crises	53	53	53	53	53	53	53	53
Loglik	-158.6536	-152.3184	-96.9541	-92.0160	-153.8640	-147.3026	-93.9703	-89.8434
WaldTestChi2	34.2444	34.4022			37.1633	38.3066		
WaldTestPval	0.0078	0.0112			0.0032	0.0035		
AUROC	0.8557	0.8632	0.6979	0.7160	0.8684	0.8716	0.7060	0.7132
AUROCse	0.0261	0.0258	0.0342	0.0339	0.0261	0.0256	0.0338	0.0349
Regression	cloglog	cloglog	logit	logit	cloglog	cloglog	logit	logit

Note: Exponentiated coefficients; z statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Dependent variable is dummy for start of banking crisis. cloglog refers to the regressor assuming a Gumbel distribution. logit refers to the regressor assuming a Logistic distribution.

Table 7. No Previous Lending Boom. RE-Mundlak and FE-clogit Models. Regression of Banking Crises on Aggregate Bonanzas. Odds Ratios. All Countries, 1973-2008

	Baseline Bonanzas (1 sd)		Intense Bonanzas (2 sd)	
	RE-Mundlak (5)	FE-clogit (5)	RE-Mundlak (5)	FE-clogit (5)
Bonanza	2.647**	2.959**	7.517***	5.455**
	(2.071)	(1.968)	(2.849)	(2.072)
Competition Risk	1.475*	1.626**	1.505*	1.609*
	(1.863)	(1.972)	(1.951)	(1.933)
Int. Liberalization	0.519	0.373	0.574	0.412
	(-1.331)	(-1.542)	(-1.118)	(-1.398)
Currency crisis (t)	3.910**	3.988**	4.118**	4.065**
	(2.398)	(1.990)	(2.548)	(2.054)
Moral Hazard	0.948	0.960	0.930	0.947
	(-0.705)	(-0.436)	(-0.904)	(-0.594)
Banking supervision	0.595	0.731	0.602	0.673
	(-1.219)	(-0.624)	(-1.197)	(-0.761)
Controls 1	Yes	Yes	Yes	Yes
Controls 2	Yes	Yes	Yes	Yes
Obs	1049	463	1049	463
Countries	60	26	60	26
Crises	34	34	34	34
Loglik	-112.2625	-67.0193	-112.2389	-67.0241
WaldTestChi2	24.6971		22.4511	
WaldTestPval	0.1017		0.1680	
AUROC	0.8515	0.6018	0.8519	0.6068
AUROCse	0.0308	0.0414	0.0316	0.0419
Regression	cloglog	logit	cloglog	logit

Note: Exponentiated coefficients; z statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Dependent variable is dummy for start of banking crisis. cloglog refers to the regressor assuming a Gumbel distribution. logit refers to the regressor assuming a Logistic distribution.

Table 8. RE-Mundlak and FE-clogit Models. Regression of Banking Crises on Lending Booms and Aggregate Bonanzas (1 sd). Odds Ratios. All Countries, 1973-2008

	RE-Mundlak	RE-Mundlak	RE-Mundlak	RE-Mundlak	RE-Mundlak	RE-Mundlak	RE-Mundlak	RE-Mundlak	RE-Mundlak
Lending Boom (1 sd)	4.057***	3.606***	3.425***	3.909***	3.745***	3.113***	4.514***	3.969***	3.219***
	[1.229]	[1.101]	[1.264]	[1.191]	[1.142]	[1.199]	[1.572]	[1.414]	[1.410]
Bonanza		2.457***	2.229*		2.855***	2.250*		3.089***	2.484*
		[0.762]	[0.919]		[0.899]	[0.946]		[1.112]	[1.156]
Bon(1 sd)×Boom(1 sd)			1.470			2.004			1.700
			[0.974]			[1.410]			[1.328]
Controls 1	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Controls 2	No	No	No	No	No	No	Yes	Yes	Yes
Bon+BoomB			3.2766**			4.5100***			4.2236**
Bon+BoomSE			1.6707			2.4584			2.6272
Obs	1208	1208	1208	1208	1208	1208	1208	1208	1208
Countries	60	60	60	60	60	60	60	60	60
Crises	53	53	53	53	53	53	53	53	53
Loglik	-208.0543	-203.1306	-202.5425	-191.6204	-185.3774	-184.8439	-160.6031	-155.0612	-154.6240
AUROC	0.6186	0.6939	0.7001	0.7675	0.7927	0.7963	0.8417	0.8608	0.8613
AUROCse	0.0336	0.0403	0.0393	0.0344	0.0319	0.0317	0.0281	0.0254	0.0260

	FE-clogit	FE-clogit	FE-clogit	FE-clogit	FE-clogit	FE-clogit	FE-clogit	FE-clogit	FE-clogit
Lending Boom (1 sd)	6.614***	5.815***	5.266***	6.994***	5.821***	5.234***	5.840***	4.528***	3.749**
	[2.320]	[2.092]	[2.184]	[2.632]	[2.249]	[2.354]	[2.491]	[2.022]	[1.982]
Bonanza		2.349**	2.053		2.670***	2.336*		3.420***	2.771*
		[0.828]	[0.925]		[0.998]	[1.106]		[1.480]	[1.478]
Bon(1 sd)×Boom(1 sd)			1.452			1.450			1.905
			[1.085]			[1.132]			[1.737]
Controls 1	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Controls 2	No	No	No	No	No	No	Yes	Yes	Yes
Bon+BoomB			2.9807*			3.3873**			5.2774**
Bon+BoomSE			1.7645			2.1104			3.9770
Obs	794	794	794	794	794	794	794	794	794
Countries	39	39	39	39	39	39	39	39	39
Crises	53	53	53	53	53	53	53	53	53
Loglik	-128.2184	-125.5018	-125.3771	-118.0778	-114.8909	-114.7776	-98.0291	-94.1628	-93.9121
AUROC	0.6186	0.6599	0.6599	0.7294	0.7556	0.7560	0.6568	0.6905	0.6911
AUROCse	0.0336	0.0373	0.0373	0.0389	0.0382	0.0382	0.0364	0.0345	0.0346

