Banking Crises and Crisis Dating: Theory and Evidence*

John Boyd
University of Minnesota, Department of Finance

Gianni De Nicolò
International Monetary Fund, Research Department

Elena Loukoianova
European Bank for Reconstruction and Development, Evaluation Department

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Abstract

We formulate a simple theoretical model of a banking industry which we use to identify and construct theory-based measures of systemic bank shocks (SBS). These measures differ from "banking crisis" (BC) indicators employed in many empirical studies, which are constructed using primarily information on government actions undertaken in response to bank distress. Using both country-level and firm-level samples, we show that SBS indicators consistently predict BC indicators based on four major BC series that have appeared in the literature, indicating that BC indicators actually measure lagged policy responses to systemic bank shocks. We then re-examine the impact of macroeconomic factors, bank market structure, deposit insurance, and external shocks on the probability of a systemic bank shocks (SBS) and on "banking crisis" (BC) indicators. We find that the impact of these variables on the likelihood of a policy response to banking distress *is totally different* from that on the likelihood of a systemic bank shock. Disentangling the effects of systemic bank shocks and policy responses turns out to be crucial in understanding both the roots of bank fragility and the relevant policy implications. Many findings of a large empirical literature need to be re-assessed and/or re-interpreted.

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I. INTRODUCTION

The financial crisis of 2007 and 2008 has spurred renewed interest in banking crises. Some have stressed their similarities across countries and historical episodes (e.g. Reinhart and Rogoff, 2008a, 2009), while others have emphasized differences, both historical (e.g. Bordo, 2008) and as related to the specific mechanics of the shock triggering a crisis (e.g. Gorton, 2008). As pointed out by Allen and Gale (2007), however, the empirical literature on bank fragility has mainly focused on documenting empirical regularities. The definition and measurement of the object of study—what a banking crisis is, when it occurs, and how long it lasts— has been loosely related to theory. As a result, this literature offers many—often contrasting—findings, which vary considerably in terms of samples used, banking crisis definitions and relevant dating.

This paper reexamines the empirical evidence on the determinants of bank fragility. Our main contribution is to disentangle an adverse shock to the banking industry from the attendant restorative policy response. We demonstrate that disentangling these effects is crucial to understanding the determinants of bank fragility and those of the policy responses to banking distress.

We derive measures of systemic bank shocks (SBS) using a simple model of a banking industry in which an adverse shock to the banking system, as well as government responses, are explicitly defined. The main objective of the theoretical exercise is to obtain well-defined measures of an adverse shock to banking that can be obtained from or proxied by available data. By contrast, a large portion of the empirical literature has employed "banking crisis" (BC) indicators based on dating schemes that identify: crisis beginning dates, ending dates, and indicate whether the crisis was "systemic" or not. As documented in

Boyd, De Nicolò and Loukoianova (2009) (BDNL henceforth), these schemes do not rely on any theory to identify accounting or market measures that capture the *realization* of systemic bank shocks. Rather, in virtually all cases what is measured is a government response to a perceived crisis—not the onset or duration of an adverse shock to the banking industry.

It is important to note that this literature has interpreted an SBS event and a BC event as one and the same. There are two fundamental problems with that approach. First, the two events actually may occur on different dates. Second, one event is bad for the industry (an SBS shock), while the other is good for it (government intervention to a perceived problem). Thus, as stressed in De Nicolò et al (2004), a researcher using these BC indicators will be unable to disentangle the effects of an adverse shock to the banking industry from the effects of the restorative policy response.

We re-examine the empirical evidence presented in a large empirical literature on the determinants of bank fragility and the attendant policy responses using two large samples: a country-level dataset and a firm-level dataset. While the use of the country-level dataset is standard, employing individual bank data is novel as it allows us to significantly extend the empirical analysis for three important reasons. First, with this dataset we can use SBS indicators which better capture the realization of systemic bank shocks. These are constructed on the basis of sharp declines in bank profitability, taking into account banks' capitalization. Second, the impact of systemic bank shocks and policy responses can be gauged taking into account the differential impact of these shocks on each bank in a country. Tests on this sample are also more powerful, as we use random effect Logit regressions that exploit more fully the information contained in banks' heterogeneity.

The explanatory variables that we study are variables that the existing literature has identified as important determinants of the probability that a country will experience a banking crisis. These include the bank market structure, presence or lack of deposit insurance, and the occurrence of an external shock, (e.g. a currency crisis)[1].

We find that each of these explanatory variables has a different effect on the probability of an adverse shock to the banking industry (represented by SBS indicators) and on the probability of a government intervention (represented by BC indicators). As we hope to make clear, this has led to a great deal of confusion in the interpretation of many empirical results and, we argue, to a number of unwarranted policy implications.

We obtain five key results. First, we show that there are significant discrepancies among the four BC indicators in their dating the beginnings and endings of banking crises. Thus, there is considerable disagreement among researchers in dating the same episodes of financial distress. Second, we show that our SBS indicators consistently and robustly predict all four BC indicators. This provides support for the notion that BC indicators represent lagged government responses to adverse banking shocks.

Third, more concentrated banking systems significantly increase the probability of a systemic bank shock. However, these variables do not significantly affect the probability of a government response. As will be discussed, this finding is at odds with what has been reported elsewhere in the literature.

Fourth, the data suggest that the probability of a government response to bank distress identified by the BC indicators will be higher in banking systems with formal deposit

[1] This is a very large literature and it is impossible to review all or even the majority of the related articles. We have selectively chosen a few studies, but the issues we raise would be relevant to much work besides the studies we have singled out for attention.

insurance. This finding has been obtained previously in the literature and has been interpreted as evidence that deposit insurance results in greater moral hazard—and thus inherently riskier banking systems. In reality however, all that is occurring is that, in the presence of formal deposit insurance the government is more likely to respond to a negative shock of a given size. This is because, as we find, that the probability of a systemic bank shock *does not* depend on whether a deposit insurance system is in place.

Fifth, we find that the occurrence of currency crises increases both the probability of a systemic bank shock as well as a government response to bank distress, as represented by BC indicators. However, while worsening of the terms of trade, financial openness and the flexibility of exchange rate arrangements may affect the probability of a government response, only the latter variable has a significant impact on the probability of a systemic bank shock.

The rest of the paper proceeds as follows. Section II presents a theoretical model in which banking problems are produced by the arrival of exogenous shocks to the industry[2]. Section III constructs BC indicators based on four major crisis classifications that have been employed extensively in the empirical literature and examines their discrepancies. In Section IV we employ a large country-level panel dataset similar to those employed by others in this literature, and show that our SBS indicators consistently and robustly predict all four BC indicators. Furthermore, we assess the impact of bank concentration, deposit insurance, and external shocks on the probability of a systemic bank shock and, separately, on the probability of a government response to bank distress. In section V we carry out a similar

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[2] The shocks we model are exogenous to the banking industry and may, but need not, be exogenous to the economy. This will become clear when the analysis proceeds.

empirical analysis using the firm-level dataset. Remarkably, with this finer data set and richer statistical specification all earlier main results are confirmed. Section VI concludes.

II. A Simple Banking Model

In this section, we present a simple model of a banking industry and a government deposit insurer, and use its comparative statics to identify measures of systemic bank shocks. The banks in the model are Cournot-Nash competitors that raise insured deposits, make risky loans, and hold risk free government bonds. The deposit insurer bails out the banks when they fail. Thus, the economy is composed of a "government" and three classes of agents: entrepreneurs, depositors, and banks. All agents are risk-neutral, and time is discrete.

Entrepreneurs

There is a continuum of entrepreneurs indexed by their reservation income levels $a \in [0,1]$, which is distributed uniformly on the unit interval. Entrepreneurs have no initial resources but have access to identical risky projects that require a fixed amount of date t investment, standardized to 1, and yield a random output at date $t+1$. Specifically, at date t the investment in a project yields Y with probability $P_{t+1} \in (0,1)$, and 0 otherwise. The probability of success P_{t+1} is a random variable independent across entrepreneurs. Its realization is observed by them at date $t+1$. Hence, entrepreneurs make their date t decisions on the basis of their conditional expectations of P_{t+1}, denoted by $E_t P_{t+1}$.

Entrepreneurs are financed by banks with simple debt contracts. The contract pays the bank a loan interest rate R^L if the project is successful. Thus, an entrepreneur with reservation income level a will undertake the project if

$$E_t P_{t+1}(Y - R^L) \geq a \quad . \tag{1}$$

Let a^* denote the value of a that satisfies (1) at equality. The total demand for loans is then given by $X_t \equiv F(a^*) = \int_0^{a^*} f(a)da$, where $f(.)$ is the density of the uniform distribution function. This defines implicitly the inverse loan demand function:

$$R^L(X_t, E_t P_{t+1}) = Y - (E_t P_{t+1})^{-1} X_t \tag{2}$$

Bonds

One-period bonds are supplied by the government in amounts specified below. For simplicity, we assume that only banks can invest in bonds.[3] A bond purchased at date t yields a gross interest rate r_t at date $t+1$.

Depositors

Depositors invest all their funds in a bank at date t to receive interest plus principal at date $t+1$. Deposits are fully insured, so that the total supply of deposits does not depend on risk, and is represented by the upward sloping inverse supply curve $R^D\left(Z_t\right) = \alpha_t Z_t$, where Z_t

[3] If we assume that deposits provide valued services to depositors besides the interest they pay, then they may be held even if they have a rate or return dominated by bonds. For present purposes, modeling all this is a needless complication.

denotes total deposits. The slope of this function is a random variable, to be described below, whose realization is observed at date t.

Banks

Banks collect insured deposits, and pay a flat rate insurance premium standardized to zero. On the asset side, banks choose the total amount of lending and the amount of bonds. In both loan and deposit markets banks are symmetric Cournot-Nash competitors. Banks are perfectly diversified in the sense that for any positive measure of entrepreneurs financed, $P_{t+1} \in (0,1)$, is also the fraction of borrowers whose project turns out to be successful at date $t+1$. Banks observe the realization of P_{t+1} at date $t+1$. Hence, as for the entrepreneurs, banks make their date t decisions on the basis of their conditional expectations $E_t P_{t+1}$.

Government

The government supplies a fixed amount of bonds to the market, denoted by $\overline{B}$. The government also guarantees deposits. It will *intervene* whenever bank deposits payments cannot be honored in part or in full. When this occurs, the government will pay depositors all the claims unsatisfied by banks and all banks will be bailed out. These payments will be financed by issuing additional bonds, which will be purchased by banks which collect new deposits at date $t+l$, where $l \geq 1$.[4]

[4] In this very simple set-up, banks are identical and exposed to the same risks. Thus, if one bank fails, all banks fail. A more realistic assumption would be that some banks fail and some do not. It would be relatively easy to augment the current model with this feature, for example, by assuming that the shock to the loan portfolio involves just not all banks, but a fraction of them. For our purposes, however, this is not essential, since the comparative statics on which our systemic bank shock indicators are based would be essentially the same.

The realization of a systemic banking shock occurs at date $t+1$ and, by definition, occurs when the banking system's profits are negative. The government's response to such a shock will be triggered when the government is able to ascertain that the banking system has become insolvent. If the government observes date $t+1$ bank profits with a lag, then $l > 1$.

Sequence of events

In period t, suppose realized bank profits are non-negative. Banks collect deposits, entrepreneurs demand, and banks supply funds based on $E_t P_{t+1}$. Deposits, bank loans, and investment in bonds are determined for period t. *In period* $t+1$, P_{t+1} is realized and observed by entrepreneurs and banks. Borrowers pay loans and in turn, banks pay depositors, if possible. If bank profits are non-negative, depositors are paid in full. If profits are negative, depositors cannot be paid in full, and by definition, this is a systemic bank shock. Depositors are paid *pro-rata* by the banks. The government *responds* to the crisis at $t+l$ by issuing bonds and paying depositors any claim unsatisfied by banks.

Equilibrium

We describe the equilibrium at date t by dropping time subscripts from all variables, and define $p \equiv E_t P_{t+1}$.

The bank problem

Let D_i denote total deposits of bank i, $Z \equiv \sum_{i=1}^{N} D_i$ denote total deposits, and $D_{-i} \equiv \sum_{j \neq i} D_j$ denote the sum of deposits chosen by all banks except bank i. Let

$L_{-i} \equiv \sum_{j \neq i} L_j$ denote the sum of loans chosen by all banks except bank i. Each bank chooses deposits, loans, and bond holdings b so as to maximize expected profits, given the choices of other banks. Thus, a bank chooses $(L, b, D) \in R_+^3$ to maximize:

$$pR^L(L_{-i} + L, p)L + rb - R_D(D_{-i} + D)D \qquad (3)$$

subject to $$L + b = D. \qquad (4)$$

The government's policy function

Let $\Pi_t(.)$ denote current *realized* aggregate profits. A government intervention is described by the indicator function: $I^G{}_t(\Pi_{t-l})$ = 1 if $\Pi_{t-l} < 0$, and 0 otherwise. The government supplies bonds in the amount $B_t^S = \overline{B} + B_t(\Pi_{t-l})$, where $B_t(\Pi_{t-l}) = I_t^G(\Pi_{t-l})\Pi_{t-l}$.

Given p, an **equilibrium** is a total amount of loans X, total bonds B, total deposits Z, bond interest rates, loan rates, deposit rates, and government responses such that: a) the banking industry is in a symmetric Nash equilibrium; b) the bond market is in equilibrium; and c) the government meets its commitment to deposit insurance.

Comparative statics

We illustrate the comparative statics of the model using a simple linear specification: the loan supply is given by $R^L(X,p) = Y - p^{-1}X$, and the demand for deposits is given by $R^D(Z) = \alpha Z$. The solutions for all endogenous variables are:

$$X = \frac{N}{N+1}\frac{pY}{1+\alpha} - \frac{\alpha}{1+\alpha}B^S \ ; \qquad Z = \frac{N}{N+1}\frac{pY}{1+\alpha} + \frac{1}{1+\alpha}B^S \ ; \qquad B = B^S \ ;$$

$$r = \frac{\alpha}{1+\alpha}\left(\frac{N+1}{N}B^S + pY\right) \ ; \ R^L = Y\frac{1+\alpha(N+1)}{(N+1)(1+\alpha)} + p^{-1}\frac{\alpha}{1+\alpha}B^S \ ; R^D = \frac{\alpha}{1+\alpha}\left(\frac{N}{N+1}pY + B^S\right)$$

$$R^L - R^D = \frac{Y}{N+1}\left(\frac{1+\alpha(N(1-p)+1)}{(1+\alpha)}\right) + (p^{-1}-1)\frac{\alpha}{1+\alpha}B^S$$

The following table summarizes changes in the endogenous variables in response to an adverse shock.

	Adverse shocks		
	p decreases	***α increases***	***Y decreases***
Endogenous variables			
Total Loans	↓	↓	↓
Total Deposits	↓	↓	↓
Bond interest rate	↓	↑	↓
Loan rate	↑	↑	↑
Deposit rate	↓	↑	↑
Realized profits	↓	↓	↓

We can see from this table that a systemic bank shock can be triggered by shocks to the technology (p and Y); to preferences or wealth (α); to a decline in firms' probability of a good outcome (a decline in p); to a decline in firms' demand for loans due to a decline in Y; or, finally, to a decline in consumers' demand for deposits, prompted by a decline in α. Note that these properties hold under any market structure, that is, for any value of *N*.

Such adverse shocks are for the most part unobservable, but their occurrence results in predictable changes in certain variables that are observable. In particular, *independently of the source of the shock*, aggregate loans and deposits will decline, loan rates will increase, and profits will decline. By contrast, the deposit rate and the bond rate will move in a different direction depending on the source of the shock

Thus, the model allows us to identify a systemic bank shock with a severe decline in loans, deposits, and bank profits. Thus, in our empirical investigation we will use these properties of the model to create empirical measures of systematic banking shocks that can be constructed with the two different samples we use.

We next turn to the banking crisis (BC) indicators.

III. "Banking Crises" indicators and their discrepancies

A variety of classifications of systemic banking crises have been used since the mid 1990s by many researchers. Here we consider four systematic and generally comprehensive classifications well known in the literature and widely used in empirical work. These four classifications are all updates, modifications and/or expansions of the classification of banking crises first compiled by Caprio and Kinglebiel (CK) (1996, 1999).