Exponentiated coefficients; Standard errors in brackets, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9. Robustness Check. Including All Observations (without dropping first three years after a crisis). RE-Mundlak Model. Regression of Banking Crises on Aggregate Bonanzas (1 sd). Odds Ratios. All Countries, 1973-2008

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Bonanza	3.262***	3.314***	2.950***	2.743**	3.818***	3.528***	3.195***
	(3.913)	(3.899)	(3.489)	(2.439)	(3.907)	(3.612)	(2.603)
Lending Boom (1 sd)			3.135***	3.031***		3.130***	2.841***
			(3.825)	(3.074)		(3.573)	(2.752)
Bon(1 sd)×Boom(1 sd)				1.251			1.179
				(0.345)			(0.236)
Controls 1	No	Yes	Yes	Yes	Yes	Yes	Yes
Controls 2	No	No	No	No	Yes	Yes	Yes
Bon+BoomB				3.4320**			3.7664**
Bon+BoomSE				1.6934			2.0923
Obs	1407	1407	1407	1407	1407	1407	1407
Countries	60	60	60	60	60	60	60
Crises	54	54	54	54	54	54	54
Loglik	-222.6070	-207.4981	-200.9946	-200.8131	-181.1475	-175.3575	-175.0303
WaldTestChi2	0.0966	7.7021	6.6290	6.8884	33.8121	33.3141	33.7340
WaldTestPval	0.7560	0.3596	0.4685	0.5487	0.0089	0.0103	0.0136
AUROC	0.5766	0.7530	0.7780	0.7812	0.8385	0.8407	0.8409
AUROCse	0.0473	0.0334	0.0325	0.0319	0.0263	0.0264	0.0269

Note: Exponentiated coefficients; z statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Dependent variable is dummy for start of banking crisis. cloglog refers to the regressor assuming a Gumbel distribution. logit refers to the regressor assuming a Logistic distribution.

Table 10. Robustness Check. Including All Observations (without dropping first three years after a crisis). FE-clogit Model (conditional logit). Regression of Banking Crises on Aggregate Bonanzas (1 sd). Odds Ratios. All Countries, 1973-2008

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Bonanza	3.400***	3.921***	3.247***	3.063**	3.890***	3.327***	3.282**
	(3.815)	(4.046)	(3.388)	(2.507)	(3.659)	(3.138)	(2.491)
Lending Boom (1 sd)			3.616***	3.471***		3.114***	3.084***
			(3.928)	(3.259)		(3.122)	(2.688)
Bon(1 sd)$\times$Boom(1 sd)				1.164			1.038
				(0.211)			(0.048)
Controls 1	No	Yes	Yes	Yes	Yes	Yes	Yes
Controls 2	No	No	No	No	Yes	Yes	Yes
Bon+BoomB				3.5668**			3.4071**
Bon+BoomSE				2.0137			2.1525
Obs	968	968	968	968	968	968	968
Countries	39	39	39	39	39	39	39
Crises	54	54	54	54	54	54	54
Loglik	-152.7057	-141.6181	-134.5676	-134.5454	-125.2554	-120.6929	-120.6918
AUROC	0.5920	0.7181	0.7525	0.7530	0.6343	0.6575	0.6576
AUROCse	0.0317	0.0368	0.0372	0.0372	0.0347	0.0362	0.0362

Note: Exponentiated coefficients; z statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Dependent variable is dummy for start of banking crisis. cloglog refers to the regressor assuming a Gumbel distribution. logit refers to the regressor assuming a Logistic distribution.

Table 11. Robustness Checks. RE-Mundlak Model. Bonanzas as % of GDP, RR Bonanzas, Subsample 1973–2006, and Different Lending Booms. Regression of Banking Crises on Aggregate Bonanzas. Odds Ratios. All Countries, 1979-2008 (except subsample)

	Bonanza (1 sd) as% of GDP		RR Bonanzas		Subsample 1973-2006		Lending Boom (2 sd)		GVL Lending boom	
	RE-Mundlak (5)	RE-Mundlak (7)	RE-Mundlak (5)	RE-Mundlak (7)	RE-Mundlak (5)	RE-Mundlak (7)	RE-Mundlak (5)	RE-Mundlak 7)	RE-Mundlak (5)	RE-Mundlak (7)
Bonanza	4.379***	3.525***	3.112***	3.018***	3.735***	2.503*	3.616***	2.959***	3.616***	4.404***
	(4.521)	(3.045)	(3.407)	(2.782)	(3.340)	(1.859)	(3.684)	(2.829)	(3.684)	(3.101)
Lending Boom		3.548***		4.467***		2.112		4.036**		1.218
		(2.840)		(3.379)		(1.415)		(2.106)		(0.327)
Bon×Boom		1.815		0.840		2.595		3.672		0.552
		(0.783)		(-0.256)		(1.069)		(1.167)		(-0.604)
Controls 1	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls 2	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bon+BoomB		6.3977***		2.5339		6.4962**		10.8653**		2.4319
Bon+BoomSE		4.0563		1.4818		4.7800		11.6116		2.0929
Obs	1208	1208	1198	1198	1123	1123	1208	1208	1208	1007
Countries	60	60	59	59	60	60	60	60	60	44
Crises	53	53	52	52	43	43	53	53	53	38
Loglik	-158.0835	-148.7697	-162.0331	-154.8729	-140.7628	-136.4434	-162.0725	-155.9226	-162.0725	-117.5222
WaldTestChi2	38.2865	39.0174	36.1043	37.5577	21.3375	21.3956	37.8349	35.9954	37.8349	28.5347
WaldTestPval	0.0022	0.0028	0.0044	0.0044	0.2116	0.2599	0.0026	0.0071	0.0026	0.0544
AUROC	0.8616	0.8682	0.8435	0.8562	0.8487	0.8545	0.8543	0.8594	0.8543	0.8799
AUROCse	0.0250	0.0259	0.0269	0.0266	0.0266	0.0284	0.0250	0.0256	0.0250	0.0249

Note: Exponentiated coefficients; Standard errors in brackets, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Dependent variable is dummy for start of banking crisis. cloglog refers to the regressor assuming a Gumbel distribution. logit refers to the regressor assuming a Logistic distribution.

Table 12. Robustness Checks. FE-clogit Model. Bonanzas as % of GDP, RR Bonanzas, Subsample 1973–2006, and Different Lending Booms. Regression of Banking Crises on Aggregate Bonanzas. Odds Ratios. All Countries, 1979-2003 (except subsample)

	Bonanza (1 sd) as% of GDP		RR Bonanzas		Subsample 1973-2006		Lending Boom (2 sd)		GVL Lending boom	
	FE-clogit (5)	FE-clogit (7)	FE-clogit (5)	FE-clogit (7)	FE-clogit (5)	FE-clogit (7)	FE-clogit (5)	FE-clogit 7)	FE-clogit (5)	FE-clogit (7)
Bonanza	5.679***	4.208***	2.915***	2.655**	4.363***	2.709*	4.722***	3.526***	4.722***	5.029***
	(4.489)	(3.111)	(2.856)	(2.269)	(3.336)	(1.782)	(3.740)	(2.839)	(3.740)	(2.932)
Lending Boom		3.848**		5.455***		3.078*		2.430		1.777
		(2.501)		(3.243)		(1.919)		(0.913)		(0.791)
Bon×Boom		1.876		0.851		2.158		‡		0.446
		(0.704)		(-0.192)		(0.764)		(0.010)		(-0.683)
Controls 1	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls 2	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BonIFBoomB		7.8929***		2.2600		5.8455**		‡		2.2429
BonIFBoomSE		6.2342		1.6728		4.8993		‡		2.3328
Obs	794	794	767	767	598	598	794	794	794	594
Countries	39	39	38	38	33	33	39	39	39	28
Crises	53	53	52	52	43	43	53	53	53	38
Loglik	-96.6036	-90.1444	-101.9156	-94.9220	-89.4303	-85.4989	-99.7021	-94.3120	-99.7021	-74.3796
WaldTestChi2										
WaldTestPval										
AUROC	0.6795	0.7083	0.6477	0.6812	0.6859	0.7111	0.6694	0.6938	0.6694	0.6755
AUROCse	0.0350	0.0345	0.0367	0.0359	0.0403	0.0417	0.0338	0.0339	0.0338	0.0403

Note: Exponentiated coefficients; Standard errors in brackets, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. ‡: Odds ratios larger than 100. Dependent variable is dummy for start of banking crisis. cloglog refers to the regressor assuming a Gumbel distribution. logit refers to the regressor assuming a Logistic distribution.

Table 13. Regions and Income Groups. RE-Mundlak and FE-clogit Models. Regression of Banking Crises on Aggregate Bonanzas. Odds Ratios. 1973-2008

	Baseline (1 sd) bonanzas		Intense (2 sd) bonanzas	
	RE-Mundlak (7)	FE-clogit (7)	RE-Mundlak (7)	FE-clogit (7)
Developing country indicator (LDC)				
Bonanza	9.820**	20.591**	12.086**	10.272*
	(2.268)	(2.396)	(2.134)	(1.778)
Bon×LDC	0.213	0.123	0.778	0.847
	(-1.513)	(-1.604)	(-0.213)	(-0.121)
Bon+LDCPval	0.1008		0.1927	
Regional groups				
Bonanza	3.035	4.700*	7.398**	6.669*
	(1.445)	(1.803)	(2.145)	(1.809)
Bon×Latam	0.817	0.465	1.530	0.359
	(-0.202)	(-0.680)	(0.293)	(-0.551)
Bon×SouthAsia	0.000	0.000	0.000	0.000
	(-0.000)	(-0.006)	(-0.000)	(-0.013)
Bon×EastAsia	4.254	3.882	24.941*	9.109
	(1.087)	(0.937)	(1.869)	(1.411)
Bon×MeAfr	0.000	0.000	0.000	0.000
	(-0.000)	(-0.008)	(-0.000)	(-0.010)
Bon+LatamPval	0.8398		0.7696	
Bon+SouthasiaPval	1.0000		1.0000	
Bon+EastasiaPval	0.2769		0.0616	
Bon+MeafrPval	0.9999		1.0000	
Income groups				
Bonanza	9.810**	20.415**	11.949**	12.628*
	(2.099)	(2.352)	(2.163)	(1.912)
Bon×Low	0.000	0.000	0.000	0.000
	(-0.000)	(-0.017)	(-0.000)	(-0.006)
Bon×Middle	0.533	0.274	2.906	1.273
	(-0.545)	(-0.920)	(0.841)	(0.164)
Bon×Upper	0.229	0.108	1.161	0.894
	(-1.194)	(-1.512)	(0.105)	(-0.065)
Bon+LowincomePval	0.9999		1.0000	
Bon+MiddleincomePval	0.0618		0.0310	
Bon+UpperincomePval	0.0867		0.0529	
Controls 1	Yes	Yes	Yes	Yes
Controls 2	Yes	Yes	Yes	Yes
Obs	1108	693	1108	693
Countries	60	38	60	38
Crises	51	51	51	51

Note: Exponentiated coefficients; z statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. 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 14. Developing Countries. RE-Mundlak and FE-clogit Models. Regression of Banking Crises on Aggregate Bonanzas. Odds Ratios. 1973-2008