The first classification is due to Demirgüç-Kunt and Detragiache (2002, 2005, hereafter DD), and appear to be the first to have introduced an explicit definition of a systemic banking crisis. The second classification is that compiled by Caprio et al. (2005) (CEA henceforth). CEA updated and extended the earlier CK classification. The third classification is the one recently compiled by Reinhart and Rogoff (2008b) (RR henceforth). The classification criteria used in RR are essentially those used in Kaminsky and Reinhart (1999), whose classification was, in turn, based on CK's classification. Finally, the fourth classification is one recently constructed by Laeven and Valencia (2008) (LV henceforth), which extends previous classifications both in time and country coverage. This classification seems to be considered the most complete to date, and has been already used in recent empirical work (see e.g.. Cecchetti, Kohler and Upper, 2009).

In BDNL we carry out a detailed review of the criteria used to identify banking crises dates and duration. That review demonstrates that crisis dating in all these classifications depends on information obtained from bank regulators and/or central banks, and what is measured is a government response to a perceived crisis. If such interventions were *contemporaneous* to systemic bank shocks, they could serve as reasonable proxies of these shocks. However, as we show below, these measures of policy responses are *not* contemporaneous to the realization of systemic bank shocks.

Next, we construct four series of binary BC indicators that will be used in our own empirical work. Each of the four binary BC indicators is set to 1 if a country-year is classified as a crisis year and 0 otherwise. The series are denoted by DD (Demirgüç-Kunt and Detragiache, 2005), CEA (Caprio et al. ,2005), RR (Reinhart and Rogoff, 2008b), and LV (Laeven and Valencia, 2008).

We consider two versions of each indicator. The first *excludes* all country-years classified as crisis after the first crisis year. In practice, this kind of indicator identifies crises' *starting dates.* These starting dates have been used extensively in event-type analyses since

IMF (1998) and Kaminsky and Reinhart (1999). The second version includes all crisis country-years, beginning with and beyond the starting date.

Differing from DD and CEA, the RR and LV classifications do not report crisis durations. For these classifications we have used the duration and country years of the CEA classification, or the DD duration when the CEA duration was not available. In this way, we preserve the starting dates of the original classifications, but we augment them with the applicable duration of either the CEA or DD classifications.

Table 1 reports statistics (Panel A), and pair-wise comparisons of crisis dating (Panel B), across classifications. The most striking fact is that for many crisis episodes the dating classifications differ considerably both in terms of the starting date and the duration. For example, 15 country years are classified as first crisis years by RR but not by DD, while the reverse is true for 30 country years (Panel B, second line). Alternatively, Panel B, shows the ratio of total crisis ranking discrepancies divided by total crisis rankings. This varies between 24.5% and 49.5%. In other words, in terms of dating crises (which is the heart of the matter), the different methods are in disagreement roughly between a quarter and a half of the time. All four classifications only agree on 41 dates of crisis.[5]

These widespread discrepancies across banking crisis classifications indicate that there is disagreement among researchers in dating the same episodes of financial stress. This makes the robustness or the comparability of many results obtained in a large empirical literature problematic. Indeed, when we turn to our empirical analysis with the four BC indicators, it is not surprising that they often produce significantly different results. These discrepancies however compel us to use all four of them in our empirical analysis

[5] Some discrepancies for specific countries have been previously noted by Rancière, Tornell and Westermann (2008) and Von Hagen and Ho (2007).

IV. Evidence from cross-country data

We begin our empirical investigation using a country-level dataset that merges and updates the large annual cross-country panel dataset used extensively in DD (2005) and Beck et al. (2006), with data for up to 91 countries for the 1980-2002 period.

We proceed in three steps. First, we describe the benchmark specification of Logit regressions with BC indicators as dependent variables. Second, we construct our theory-based indicators of systemic bank shocks (SBS indicators) for this sample and include *lagged* SBS indicators as additional explanatory variables in these regressions. This gives an assessment of the extent to which SBS indicators *predict* BC indicators. Third, we re-examine the evidence on the impact of bank market structure, deposit insurance and external shocks on banking fragility, estimating Logit regressions separately with BC and SBS indicators as dependent variables.

A. Benchmark Logit Regressions

In our benchmark Logit regressions with BC indicators as dependent variables, we use the following set of explanatory variables employed by Demirgüç-Kunt and Detragiache (2005) and Beck et al (2006): measures of the macroeconomic environment (real GDP growth, the real interest rate, inflation, changes in the terms of trade, and exchange rate depreciation); a measure of potential vulnerability of a country to a run on its currency (the ratio of M2 to international reserves); a measure of the economic size of a country (real GDP per capita); and a measure of financial system development (bank credit to private sector GDP). Finally, we include real bank credit growth lagged twice, which in this literature has been employed as a proxy measure for credit booms.

Versions of the four BC indicators that exclude all crisis years except the first have been sometimes used as dependent variables in this literature.[6] We will not follow this practice, since the use of BC indicators constructed by excluding crisis years after the first one seems unwarranted for at least two reasons. First, as we have shown in section II, the BC classifications actually index a variety of government measures to address banking distress. Therefore, deleting observations of years during which a government implements measures in response to continued banking distress significantly reduces the informational content of these classifications. Second, excluding these observations requires taking a stand on the duration of a crisis. As documented in Table 1 of section III, excluded observations account for a sizeable portion of the sample, ranging from 10 to 15 percent of available country years, inducing sample biases difficult to control. As pointed out by Boyd et al. (2005), this procedure can be particularly troublesome for countries where multiple crises have occurred. For these reasons, we carry our empirical analysis using BC indicators that include all crisis-years observations.[7]

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[6] This exclusion has been made on the ground that "the behavior of some of the explanatory variables is likely to be affected by the crisis itself, and this could cause problems for the estimation" (Demirgüç-Kunt and Detragiache, 2002, p.1381).

[7] However, in BDNL (Table 2) we report results using the version of the four BC indicators that excludes all crisis years except the first. We also employed two different samples to account for differences in results due to either country or crisis coverage. We found that real GDP growth and real interest rates are the only variables that enter significantly (negatively and positively respectively) in all regressions. For all other explanatory variables, there is at least one specification that yields results different from all the others. These differences in results occur not only between specifications within the same sample, but also comparing results of the same regressions between samples.

B. Measures of Systemic Bank Shocks

For this sample, our choice of SBS indicators is dictated by data availability. Aggregate bank profits are unavailable in our dataset, This leaves us with changes in loans and deposits, which are available for almost all nations.

We construct two types of SBS indicators, one based on aggregate bank loans and the other based on aggregate bank deposits. For loans, we construct two indicator variables, SBSL25 and SBSL10, which represent sharp decreases in loan growth. They are equal to one if real domestic lending growth is lower than the 25% and 10%-percentile of the entire distribution of real domestic bank credit growth across countries. The second indicators represent sharp decreases in total bank deposits as a fraction of GDP. Analogously, we construct two indicator variables, SBSD25 and SBSD10, equal to one if the growth rate of the deposit-to-GDP ratio is lower than the 25% and 10% percentile of its distribution across countries respectively.[8]

C. SBS indicators predict BC indicators

If BC indicators are contemporaneous to systemic bank shock realizations, then *SBS indicators should not predict BC indicators.* As shown in Table 2, however, this is not the case.

As shown in regressions 1-4, lagged SBS lending indicators predict all BC indicators and this is true using both the 10th percentile cut-off and the 25th percentile cut-off . As shown in regressions 5-8, however, while SBS lagged *deposit* indicators are always positively associated with BC indicators, the relevant coefficients are (weakly) significant in only two specifications. This suggests that depositors may react to a systemic bank shock

[8] Our choice of indicator thresholds is also dictated by data availability. We cannot set the thresholds for each country individually, since the time dimension of the sample is not long enough to do that in a meaningful way.

with a lag due to information asymmetries. Or they might not react at all if implicit or explicit guarantees on deposits are in place. The idea of a lagged depositor response is also supported by our finding, reported in BDNL (table 6), that SBS lending indicators *predict* SBS deposit indicators.

In sum, BC indicators systematically record systemic bank shocks with a lag. Arguably, this is because these indicators index the (lagged) start and duration of *policy responses to banking distress.* Thus, SBS and BC indicators measure very different things: a systemic bank shock and the government response to bank distress, respectively. The economic importance of these differences is illustrated next.

D. Bank Market Structure

In an extensive set of Logit regressions using the DD crisis classification, Beck et al. (2006) conclude that banking crises are less likely in more concentrated banking systems. Table 3 reports the results of our baseline Logit specifications with BC and SBS indicators as dependent variables, where we have added a bank concentration measure identical to those used by Beck et.al (2006), denoted by *avgherf,* which is an inter-temporal average of the Hirschman-Herfindhal index for each country.

Interestingly, regressions 1-4 indicate that there is no evidence of a significant relationship between bank concentration and the probability of a government response to banking distress.[9] Thus, the Beck et al (2006) results do not seem robust to either: the definition of a BC event, changes in sample composition, or the choice of other explanatory

[9] We should note that our baseline specification differs slightly from the one used by Beck et al (2006). However, we have been able to essentially replicate their results using their identical specification and sample. Moreover, in BDNL (Table 7) we present Logit regressions with the average C3 concentration ratio as an alternative measure of bank concentration, obtaining identical results

variables. By contrast, and in all specifications with our SBS indicators as dependent variables (regressions 5-8), *systemic bank shocks are more likely to occur in more concentrated banking systems.*

Properly interpreted, these results are not necessarily inconsistent with those reported by Beck et al (2006), because the dependent variables are completely different. However, the results presented in Table 2 are perfectly consistent with the implications of the models by Boyd and De Nicolò (2005) and De Nicolò and Lucchetta (2009), as well as with the empirical evidence reported in Boyd, De Nicolò and Jalal (2006 and 2009) and De Nicolò and Loukoianova (2007).

E. Deposit Insurance

In Logit regressions of the type illustrated so far, Demirgüç-Kunt and Detragiache (2002) find—and Barth, Caprio and Levine (2004, 2006) and Beck et al.(2006) confirm—that banking "crises" are more likely in countries with deposit insurance systems is in place. These findings have been interpreted as consistent with the standard moral hazard incentives created by deposit insurance and other government guarantees. Yet, this argument is valid only in a partial equilibrium context *and* absent sufficiently strong countervailing regulations limiting banks' risk-taking, such as capital requirements. In a general equilibrium context, and allowing contracts in nominal terms because of a non-trivial role for money, this simple moral hazard argument does not necessarily hold (e.g. Boyd, Chang and Smith 2002 and 2004).

Table 4 reports the results of Logit regressions with the BC and SBS indicators as dependent variables, in which we retain the Herfindhal index as a control and, in addition, we include the indicator variable *di,* which takes on the value 1 if a government deposit insurance system is in place, and zero otherwise. This variable is obtained from Demirgüç-Kunt and Detragiache (2002).

As shown in regressions 1-4, there is evidence of a positive and significant relationship between the BC indicators and the deposit insurance variable, although it is not statistically significant for the RR indicator (regression 3). However, this result essentially suggests that *policy responses to systemic bank shocks are more likely if a deposit insurance system is in place.* This seems an unsurprising finding in light of the stronger commitment of governments to intervene in the presence of explicit deposit guarantees.

Again, results are different when we use our SBS indicators as dependent variables. As shown in regressions 5-8, in all specifications the probability of a systemic bank shock does not depend on whether there is a deposit insurance system in place. To explore this issue further, in BDNL (Table 10) we report Logit regressions where we have added an index of "moral hazard" associated with design features of deposit insurance systems as used in Beck et al (2006), and find no evidence that more generous deposit insurance systems induce a higher probability of a government response to banking distress.

In sum, the presence of deposit insurance makes government responses to systemic bank shocks more likely, but it has no effect on the probability of a systemic bank shock..

F. External factors and currency crises

There is a substantial literature on external shocks to an economy and their effects on the incidence of banking crises, but the results of this literature often diverge. For example, Kaminsky and Reinhart (1999) found that the occurrence of a banking crisis is a predictor for a currency crisis, while indicators of real, rather than monetary, activity best predict the occurrence of both kinds of crises. As observed in Demirgüç-Kunt and Detragiache (2005), however, their analysis was based on a relatively small sample of 20 countries. They investigated mostly fixed exchange rate arrangements and the impact of several potential determinants of both kinds of crises was not examined jointly. Eichengreen and Rose (1998) and Arteta and Eichengreeen (2002) have also examined the impact of "external" shocks on banking crises. One of their main findings is that exchange rate arrangements do not appear to have a significant impact on banking "crises", as measured by BC-type indicators. By contrast, Domac and Martinez-Peira (2003) find that banking "crises", as measured by BC-type indicators, are less likely in countries with a fixed exchange rate arrangement for a sample of developing economies.

Here we re-examine the role of "external" factors in determining the four measures of government responses to banking distress (BC indicators) as well as of our two measures of systemic bank shocks (SBS indicators). As before, our focus is on illustrating the differences in the results obtained by using BC indicators and SBS indicators

To this end, we refine the specification of the Logit regressions in the previous sections, which was adopted to facilitate broad comparisons with the results of previous studies. First, we use lagged values of all explanatory variables. This specification is more satisfactory than using contemporaneous variables, since it delivers an interpretation of these regressions as "forecasting" equations, where both simultaneity biases and endogeneity issues are less relevant. Second, we replace the measure of exchange rate depreciation and the proxy measure of potential vulnerability of a country to a run of the currency (the ratio of M2 to international reserves) with a currency crises indicator. This indicator is constructed using monthly data following the algorithm implemented in Frankel and Wei (2004): it equals 1 if the sum of exchange rate depreciation and loss of international reserves is lower than the 25th percentile of the entire cross country distribution.

Finally, we introduce two additional explanatory variables. The first is a measure of financial openness, given by the sum of countries' external assets and liabilities over GDP as estimated by Lane and Milesi-Ferretti (2005). The second is the index of the degree of flexibility of exchange rate arrangements constructed by Reinhart and Rogoff (2004), which classifies the degree of flexibility in increasing order. . Taking into account these measures is novel, ansd motivated by the contrasting results in the literature concerning the role of financial openness and exchange rate arrangements,

Table 5 illustrates Logit regressions with BC and SBS indicators as dependent variables. In these regressions we have retained bank concentration and deposit insurance variables as controls.

With regard to the regressions with BC indicators as dependent variables (regressions 1-4), two results stand out. First, changes in terms of trade (*totch)*, financial openness (*finopen),* and the flexibility of exchange rate arrangements (*erclassrr)* do not enter significantly in any regression. These variables have been mentioned in the literature discussed above as potentially important determinants of banking fragility. However, they do not appear to be significant determinants of policy responses to banking distress, as represented by BC indicators. Second, policy responses to bank distress appear to be positively associated with currency crises, as the relevant coefficients are positive in all regressions and significant in three out of the four regressions 1-4.

By contrast, different results are obtained with the SBS indicators as dependent variables (regressions 5-8). There is some evidence that changes in terms of trade (*totch)*, financial openness (*finopen),* and the flexibility of exchange rate arrangements (*erclassrr)* have a significant impact on the probability of a systemic bank shock, although the coefficients associated with the relevant variables are not always statistically significant. On the other end, currency crises predict the probability of a systemic bank shock, and significantly so in three out of four regressions.[10]

In sum, thre is a positive and significant impact of currency crises on both the probability of a government response to banking distress, as represented by BC indicators, as well as the probability of systemic bank shocks. However, the role of terms of trade, financial openness and exchange rate arrangements appears to affect only the probability of a systemic bank shock in some specifications, but not government response in all specifications. As shown next, a better gauge of the relationship between bank fragility and these variables is better uncovered by firm-level data, to which we turn.

V. EVIDENCE FROM BANK-LEVEL DATA

In this section we carry out some of the key tests conducted above using the bank-level dataset employed in Boyd, De Nicolò and Jalal (2006, 2009) and De Nicolò and Loukoianova (2007). This dataset includes bank accounting data of about 3,000 banks in 134 emerging eand developing countries over the period 1993 to 2004, which is from the *Bankscope* (Fitch-IBCA) database. Specifically, it includes all commercial banks

[10] A similar result emerges from the analysis of the impact of bank dollarization on bank fragility. De Nicolò, Honohan and Ize (2005) find that dollarization is positively associated with bank fragility using a theory-based indicator of systemic bank shock, the Z-score of large banks, as well as measures of aggregate non-performing loans. By contrast, Arteta (2003) finds no effects using a version of BC indicators.