	Baseline Bonanzas (1 sd)				Intense Bonanzas (2 sd)			
	RE-Mundlak (5)	RE-Mundlak (7)	FE-clogit 5)	FE-clogit (7)	RE-Mundlak (5)	RE-Mundlak (7)	FE-clogit 5)	FE-clogit (7)
Bonanza	2.744**	1.858	2.792**	1.711	14.300***	6.841**	14.984***	6.560**
	(2.367)	(1.213)	(2.156)	(0.920)	(4.891)	(2.549)	(4.147)	(2.110)
Lending Boom (1 sd)		1.625		2.386		1.375		1.978
		(0.856)		(1.380)		(0.571)		(1.084)
Bon()×Boom(1 sd)		3.697		2.988		5.436		3.589
		(1.311)		(1.038)		(1.315)		(0.918)
Competition Risk	1.616***	1.713***	1.465*	1.504**	1.698***	1.723***	1.484*	1.479*
	(2.619)	(2.886)	(1.843)	(1.973)	(2.870)	(2.947)	(1.897)	(1.835)
Int. Liberalization	0.579	0.571	0.515	0.540	0.627	0.534	0.593	0.568
	(-1.210)	(-1.219)	(-1.241)	(-1.149)	(-0.990)	(-1.288)	(-0.969)	(-1.044)
Currency crisis (t)	5.209***	5.087***	5.550***	4.496**	6.216***	5.649***	5.783***	4.732***
	(3.207)	(3.126)	(2.912)	(2.525)	(3.551)	(3.332)	(3.024)	(2.633)
Moral Hazard	0.939	0.928	0.977	0.975	0.910	0.922	0.972	0.980
	(-0.815)	(-0.971)	(-0.273)	(-0.294)	(-1.142)	(-1.006)	(-0.328)	(-0.231)
Banking supervision	0.585	0.565	0.565	0.534	0.533	0.450*	0.437*	0.421*
	(-1.320)	(-1.328)	(-1.261)	(-1.381)	(-1.497)	(-1.699)	(-1.671)	(-1.737)
Controls 1	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls 2	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bon+BoomB		6.8673**		5.1104*		37.1896***		23.5444***
Bon+BoomSE		5.9465		4.5661		39.0456		24.9830
Obs	691	691	523	523	691	691	523	523
Countries	41	41	29	29	41	41	29	29
Crises	42	42	42	42	42	42	42	42
Loglik	-124.1806	-121.4721	-81.8578	-78.9612	-117.1909	-114.5270	-76.1318	-74.4014
WaldTestChi2	16.0892	17.2950			15.8419	18.0415		
WaldTestPval	0.5175	0.5029			0.5351	0.4529		
AUROC	0.8120	0.8206	0.7752	0.7749	0.8374	0.8421	0.8019	0.7905
AUROCse	0.0324	0.0333	0.0337	0.0357	0.0320	0.0322	0.0334	0.0351
Regression	cloglog	logit	cloglog	logit	cloglog	logit	cloglog	logit

Note: Exponentiated coefficients; z statistics in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Dependent variable is dummy for start of banking crisis. cloglog refers to the regressor assuming a Gumbel distribution. logit refers to the regressor assuming a Logistic distribution.

Table 15. Upper and Middle Income Countries. RE-Mundlak and FE-clogit Models. Regression of Banking Crises on Aggregate Bonanzas. Odds Ratios. 1973-2008

	Baseline Bonanzas (1 sd)				Intense Bonanzas (2 sd)			
	RE-Mundlak (5)	RE-Mundlak (7)	FE-clogit 5)	FE-clogit (7)	RE-Mundlak (5)	RE-Mundlak (7)	FE-clogit 5)	FE-clogit (7)
Bonanza	3.848***	2.322	4.546***	2.358	19.214***	10.188***	21.335***	8.571**
	(2.936)	(1.533)	(2.866)	(1.361)	(4.879)	(2.766)	(4.330)	(2.173)
Lending Boom (1 sd)		1.988		2.234		1.392		1.817
		(1.106)		(1.093)		(0.532)		(0.815)
Bon()×Boom(1 sd)		6.149*		6.153		3.198		3.517
		(1.720)		(1.530)		(0.876)		(0.828)
Competition Risk	1.224	1.335	0.971	0.964	1.364	1.359	1.044	1.009
	(0.908)	(1.254)	(-0.109)	(-0.136)	(1.370)	(1.376)	(0.162)	(0.033)
Int. Liberalization	0.489	0.488	0.432	0.463	0.568	0.446	0.575	0.523
	(-1.453)	(-1.396)	(-1.412)	(-1.258)	(-1.084)	(-1.456)	(-0.922)	(-1.053)
Currency crisis (t)	7.197***	7.393***	10.285***	9.248***	9.334***	8.700***	11.979***	9.230***
	(3.587)	(3.456)	(3.337)	(3.011)	(3.982)	(3.712)	(3.499)	(3.062)
Moral Hazard	1.018	1.012	1.114	1.129	0.969	0.982	1.088	1.099
	(0.194)	(0.130)	(1.083)	(1.193)	(-0.318)	(-0.192)	(0.828)	(0.916)
Banking supervision	0.524	0.506	0.447	0.421*	0.542	0.413*	0.392*	0.377*
	(-1.461)	(-1.467)	(-1.563)	(-1.661)	(-1.374)	(-1.715)	(-1.666)	(-1.725)
Controls 1	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls 2	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bon+BoomB		14.2764***		14.5078***		32.5815***		30.1421***
Bon+BoomSE		13.0902		15.0125		35.1563		35.1283
Obs	577	577	440	440	577	577	440	440
Countries	35	35	25	25	35	35	25	25
Crises	37	37	37	37	37	37	37	37
Loglik	-101.9480	-97.5910	-64.1169	-60.4849	-95.9831	-92.8017	-58.9380	-57.7785
WaldTestChi2	16.5226	19.8657			15.6626	18.7509		
WaldTestPval	0.4871	0.3404			0.5479	0.4073		
AUROC	0.8445	0.8600	0.7963	0.7944	0.8584	0.8729	0.8081	0.8045
AUROCse	0.0309	0.0317	0.0309	0.0335	0.0310	0.0303	0.0323	0.0340
Regression	cloglog	logit	cloglog	logit	cloglog	logit	cloglog	logit

Note: Exponentiated coefficients; z statistics in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Dependent variable is dummy for start of banking crisis. cloglog refers to the regressor assuming a Gumbel distribution. logit refers to the regressor assuming a Logistic distribution.

Table 16. Decomposing Flows. RE-Mundlak and FE-clogit Models. Regression of Banking Crises on Bonanzas. Odds Ratios. All Countries, 1973-2008

	Baseline Bonanzas (1 sd)				Intense Bonanzas (2 sd)			
	RE-Mundlak (5)	RE-Mundlak (7)	FE-clogit 5)	FE-clogit (7)	RE-Mundlak (5)	RE-Mundlak (7)	FE-clogit 5)	FE-clogit (7)
FDI Bonanza	2.152*	2.074	1.983	1.883	4.069***	3.290*	4.270**	2.997
	(1.763)	(1.248)	(1.284)	(0.915)	(2.641)	(1.722)	(2.227)	(1.309)
Bon()×Boom(1 sd)		0.638		0.578		1.778		2.955
		(-0.478)		(-0.477)		(0.511)		(0.743)
Bon+BoomB		1.3227		1.0876		5.8507*		8.8553*
Bon+BoomSE		0.9631		1.0234		5.3502		10.7809
Portfolio-Equity Bonanza	3.066***	3.208**	3.671***	3.649**	6.833***	7.925***	8.530***	9.560***
	(2.654)	(2.432)	(2.761)	(2.395)	(3.958)	(3.750)	(3.620)	(3.322)
Bon()×Boom(1 sd)		0.751		1.065		0.559		1.236
		(-0.352)		(0.061)		(-0.618)		(0.185)
Bon+BoomB		2.4103		3.8859		4.4270*		11.8196**
Bon+BoomSE		1.7999		3.6802		3.8820		13.0012
Debt Bonanza	2.721***	2.098	3.395***	2.588*	5.356***	1.027	8.916***	1.704
	(2.807)	(1.605)	(3.010)	(1.878)	(3.279)	(0.021)	(3.573)	(0.452)
Bon()×Boom(1 sd)		1.073		0.998		6.051		8.432
		(0.090)		(-0.002)		(1.202)		(1.377)
Bon+BoomB		2.2526		2.5839		6.2148		14.3681***
Bon+BoomSE		1.4312		2.0242		4.7227		14.0673
Obs	1106	1106	693	693	1106	1106	693	693
Countries	60	60	38	38	60	60	38	38
Crises	51	51	51	51	51	51	51	51

Note: Exponentiated coefficients; z statistics in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Dependent variable is dummy for start of banking crisis. cloglog refers to the regressor assuming a Gumbel distribution. logit refers to the regressor assuming a Logistic distribution.

Table 17. Decomposing Flows. RE-Mundlak and FE-clogit Models. Regression of Banking Crises on Bonanzas. Odds Ratios. Upper and Middle Income Countries, 1973-2008

	Baseline Bonanzas (1 sd)				Intense Bonanzas (2 sd)			
	RE-Mundlak (5)	RE-Mundlak (7)	FE-clogit 5)	FE-clogit (7)	RE-Mundlak (5)	RE-Mundlak (7)	FE-clogit 5)	FE-clogit (7)
FDI Bonanza	2.131	2.211	1.999	2.226	4.551**	2.975	4.315*	3.516
	(1.293)	(1.079)	(0.994)	(0.957)	(2.300)	(1.288)	(1.895)	(1.354)
Bon()×Boom(1 sd)		0.495		0.471		3.098		2.869
		(-0.555)		(-0.501)		(0.857)		(0.606)
Bon+BoomB		1.0957		1.0487		9.2164		10.0853
Bon+BoomSE		1.1531		1.3598		10.0013		15.6325
Portfolio-Equity Bonanza	4.467***	4.067**	4.739**	3.841**	12.756***	10.645***	10.928***	8.837***
	(2.833)	(2.463)	(2.570)	(1.970)	(4.064)	(3.433)	(3.291)	(2.618)
Bon()×Boom(1 sd)		1.342		1.489		1.909		2.055
		(0.275)		(0.327)		(0.529)		(0.516)
Bon+BoomB		5.4601*		5.7176		20.3252**		18.1567**
Bon+BoomSE		5.6121		6.3183		24.1649		23.5387
Debt Bonanza	4.842***	4.182***	5.925***	4.880**	7.359**	1.978	20.627***	1.685
	(3.314)	(2.661)	(3.050)	(2.389)	(2.573)	(0.512)	(2.961)	(0.336)
Bon()×Boom(1 sd)		1.531		1.292		8.513		37.597*
		(0.380)		(0.199)		(1.186)		(1.703)
Bon+BoomB		6.4026**		6.3059		16.8388**		63.3501***
Bon+BoomSE		6.5508		7.3394		21.1978		92.2121
Obs	512	512	363	363	512	512	363	363
Countries	35	35	24	24	35	35	24	24
Crises	35	35	35	35	35	35	35	35

Note: Exponentiated coefficients; z statistics in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Dependent variable is dummy for start of banking crisis. cloglog refers to the regressor assuming a Gumbel distribution. logit refers to the regressor assuming a Logistic distribution.