(unconsolidated accounts) for which data are available. The sample comprises all banks operating in each period, including those which exited either because they were absorbed by other banks or because they were closed.[11]

Using a firm-level dataset has two key advantages over the country dataset used thus far. First, it allows us to construct our theory-based SBS indicators based on severe declines in profits and, importantly, taking banks' capital buffers into account. As noted earlier, using these direct measures of systemic bank shocks was not feasible with the country dataset due to the unavailability of relevant data. Second, individual bank data and the almost universal coverage of banks in the country considered allow us to conduct more powerful tests. Banking systems heterogeneity and, specifically, the fact that bank systemic shock may affect banks in the same country differentially, are all factors taken fully into account in these regressions. In addition, we can employ better measures of some determinants of bank fragility, such as bank market structure, since these variables can now be constructed as time series and not as period averages.

Using this different dataset also allows us to compare the results obtained with the country dataset in order to assess the extent to which bank heterogeneity can affect the results. The comparison with the previous work is not perfect, as the period covered by the bank-level dataset is shorter than the one of the previous dataset. Yet, such a comparison is still appropriate as we retain about two thirds of the observations classified by BC indicators as "crisis" years for about 60 countries.

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[11] Coverage of the Bankscope database is incomplete in some countries for the earlier years (1993 and 1994), but from 1995 coverage in almost all countries is about 95 percent of all banking systems' assets.

A. Measures of Systemic Bank Shocks

As observed in Boyd, De Nicolò and Jalal (2009), the best empirical measure of actual failure in banking is arguably a binary indicator indicating whether a sample bank "survived" or "failed". Yet, such data are difficult to obtain since actual bank failures are quite uncommon occurrences and failing banks are usually rescued by government.

However, consistent with the implications of our model's comparative statics exercise, we can define two measures capturing extreme adverse realizations of bank profits. Specifically, we construct two firm-level SBS indicators based on the overall distribution of the sum of profits and equity capital standardized by assets: FAIL5 and FAIL10, corresponding to the 5th and 10th percentile of the entire distribution of this sum across time and countries. Thus, in the relevant Logit regressions, these measures can capture a systemic bank shock through a sharp drop in the sum of the profits and the capital of the banking system, standardized by total assets.

To account for bank heterogeneity across countries, we estimated random coefficient Logit regressions. Standard likelihood ratio tests confirmed the superiority of this specification over a pooled specification, indicating the importance of taking bank heterogeneity into account in our tests. In all Logit regressions presented below, all explanatory variables are lagged one period as in section IV.

In this case, our baseline specification includes standard macroeconomic variables available for all countries in the sample as controls: GDP growth (growth), the inflation rate (infl), GDP per capita (gdppc), and exchange rate depreciation (depr). In addition, we also control for bank size with the log of assets (lasset) .

B. SBS indicators predict BC indicators

As before, we use lagged SBS indicators as an additional explanatory variable in the Logit regressions with BC indicators as the dependent variables. As shown in Table 6, in all specifications the SBS indicators predict the BC indicators with high significance, suggesting yet again that these BC indicators capture lagged government responses to banking distress.

Notably, key macroeconomic variables predict BC indicators with a significance much stronger than what was obtained with the country data. As expected, higher GDP growth predicts a lower probability of government response to bank distress. Importantly, inflation enters positively and significantly in all regressions on BC indicators. By contrast, in the regressions based on country data we found that the effect of inflation on BC indicators was at best mixed.

In sum, the ability of SBS indicators to predict BC indicators found in country data is confirmed, even more strongly statistically, using bank-level data.

C. Bank Concentration, Deposit Insurance and External Shocks

Mirroring what was done previously, the last set of regressions compares Logit regressions with BC and SBS indicators as dependent variables, focusing on the impact on these indicators of measures of bank concentration, the existence of explicit deposit insurance system, and selected variables indexing the external environment and currency crises.

Table 7 reports the relevant regressions, with BC indicators as dependent variables (regressions 1-4), and with SBS indicators as dependent variables (regressions 5 and 6).

With regard to bank concentration market structure, we find a positive and significant impact of bank concentration (hhib) on the probability of a government response to bank distress. This result is consistent with those obtained in several studies in the literature that have used only country data reviewed previously. At the same time, we find a positive and significant relationship between bank concentration and the probability of a systemic bank shock. Again, the stark contrast between BC indicators and SBS indicators discussed previously finds further confirmation using bank-level data.

With regard to deposit insurance, the results we obtain with bank-level data mirror those obtained with country level data. Specifically, the probability of a government response to bank distress is significantly higher when an explicit deposit insurance system is in place, consistent with governments' firmer commitment to intervene under explicit depositors' protection schemes. By contrast, the existence or the absence of an explicit deposit insurance system does not have a significant impact on the probability of a systemic bank shock Again, all previous results are confirmed with the bank-level dataset.

The impact of variables related to the external environment and currency crises is stronger than that obtained using country-level data. First, financial openness is associated with a lower probability of a policy response to bank distress, but has no effect on the probability of a systemic bank shock. Second, more flexible exchange rate arrangements are associated with a lower probability of a policy response to bank distress as well as a lower probability of a systemic bank shock. This evidence did not show up with country level data, and supports some of the argument made in the literature about the comparatively stronger resilience to external shocks of countries with more flexible exchange rate arrangements. Finally, currency crises appear to have no impact, or even a negative impact on the probability of a policy response to banking crisis. By contrast, the probability of a bank systemic shock is higher following a currency crisis, consistent with the previous findings based on country-level data.

All in all, the evidence obtained with this bank-level dataset supports all previous main findings regarding the key differences between BC and SBS indicators. It also provides some indication that the use of bank-level data may be more informative in assessing the determinants of bank fragility, as witnessed by the uncovering of a significant impact of the flexibility of exchange rate arrangements on the probability of a systemic bank shock.

VI. Conclusion

We have used a simple model to derive consistent measures of bank systemic shocks so as to disentangle these shocks from government responses to banking distress. We argued that doing this provides a more solid ground to understanding bank fragility and its determinants. We hope to have demonstrated this to be the case. In particular, we have shown that key macroeconomic variables and structural indicators studied in the literature have systematically different effects on systemic bank shocks and on government responses to them.

We found overwhelming evidence that widely employed schemes for dating banking crises (BC indicators) measure lagged government responses to banking crises, not crises *per se*. Whether, and to what extent, mixing the realization of banking shocks and the restorative policy response has been problematic for empirical research and has been an open question (De Nicolò et al., 2004, and Von Hagen and Ho, 2007). Our approach to this question was to begin by structuring and solving a model in which systematic shocks to the banking industry were exogenous, and observed by the authorities with a lag. Comparative static properties of the model were then employed to identify a set of theory-based systematic bank shocks (SBS) that could result in banking crises. The next step was to demonstrate that these shocks systematically predict the BC indicators. We concluded that our indicators of systemic bank shocks consistently predict BC indicators constructed on the basis of four different major banking crisis classifications used extensively in the literature.

The potential problem caused by this finding is not just the lead-lag relationship. Rather, it is that when researchers thought they were identifying a banking crisis, they were actually identifying restorative government interventions. The latter would be expected to have very different determinants and effects than the former.

Our results are quite troubling for many previous studies.

There are important policy implications here. Our previous research on bank competition and banking stability (Boyd and De Nicolò (2005), Boyd, De Nicolò and Jalal (2009) and De Nicolò and Lucchetta (2009) has challenged the conventional wisdom that competition leads to instability. There is now a substantial and on-going debate on this issue. One seemingly important piece of evidence in the debate has been the empirical finding that more competition leads to a higher probability of banking crisis arrival. What we have presented suggests that result is incorrect and that the relationship is actually of opposite sign. As we have documented elsewhere (Boyd and De Nicolo, 2005), policy-makers have for decades assumed that there exists an unfortunate trade-off between competition and stability in the banking industry. If that assumption is incorrect, many policies need re-thinking. To be sure, this is still an on-going debate.

Similarly, previous research has concluded that the presence of deposit insurance worsens moral hazard problems and increases the likelihood of banking crises, *ceteris paribus* (Demirgüç-Kunt and Detragiache, 2002, and Beck et al. 2006). We find that this is not so, but when deposit insurance is present, the authorities are more likely to intervene or to intervene more forcefully. Again, in the BC indicators the two separate effects—crisis occurrence and policy response—are co-mingled and may be misinterpreted. . From a policy perspective, the moral hazard problems created by deposit insurance may be smaller than thought - or may not even exist. If true, policy makers should have less reason to be concerned about this "side effect" of deposit insurance systems. This topic simply needs more research.

Last, we found indicators of external shocks to have a significant impact on SBS indicators but not on BC indicators, again confirming the importance of disentangling shocks and government responses to shocks.

To close, we believe that many empirical results of a large literature need to be re-interpreted and the role of some cross-country determinants of bank fragility need to be reassessed. Understanding bank fragility and the identification of policies capable of reducing its potential welfare costs is still a field in its infancy. In light of our results and the reality of banking distress experienced recently, the need for more research is clearly a matter of more than academic interest.

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Table 1. Statistics of BC Indicators

DD: Demirgüç-Kunt and Detragiache (2005); CEA: Caprio et al. (2005); RR: Reinhart and Rogoff (2008b); LV: Laeven and Valencia (2008)

Panel A : Summary Statistics of Classifications of Systemic Banking Crises

	Total country years	Total country years excluding crisis years after the first	Total country years excluding crisis years after the first as % of total country years	Total crisis country years	Total crisis country years as % of total country years	Total number of systemic crises	Average crisis duration in years
DD	2350	2070	88.1	363	15.4	83	4.4
CEA	2143	1833	85.5	382	17.8	78	4.9
RR	2375	2171	91.4	300	12.6	69	4.3
LV	2275	2021	88.8	339	14.9	84	4.0

Panel B : Pairwise Comparisons

Classifications A	B	Total country years in common	Number of country years A = NO crisis B= crisis	Number of country years A = crisis B=NO crisis	Total country years discrepancies	Total agreed country years	Total discrepancies as % of common country years	Total discrepancies as % of agreed crisis country years + discrepancies
Only first crisis country year								
DD	CEA	1720	14	20	34	55	2.0	38.2
DD	RR	1986	15	30	45	46	2.3	49.5
DD	LV	1920	15	21	36	57	1.9	38.7
CEA	RR	1777	7	18	25	55	1.4	31.3
CEA	LV	1769	10	10	20	67	1.1	23.0
LV	RR	1976	22	12	34	55	1.7	38.2
All crisis country years								
DD	CEA	2118	109	93	202	263	9.5	43.4
DD	RR	2187	48	115	163	248	7.5	39.7
DD	LV	2090	65	95	160	264	7.7	37.7
CEA	RR	1979	41	123	164	259	8.3	38.8
CEA	LV	2089	19	65	84	259	4.0	24.5
RR	LV	2275	99	60	159	240	7.0	39.8

Table 2. Logit Regressions: SBS indicators Predict BC Indicators

Dependent variables are the BC indicators with all crisis dates: DD, CEA, RR and LVE. All regressions are full sample regressions including all available observations for each classification. Explanatory variables: *rgdpgr* is the GDP growth rate; rint is the real interest rate; *infl* is the percentage change in the GDP deflator; *totch* is the change in the terms of trade; *depr* is the exchange rate depreciation vs. the US$; *m2res* is the ratio of M2 to foreign exchange reserves; *rgdpcp* is real GDP per-capita; *privcrd_gdp* is bank credit to the private sector to GDP; *L2.domcredgr* is real domestic bank credit growth to the private sector lagged twice. *L.SBSL25* and *L.SBSL10* are lagged SBS lending indicators. Standard errors are clustered by country. Robust p-values are reported in brackets, with *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	DD	CEA	RR	LV	DD	CEA	RR	LV
rgdpgr	-0.0672***	-0.0869***	-0.0840***	-0.0767***	-0.0674***	-0.0872***	-0.0840***	-0.0771***
	[0.000437]	[1.90e-05]	[3.25e-06]	[0.000272]	[0.000430]	[1.68e-05]	[2.34e-06]	[0.000249]
rint	0.000177	0.000174	0.000345**	0.000140	0.000151	0.000122	0.000293*	9.83e-05
	[0.119]	[0.109]	[0.0490]	[0.202]	[0.155]	[0.229]	[0.0674]	[0.340]
infl	0.000161	0.000163	-0.000906	0.000108	0.000130	9.97e-05	-0.000912	5.70e-05
	[0.405]	[0.289]	[0.122]	[0.507]	[0.477]	[0.506]	[0.113]	[0.720]
totch	-0.00102	-0.00169	-0.00179	-0.00257	-0.00104	-0.00150	-0.00201	-0.00259
	[0.803]	[0.618]	[0.673]	[0.471]	[0.794]	[0.638]	[0.622]	[0.449]
depr	0.341	0.298	0.706*	0.430	0.388	0.393	0.767**	0.508*
	[0.273]	[0.327]	[0.0565]	[0.165]	[0.197]	[0.195]	[0.0394]	[0.0977]
m2res	0.00204*	0.00114	0.00187**	0.00147	0.00202**	0.00113	0.00187**	0.00144*
	[0.0540]	[0.220]	[0.0464]	[0.109]	[0.0453]	[0.174]	[0.0335]	[0.0799]
rgdpcp	-1.30e-05	-1.74e-05	-1.49e-05	-2.12e-05	-1.40e-05	-1.95e-05	-1.79e-05	-2.32e-05
	[0.529]	[0.573]	[0.640]	[0.323]	[0.499]	[0.533]	[0.580]	[0.287]
privcrd_gdp	0.00113***	-0.164	-0.0884	-0.129	0.00111***	-0.179	-0.0991	-0.138
	[0.000497]	[0.239]	[0.414]	[0.269]	[0.000759]	[0.242]	[0.402]	[0.271]
L2.rdomcredgr	0.00218	-0.00209	-0.00274	-0.00130	0.00261	-0.00143	-0.00254	-0.000574
	[0.560]	[0.502]	[0.413]	[0.733]	[0.496]	[0.654]	[0.451]	[0.881]
L.SBSL10	**0.365****	**0.785*****	**0.771*****	**0.664*****				
	[0.0469]	[2.72e-05]	[2.61e-05]	[0.000482]				
L.SBSD10					**0.212**	**0.340***	**0.182**	**0.336***
					[0.343]	[0.0922]	[0.482]	[0.0971]
Constant	-1.402***	-1.104***	-1.603***	-1.306***	-1.381***	-1.035***	-1.505***	-1.252***
	[0]	[8.47e-07]	[0]	[0]	[0]	[3.55e-06]	[0]	[2.40e-10]
Observations	1707	1529	1707	1633	1707	1529	1707	1633
# of countries	91	81	91	87	91	81	91	87
Pseudo-R2	0.0420	0.0825	0.0802	0.0807	0.0405	0.0734	0.0704	0.0746
L.SBSL25	**0.412*****	**0.576*****	**0.519*****	**0.448*****				
	[0.00388]	[0.000126]	[0.000126]	[0.00541]				
L.SBSD25					**0.152**	**0.143**	**0.0542**	**0.127**
					[0.415]	[0.425]	[0.763]	[0.487]