Table 18. Decomposing Flows. RE-Mundlak and FE-clogit Models. Regression of Banking Crises on Baseline Bonanzas (1 sd) by Type of Flow. Odds Ratios. All Countries, 1973-2008

	RE-Mundlak (5)	RE-Mundlak (6)	RE-Mundlak (7)	FE-clogit 5)	FE-clogit (6)	FE-clogit (7)
FDI Bonanza	2.298*	2.136	2.539	2.043	1.647	2.097
	(1.896)	(1.621)	(1.550)	(1.307)	(0.855)	(1.087)
Portfolio-Equity Bonanza	3.296***	3.258***	3.746**	3.816***	3.615**	3.643**
	(2.647)	(2.593)	(2.540)	(2.654)	(2.486)	(2.292)
Debt Bonanza	3.153***	2.395**	2.596*	3.514***	2.612**	2.715*
	(3.046)	(2.222)	(1.924)	(2.935)	(2.099)	(1.865)
Lending Boom (1 sd)		4.264***	5.331***		3.724***	4.367**
		(3.551)	(3.046)		(2.663)	(2.239)
FDI Bon×Boom(1 sd)			0.550			0.485
			(-0.604)			(-0.627)
Port-Equity Bon×Boom(1 sd)			0.867			1.096
			(-0.155)			(0.085)
Debt Bon Bon×Boom(1 sd)			0.659			0.868
			(-0.508)			(-0.155)
FDIBon+BoomB			1.3971			1.0162
FDIBon+BoomSE			1.0937			0.9889
PortBonIFBoomB			3.2481			3.9907
PortBon+BoomSE			2.6981			3.9747
DebtBon+BoomB			1.7119			2.3556
DebtBon+BoomSE			1.1416			1.8487
Obs	1088	1088	1088	693	693	693
Countries	60	60	60	38	38	38
Crises	51	51	51	51	51	51
Loglik	-141.4760	-134.4238	-132.9333	-87.4720	-83.9690	-83.7685
WaldTestChi2	43.3799	47.0670	47.4716			
WaldTestPval	0.0018	0.0009	0.0029			
AUROC	0.8733	0.8810	0.8832	0.6989	0.7036	0.7070
AUROCse	0.0242	0.0246	0.0252	0.0324	0.0330	0.0327
Regression	cloglog	cloglog	cloglog	logit	logit	logit

Note: Exponentiated coefficients; z statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Dependent variable is dummy for start of banking crisis. cloglog refers to the regressor assuming a Gumbel distribution. logit refers to the regressor assuming a Logistic distribution.

Table 19. Decomposing Flows. RE-Mundlak and FE-clogit Models. Regression of Banking Crises on Intense Bonanzas (2 sd) by Type of Flow. Odds Ratios. All Countries, 1973-2008

	RE-Mundlak (5)	RE-Mundlak (6)	RE-Mundlak (7)	FE-clogit 5)	FE-clogit (6)	FE-clogit (7)
FDI Bonanza	4.307***	4.352**	3.004	3.689*	3.555*	1.973
	(2.625)	(2.517)	(1.502)	(1.893)	(1.772)	(0.748)
Portfolio-Equity Bon	5.118***	4.932***	6.631***	5.879***	6.765***	8.179***
	(2.960)	(2.803)	(3.107)	(2.753)	(2.849)	(2.897)
Debt Bonanza	4.859***	3.409*	1.010	8.406***	4.627**	0.870
	(2.864)	(1.957)	(0.008)	(3.179)	(2.070)	(-0.090)
Lending Boom (1 sd)		3.953***	3.436**		4.139***	2.868*
		(3.342)	(2.504)		(2.791)	(1.732)
FDI Bon×Boom(1 sd)			3.979			6.111
			(1.058)			(1.080)
Port-Equity Bon×Boom(1 sd)			0.392			0.685
			(-0.771)			(-0.283)
Debt Bon×Boom(1 sd)			5.838			16.267
			(1.088)			(1.467)
FDIBon+BoomB			11.9537**			12.0576*
FDIBon+BoomSE			13.2216			17.2811
PortBon+BoomB			2.5973			5.6026
PortBon+BoomSE			3.0402			7.2147
DebtBon+BoomB			5.8968*			14.1456**
DebtBon+BoomSE			5.7171			14.9770
Obs	1088	1088	1088	693	693	693
Countries	60	60	60	38	38	38
Crises	51	51	51	51	51	51
Loglik	-144.7274	-135.9030	-133.7872	-84.1768	-80.3994	-78.8138
WaldTestChi2	32.7317	40.0115	39.7891			
WaldTestPval	0.0361	0.0074	0.0225			
AUROC	0.8581	0.8708	0.8792	0.7153	0.7122	0.7119
AUROCse	0.0291	0.0276	0.0254	0.0308	0.0325	0.0331
Regression	cloglog	cloglog	cloglog	logit	logit	logit

Note: Exponentiated coefficients; z statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Dependent variable is dummy for start of banking crisis. cloglog refers to the regressor assuming a Gumbel distribution. logit refers to the regressor assuming a Logistic distribution.

Table 20. Decomposing flows. RE-Mundlak and FE-clogit Models. Regression of Banking Crises on Baseline Bonanzas (1 sd) by type of flow. Odds Ratios. Upper and Middle Income Countries, 1973-2008

	RE-Mundlak (5)	RE-Mundlak (6)	RE-Mundlak (7)	FE-clogit 5)	FE-clogit (6)	FE-clogit (7)
FDI Bonanza	3.199*	2.519	3.141	2.476	2.267	2.767
	(1.747)	(1.271)	(1.380)	(1.171)	(1.033)	(1.155)
Portfolio-Equity Bon	4.891***	3.872**	3.644*	3.882**	3.474*	3.322
	(2.673)	(2.269)	(1.900)	(2.043)	(1.843)	(1.600)
Debt Bonanza	7.132***	5.013***	5.872***	5.431***	4.808**	4.929**
	(3.551)	(2.778)	(2.739)	(2.769)	(2.519)	(2.286)
Lending Boom (1 sd)		1.708	2.791		2.536	2.844
		(0.879)	(1.157)		(1.338)	(1.117)
FDI Bon×Boom(1 sd)			0.421			0.367
			(-0.543)			(-0.562)
Port-Equity Bon×Boom(1 sd)			1.580			1.654
			(0.340)			(0.334)
Debt Bon×Boom(1 sd)			0.755			0.750
			(-0.211)			(-0.207)
FDIBon+BoomB			1.3211			1.0144
FDIBon+BoomSE			1.8452			1.6505
PortBon+BoomB			5.7576			5.4955
PortBon+BoomSE			7.2212			7.6554
DebtBon+BoomB			4.4338			3.6950
DebtBon+BoomSE			5.3170			4.6075
Obs	512	512	512	363	363	363
Countries	35	35	35	24	24	24
Crises	35	35	35	35	35	35
Loglik	-80.8562	-77.8427	-75.0765	-50.7535	-49.8835	-49.7172
WaldTestChi2	25.6561	28.0609	23.1627			
WaldTestPval	0.1775	0.1384	0.5102			
AUROC	0.8831	0.8924	0.8932	0.7989	0.7889	0.7872
AUROCse	0.0296	0.0295	0.0300	0.0368	0.0370	0.0370
Regression	cloglog	cloglog	cloglog	logit	logit	logit

Note: Exponentiated coefficients; z statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Dependent variable is dummy for start of banking crisis. cloglog refers to the regressor assuming a Gumbel distribution. logit refers to the regressor assuming a Logistic distribution.