Table 3. Logit Regressions: BC Indicators, SBS Indicators and Bank Concentration

Dependent variables are the BC indicators with all crisis dates: DD, CEA, RR and LV. All regressions are full sample regressions including all available observations for each classification. Explanatory variables*: rgdpgr* is the GDP growth rate; *rint* is the real interest rate; *infl* is the percentage change in the GDP deflator; *totch* is the change in the terms of trade; *depr* is the exchange rate depreciation vs. the US$; *m2res* is the ratio of M2 to foreign exchange reserves; *rgdpcp* is real GDP per-capita; *privcrd_gdp* is bank credit to the private sector to GDP; *L2.domcredgr* is real domestic bank credit growth to the private sector lagged twice; *concen_mean* is the average C3 concentration ratio; *avgherf* is the average Herfindhal index. Standard errors are clustered by country. Robust p-values are reported in brackets, with *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	DD	CEA	RR	LV	SBSL25	SBSL10	SBSD25	SBSD10
rgdpgr	-0.0850***	-0.109***	-0.0954***	-0.105***	-0.120***	-0.109***	0.0545***	0.0355
	[0.000134]	[2.92e-06]	[6.34e-05]	[8.00e-06]	[1.31e-05]	[0.000916]	[0.00172]	[0.131]
rint	0.00501	0.00503	0.00490	0.00167	-0.00921*	-0.00670*	-0.00103	-0.00299
	[0.160]	[0.367]	[0.166]	[0.596]	[0.0692]	[0.0513]	[0.726]	[0.112]
infl	0.00527	0.00518	0.00338	0.00210	-0.00180	-0.00663**	-0.00235	-0.00461**
	[0.161]	[0.343]	[0.260]	[0.524]	[0.790]	[0.0348]	[0.386]	[0.0279]
totch	0.00254	4.05e-05	-0.000178	0.000225	0.0181***	0.0136**	0.0158*	0.0268***
	[0.575]	[0.992]	[0.969]	[0.955]	[0.00142]	[0.0260]	[0.0935]	[0.00756]
depr	0.534	0.740	0.807	0.583	2.446***	3.305***	1.633***	2.576***
	[0.319]	[0.199]	[0.159]	[0.280]	[0.000275]	[6.14e-08]	[0.000618]	[8.84e-07]
m2res	0.00188*	0.000912	0.00182**	0.00103	0.00181**	-0.000329	0.00165***	0.00168
	[0.0682]	[0.250]	[0.0302]	[0.220]	[0.0257]	[0.668]	[0.00924]	[0.137]
rgdpcp	-2.12e-05	-9.21e-06	-3.80e-05	-4.09e-05	-1.81e-05	5.03e-05**	-1.42e-05	-5.68e-05***
	[0.362]	[0.779]	[0.352]	[0.129]	[0.222]	[0.0392]	[0.269]	[0.00770]
privcrd_gdp	0.00117***	-0.180	-0.0871	-0.131	-0.000645**	-5.794***	0.000835***	-0.00125
	[0.00123]	[0.297]	[0.511]	[0.418]	[0.0238]	[1.01e-05]	[6.19e-05]	[0.276]
L2.rdomcredgr	0.00287	-0.00165	-0.00224	-0.00187	-0.0134**	0.00231	-0.0142***	-0.00600
	[0.583]	[0.728]	[0.657]	[0.734]	[0.0114]	[0.646]	[0.00755]	[0.314]
avgherf	**-0.118**	**1.114**	**-0.375**	**0.255**	**1.460*** **	**1.562*** **	**0.866** **	**1.587*** **
	[0.848]	[0.221]	[0.635]	[0.767]	[4.75e-05]	[0.00135]	[0.0250]	[0.00121]
Constant	-1.335***	-1.605***	-1.433***	-1.180***	-1.539***	-1.936***	-1.705***	-3.120***
	[1.03e-05]	[0.000747]	[0.000790]	[0.00282]	[0]	[1.05e-05]	[0]	[0]
Observations	1205	1057	1205	1143	1205	1205	1205	1205
# of countries	79	69	79	75	79	79	79	79
Pseudo-R2	0.0600	0.120	0.0986	0.112	0.178	0.313	0.0672	0.157

Table 4. Logit Regressions: BC Indicators, SBS Indicators and Deposit Insurance

Dependent variables are : the BC indicators with all crisis dates (DD, CEA, RR and LV); the SBS lending indicators, *SBL25* and *.SBSL10*, and the SBS deposit indicators, *SBSD25* and *SBSD10*. Explanatory variables: *rgdpgr* is the GDP growth rate; *rint* is the real interest rate; *infl* is the percentage change in the GDP deflator; *totch* is the change in the terms of trade; *depr* is the exchange rate depreciation vs. the US$; *m2res* is the ratio of M2 to foreign exchange reserves; *rgdpcp* is real GDP per-capita; *privcrd_gdp* is bank credit to the private sector to GDP; *L2.domcredgr* is real domestic bank credit growth to the private sector lagged twice; *avgherf* is the average Herfindhal index; *di* is the binary indicator of deposit insurance. Standard errors are clustered by country. Robust p-values are reported in brackets, with *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	DD	CEA	RR	LV	SBSL25	SBSL10	SBSD25	SBSD10
rgdpgr	-0.0871***	-0.118***	-0.0980***	-0.113***	-0.119***	-0.110***	0.0546***	0.0360
	[0.000148]	[2.76e-06]	[5.69e-05]	[9.05e-06]	[1.56e-05]	[0.00107]	[0.00169]	[0.134]
rint	0.00546	0.00597	0.00537	0.00223	-0.00936*	-0.00662*	-0.000987	-0.00277
	[0.128]	[0.256]	[0.129]	[0.458]	[0.0679]	[0.0572]	[0.739]	[0.154]
infl	0.00568	0.00601	0.00374	0.00254	-0.00165	-0.00665**	-0.00231	-0.00440**
	[0.132]	[0.250]	[0.210]	[0.420]	[0.811]	[0.0276]	[0.395]	[0.0408]
totch	0.00219	-0.000736	-0.000612	-0.000527	0.0182***	0.0133**	0.0158*	0.0264***
	[0.624]	[0.867]	[0.895]	[0.897]	[0.00144]	[0.0291]	[0.0938]	[0.00697]
depr	0.523	0.762	0.801	0.596	2.434***	3.327***	1.631***	2.603***
	[0.338]	[0.223]	[0.177]	[0.294]	[0.000319]	[4.63e-08]	[0.000587]	[1.16e-06]
m2res	0.00197*	0.00116	0.00191**	0.00123	0.00179**	-0.000283	0.00167***	0.00179
	[0.0554]	[0.125]	[0.0212]	[0.123]	[0.0271]	[0.712]	[0.00880]	[0.110]
rgdpcp	-3.06e-05	-2.52e-05	-4.51e-05	-5.63e-05**	-1.63e-05	4.67e-05**	-1.55e-05	-6.43e-05***
	[0.172]	[0.438]	[0.278]	[0.0411]	[0.300]	[0.0469]	[0.285]	[0.00253]
privcrd_gdp	0.00114***	-0.219	-0.102	-0.157	-0.000647**	-5.741***	0.000831***	-0.00119
	[0.00127]	[0.195]	[0.465]	[0.332]	[0.0229]	[1.75e-05]	[4.96e-05]	[0.290]
L2.rdomcredgr	0.00295	-0.000858	-0.00196	-0.00145	-0.0134**	0.00242	-0.0142***	-0.00556
	[0.568]	[0.855]	[0.687]	[0.791]	[0.0114]	[0.628]	[0.00785]	[0.342]
avgherf	**0.189**	**1.898****	**-0.0661**	**0.878**	**1.416*****	**1.731*****	**0.904****	**1.893*****
	[0.766]	[0.0298]	[0.933]	[0.299]	[0.000249]	[0.000589]	[0.0273]	[3.49e-05]
di	**0.568***	**1.325*****	**0.549**	**1.099*****	**-0.101**	**0.334**	**0.0775**	**0.584**
	[0.0719]	[0.00185]	[0.203]	[0.00432]	[0.685]	[0.275]	[0.789]	[0.164]
Constant	-1.552***	-2.188***	-1.651***	-1.636***	-1.509***	-2.079***	-1.732***	-3.364***
	[4.84e-06]	[1.65e-06]	[9.59e-05]	[3.01e-05]	[0]	[8.52e-06]	[0]	[0]
Observations	1205	1057	1205	1143	1205	1205	1205	1205
# of countries	79	69	79	75	79	79	79	79
Pseudo-R2	0.0668	0.152	0.104	0.136	0.178	0.314	0.0673	0.162