Table 21. Decomposing flows. RE-Mundlak and FE-clogit Models. Regression of Banking Crises on Intense Bonanzas (2 sd) by type of flow. Odds Ratios. Upper and Middle Income Countries, 1973-2008

	RE-Mundlak (5)	RE-Mundlak (6)	RE-Mundlak (7)	FE-clogit 5)	FE-clogit (6)	FE-clogit (7)
FDI Bonanza	4.662**	6.317**	2.990	4.968*	5.105*	3.241
	(2.066)	(2.177)	(1.118)	(1.844)	(1.837)	(1.124)
Portfolio-Equity Bon	11.391***	10.489***	11.468***	8.174**	7.848**	6.887**
	(3.547)	(3.283)	(2.962)	(2.553)	(2.437)	(2.117)
Debt Bonanza	6.794**	6.956*	1.822	23.521***	15.121**	1.518
	(2.133)	(1.768)	(0.368)	(2.757)	(2.264)	(0.209)
Lending Boom (1 sd)		3.235*	1.211		2.575	0.916
		(1.798)	(0.184)		(1.247)	(-0.079)
FDI Bon×Boom(1 sd)			13.708			5.725
			(1.472)			(0.859)
Port-Equity Bon×Boom(1 sd)			1.575			2.033
			(0.281)			(0.414)
Debt Bon×Boom(1 sd)			27.153			64.335
			(1.383)			(1.629)
FDIBon+BoomB			40.9860**			18.5521
FDIBon+BoomSE			68.4192			34.5490
PortBon+BoomB			18.0561*			13.9980
PortBon+BoomSE			28.0135			22.9874
DebtBon+BoomB			49.4682**			97.6485
DebtBon+BoomSE			88.7348			163.4210***
Obs	512	512	512	363	363	363
Countries	35	35	35	24	24	24
Crises	35	35	35	35	35	35
Loglik	-81.5331	-75.4551	-69.2076	-48.4674	-47.7257	-45.9458
WaldTestChi2	24.3681	28.5242	29.8102			
WaldTestPval	0.2267	0.1259	0.1911			
AUROC	0.8827	0.8967	0.9070	0.8107	0.7978	0.7892
AUROCse	0.0306	0.0298	0.0298	0.0350	0.0356	0.0377
Regression	cloglog	cloglog	cloglog	logit	logit	logit

Note: Exponentiated coefficients; z statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Dependent variable is dummy for start of banking crisis. cloglog refers to the regressor assuming a Gumbel distribution. logit refers to the regressor assuming a Logistic distribution.

Table 22. 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 inflows 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 disaggregated into three categories: (i) FDI, (ii) portfolio-equity, and (iii) debt.	Computed using data from IFS database
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 obtained 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.	Computed using data from IFS database
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 Section 2.	Computed using data from WDI database, World Bank
Domestic credit to private sector	Variable FS.AST.PRVT.GD.ZS in WDI database. Original data is as percentage of GDP. Using GDP per capita in constant prices (US dollars, 2000=100) (series NY.GDP.PCAP.KD), a series of per capita real credit to private sector is obtained. For countries with missing GDP data, GDP per capita in US dollars was used (NY.GDP.PCAP.CD).	Computed using data from WDI database, World Bank
Competition risk	Variable that takes discrete values from 0 to 3, with three representing the highest competition risk. It is computed as the interaction between a dummy that takes the value 1 if an elimination of interest rate controls has taken place in any of the previous five years and an index of entry barriers to the banking industry.	Computed using data from Abiad et al. (2010)
Financial liberalization	Dummy variable that takes the value of one if an elimination of interest rate controls has taken place in any of the previous five years. Elimination of interest rate controls is proxied as a positive change in an index of interest rate controls.	Computed using data from Abiad et al. (2010)
Interest rate controls	Index of interest rate controls, considering both deposit and lending rates. Index is based in regulation of rates, considering if rates are set by the government or subject to binding ceilings or bands, or if rates are freely floating. Index takes discrete values from 0 to 4, with 4 being fully liberalized.	Abiad et al. (2010)
Entry barriers to banking industry	Index of barrier to entry in the banking industry. Index evaluates how easy it 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)

Table 23. Data Description (continuation)

Variable	Definition	Source
Capital Account Openness (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)
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 Basel 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

Table 24. Data Description (continuation)

Variable	Definition	Source
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 interest rate available, we used either the lending rate or the deposit rate and adjust for GDP deflator.	WDI database, World Bank
Fed Effective Funds Rate	This is the annual average of the daily effective funds rate reported by the FRED database of the Federal Reserve Bank of St. Louis.	Federal Reserve Bank of St. Louis
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 25. Sample. Years with Data on Net Capital Inflows in Squared Parenthesis. Year of Start of Systemic Banking Crisis in Round Parenthesis

Developing countries
Albania [1999,2008] (none)
Algeria [1978,1990] (1990)
Angola [1996,2008] (none)
Argentina [1977,2008] (1980, 1989, 1995*, 2001)
Armenia [1994,2008] (1994)
Bangladesh [1977,2008] (1987)
Barbados [1974,2008] (none)
Belarus [1995,2008] (1995)
Belize [1985,2008] (none)
Benin [1975,2008] (1988)
Bolivia [1977,2008] (1986, 1994)
Bosnia and Herzegovina [1999,2008] (none)
Botswana [1976,2008] (none)
Brazil [1976,2008] (1990*)
Bulgaria [1992,2008] (1996)
Burkina Faso [1975,1995] (1990)
Burundi [1986,2008] (1994)
Cambodia [1995,2008] (none)
Cameroon [1978,2008] (1987, 1995)
Cape Verde [1984,2008] (1993)
Central African Republic [1981,1995] (1995)
Chad [1978,1992] (1983, 1992)
Chile [1976,2008] (1976, 1981)
China [1983,2008] (1998)
Colombia [1974,2008] (1982, 1998)
Comoros [1983,1996] (none)
Congo, Republic of [1979,2008] (1992)
Costa Rica [1978,2008] (1987, 1994)
Cote d'Ivoire [1976,2008] (none)
Croatia [1994,2008] (1998)
Czech Republic [1994,2008] (1996*)
Djibouti [1996,2008] (none)
Dominica [1977,2008] (none)
Dominican Republic [1974,2008] (2003)
Ecuador [1977,2008] (1982, 1998)
Egypt [1978,2008] (1980)
El Salvador [1977,2008] (1989)
Equatorial Guinea [1988,1997] (none)
Estonia [1997,2008] (none)
Ethiopia [1978,1995] (none)
Fiji [1980,2008] (none)
Gabon [1979,2006] (none)
Gambia [1979,1998] (none)
Georgia [1998,2008] (none)
Ghana [1976,2007] (1982)
Grenada [1978,2008] (none)
Guatemala [1978,2008] (none)
Guinea-Bissau [1987,1994] (none)
Guyana [1993,2008] (1993)
Haiti [1974,2008] (1994)
Honduras [1975,2008] (none)
Hungary [1983,2008] (1991, 2008*)
India [1976,2008] (1993)
Indonesia [1982,2008] (1997)
Iran [1977,2001] (none)
Jamaica [1977,2008] (1996)
Jordan [1974,2008] (1989)
Kazakhstan [1996,2008] (2008*)
Kenya [1976,2008] (1985, 1992)
Korea [1977,2008] (1997)
Kyrgyz Republic [2000,2008] (none)
Laos [1990,2008] (none)
Latvia [1994,2008] (1995, 2008)
Libya [1978,2008] (none)
Lithuania [1994,2008] (1995)
Macedonia [1998,2008] (none)
Madagascar [1975,2006] (1988)
Malawi [1978,2003] (none)
Malaysia [1975,2008] (1997)
Maldives [1996,2008] (none)
Mali [1976,2008] (1987)
Mauritania [1976,1999] (1984)
Mauritius [1977,2008] (none)
Mexico [1980,2008] (1981, 1994)
Moldova [1995,2008] (none)
Mongolia [1993,2007] (none)
Morocco [1991,2008] (none)
Mozambique [1986,2008] (1987)
Namibia [1991,2008] (none)
Nepal [1977,2008] (1988)
Nicaragua [1978,2008] (1990, 2000)
Niger [1975,2008] (1983)
Nigeria [1978,2008] (1991)
Pakistan [1977,2008] (none)
Panama [1978,2008] (1988)
Papua New Guinea [1977,2006] (none)
Paraguay [1976,2008] (1995)
Peru [1978,2008] (1983)
Philippines [1978,2008] (1983, 1997*)
Poland [1980,2008] (1992)
Romania [1997,2008] (none)
Russia [1995,2008] (1998, 2008*)
Rwanda [1977,2006] (none)
Saudi Arabia [1974,2008] (none)
Senegal [1975,2008] (1988)
Slovakia [1994,2008] (1998)
South Africa [1974,2008] (none)
Sri Lanka [1976,2008] (1989)
Sudan [1997,2008] (none)
Suriname [1978,2008] (none)
Swaziland [1975,2008] (1995)
Syria [1978,2008] (none)
Tanzania [1977,2008] (1987)
Thailand [1976,2008] (1983, 1997)
Togo [1975,2008] (1993)
Trinidad and Tobago [1976,2008] (none)
Tunisia [1977,2008] (1991)
Turkey [1975,2008] (1982, 2000)
Uganda [1981,2008] (1994)
Ukraine [1995,2008] (1998, 2001)
Uruguay [1979,2008] (1981, 2002)
Venezuela [1974,2008] (1994)
Yemen [1991,2008] (1996)
Zambia [2000,2008] (none)
Zimbabwe [1978,1995] (1995)

Note: Borderline systemic banking crises are denoted with *. Source Laeven and Valencia (2010)

Table 26. Sample (continuation). Years with Data on Net Capital Inflows in Squared Parenthesis. Year of Start of Systemic Banking Crisis in Round Parenthesis

High income countries		
Australia [1974,2008] (none)	Hong Kong [1999,2008] (none)	Portugal [1976,2008] (2008*)
Austria [1974,2008] (2008)	Iceland [1977,2007] (none)	Singapore [1974,2008] (none)
Belgium [1976,2008] (2008)	Ireland [1975,2008] (2008)	Slovenia [1997,2008] (2008*)
Canada [1974,2008] (none)	Israel [1974,2008] (1977)	Spain [1976,2008] (1976,2008*)
Denmark [1976,2008] (2008)	Italy [1974,2008] (none)	Sweden [1974,2008] (1974,2008*)
Finland [1976,2008] (1991)	Japan [1978,2008] (1997)	Switzerland [1978,2008] (2008*)
France [1976,2008] (2008*)	Kuwait [1996,2008] (none)	United Kingdom [1974,2007] (2007)
Germany [1974,2008] (2008)	Netherlands [1974,2008] (2008)	United States [1974,2007] (1988*, 2007)
Greece [1977,2008] (2008*)	Norway [1976,2007] (1991)	

Note: Borderline systemic banking crises are denoted with *. Source Laeven and Valencia (2010)