Table 5. Logit Regressions: BC Indicators, SBS Indicators and Currency Crises

Dependent variables are the BC indicators with all crisis dates: DD, CEA, RR and LV . Explanatory variables: *rgdpgr* is the GDP growth rate; *rint* is the real interest rate; *infl* is the percentage change in the GDP deflator; *rgdpcp* is real GDP per-capita; *privcrd_gdp* is bank credit to the private sector to GDP; *avgherf* is the average Herfindhal index.; *kk_compo* is the indicator of quality of institutions; *finopen* is financial openness; *erclassrr* is the index of flexibility of exchange rate arrangements; *totch* is the change in the terms of trade; *crisis 25* and *stwins2525* are indicators of currency and twin crises respectively. Standard errors are clustered by country. Robust p-values are reported in brackets, with *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	DD	CEA	RR	LV	SBSL25	SBSL10	SBSD25	SBSD10
L.rgdpgr	-0.0907***	-0.134***	-0.127***	-0.128***	-0.117***	-0.107***	-0.0642***	-0.0748**
	[0.000985]	[3.38e-06]	[3.58e-07]	[9.93e-06]	[7.90e-08]	[0.000159]	[0.000860]	[0.0380]
L.rint	0.00523*	0.00474	0.00556*	0.00535	0.00867**	0.0101***	0.00221	0.000462
	[0.0757]	[0.204]	[0.0641]	[0.118]	[0.0327]	[4.71e-05]	[0.584]	[0.787]
L.infl	0.00450*	0.00415	0.00279	0.00479	0.0105***	0.00941***	0.00115	9.82e-05
	[0.0834]	[0.224]	[0.203]	[0.136]	[9.25e-05]	[7.93e-05]	[0.731]	[0.955]
L.rgdpcp	-2.73e-05	-1.53e-05	-2.65e-05	-5.62e-05*	-2.08e-05	-9.17e-06	-2.44e-05	-8.51e-05***
	[0.314]	[0.581]	[0.500]	[0.0571]	[0.257]	[0.782]	[0.131]	[0.000255]
L.privcrd_gdp	0.00105***	-0.251	-0.127	-0.155	-2.64e-05	-2.501***	0.000995***	-0.000123
	[0.00364]	[0.144]	[0.393]	[0.351]	[0.947]	[0.00329]	[0.000101]	[0.915]
L2.rdomcredgr	0.00542	8.70e-05	-0.00149	0.00264	-0.0126**	-0.00163	-0.0177**	-0.00874
	[0.362]	[0.988]	[0.790]	[0.704]	[0.0319]	[0.782]	[0.0147]	[0.126]
avgherf	**0.523**	**2.479****	**0.245**	**0.889**	**2.042*****	**1.632*****	**1.541*****	**2.821*****
	[0.473]	[0.0209]	[0.783]	[0.416]	[6.39e-07]	[2.72e-05]	[0.000296]	[2.30e-06]
di	**0.409**	**1.497*****	**0.547**	**1.241*****	**0.0975**	**0.383**	**-0.0899**	**0.251**
	[0.262]	[0.00315]	[0.275]	[0.00739]	[0.711]	[0.192]	[0.757]	[0.580]
L.finopen	**-0.504***	**-0.347**	**-0.527**	**-0.458**	**0.0612**	**0.274*****	**0.139**	**0.367*****
	[0.0958]	[0.330]	[0.143]	[0.163]	[0.401]	[0.000763]	[0.254]	[0.00314]
L.erclassrr	**0.0161**	**0.0134**	**-0.0364**	**-0.0336**	**-0.00505**	**0.00713**	**0.0429***	**0.0876*****
	[0.689]	[0.780]	[0.477]	[0.411]	[0.846]	[0.786]	[0.0736]	[0.00358]
L.totch	**0.00888**	**-0.000544**	**0.00266**	**0.00134**	**-0.0186****	**-0.0212*****	**-0.00557**	**-0.0123***
	[0.140]	[0.897]	[0.598]	[0.779]	[0.0189]	[0.00309]	[0.382]	[0.0838]
L.crisis25	**0.297**	**0.528****	**0.436***	**0.445***	**1.063*****	**0.700****	**0.193**	**0.503***
	[0.244]	[0.0463]	[0.0973]	[0.0671]	[5.47e-09]	[0.0109]	[0.345]	[0.0622]
Constant	-1.116*	-2.016**	-0.731	-0.887	-2.040***	-2.879***	-1.804***	-4.210***
	[0.0502]	[0.0151]	[0.262]	[0.164]	[1.47e-09]	[7.60e-11]	[4.74e-06]	[0]
Observations	931	820	931	900	931	931	931	931
# of countries	61	54	61	59	61	61	61	61
Pseudo-R2	0.0797	0.185	0.129	0.170	0.203	0.236	0.0846	0.196

Table 6. Evidence from bank-level data: SBS Indicators Predict BC Indicators

Dependent variables are the BC indicators with all crisis dates: DD, CEA, RR and LV. All explanatory variables are lagged one year (prefix L.): *gdppc* is real GDP per capita; *growth* is the GDP growth rate; *infl* is CPI inflation; *depr* is the exchange rate depreciation vs. the US$; *lasset* is banks' log of total assets. *FAIL5* and *FAIL10* are two proxy measures of bank failures according to the overall distribution of the sum of profits and equity capital standardized by assets, corresponding to the 5th and 10th percentile of the entire distribution of this sum across time and countries. The statistical model is a random effect logit model, with standard errors clustered by country. Robust p-values are reported in brackets, with *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	DD	DD	CEA	CEA	RR	RR	LV	LV
L.growth	-0.140***	-0.140***	-0.142***	-0.143***	-0.091***	-0.091***	-0.127***	-0.127***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
L.infl	0.039***	0.039***	0.011***	0.011***	0.001***	0.001***	0.012***	0.013***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
L.gdppc	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	[0.000]	[0.000]	[0.004]	[0.004]	[0.000]	[0.000]	[0.000]	[0.000]
L.lasset	0.320***	0.310***	0.333***	0.325***	0.328***	0.319***	0.387***	0.380***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
L.FAIL5	**0.845*** **		**0.765*** **		**0.656*** **		**0.729*** **	
	[0.000]		[0.000]		[0.000]		[0.000]	
L.FAIL10		**0.754*** **		**0.678*** **		**0.648*** **		**0.600*** **
		[0.000]		[0.000]		[0.000]		[0.000]
Constant	-6.869***	-6.785***	-6.086***	-6.008***	-7.819***	-7.747***	-7.969***	-7.910***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Observations	13828	13828	13475	13475	13828	13828	13774	13774
Number of banks	3172	3172	3082	3082	3172	3172	3163	3163

Table 7. Evidence from bank-level data: Determinants of BC and SBS Indicators

Dependent variables are the BC indicators with all crisis dates (DD, CEA, RR and LV), and the two SBS indicators that proxy measures of bank failures according to the overall distribution of the sum of profits and equity capital standardized by assets, corresponding to the 5^{th} and 10^{th} percentile of the entire distribution of this sum across time and countries, called *FAIL5* and *FAIL10* respectively. All explanatory variables are lagged one year (prefix L.): *gdppc* is real GDP per capita; *growth* is the GDP growth rate; *infl* is CPI inflation; *depr* is the exchange rate depreciation vs. the US$; *lasset* is banks' log of total assets, *kk_compo* is the indicator of quality of institutions; *finopen* is financial openness; *erclassrr* is the index of flexibility of exchange rate arrangements; *crisis 25* and *stwins2525* are indicators of currency and twin crises respectively. The statistical model is a random effect logit model, with standard errors clustered by country. Robust p-values are reported in brackets, with *** p<0.01, ** p<0.05, * p<0.1.

	BC Indicators				SBS Indicators	
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	DD	CEA	RR	LV	FAIL5	FAIL10
L.growth	-0.212***	-0.192***	-0.165***	-0.166***	-0.042***	-0.003
	[0.000]	[0.000]	[0.000]	[0.000]	[0.010]	[0.821]
L.infl	0.050***	0.051***	0.002***	0.051***	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.325]	[0.669]
L.gdppc	0.000***	0.000***	0.000***	0.000***	0.000	-0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.128]	[0.250]
L.lasset	0.352***	0.327***	0.429***	0.470***	0.520***	0.683***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
L.hhib	**1.984*** **	**2.203*** **	**4.104*** **	**3.065*** **	**2.432*** **	**2.307*** **
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
L.di	**0.537*** **	**1.630*** **	**1.147*** **	**1.155*** **	**0.155**	**0.277**
	[0.000]	[0.000]	[0.000]	[0.000]	[0.417]	[0.108]
L.finopen	**-1.079*** **	**-1.013*** **	**-1.032*** **	**-0.966*** **	**0.061**	**0.104**
	[0.000]	[0.000]	[0.000]	[0.000]	[0.586]	[0.323]
L.erclassrr	**-0.189*** **	**-0.256*** **	**-0.265*** **	**-0.238*** **	**-0.058*** **	**-0.048** **
	[0.000]	[0.000]	[0.000]	[0.000]	[0.005]	[0.013]
L.totch	**-0.003**	**0.008* **	**0.020*** **	**0.015*** **	**0.003**	**-0.002**
	[0.596]	[0.095]	[0.000]	[0.002]	[0.666]	[0.753]
L.crisis25	**-0.316*** **	**-0.368*** **	**-0.294** **	**-0.191**	**0.517*** **	**0.458*** **
	[0.007]	[0.003]	[0.020]	[0.119]	[0.002]	[0.002]
Constant	-5.173***	-4.910***	-7.273***	-8.187***	-11.695***	-13.229***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Observations	8551	8415	8551	8551	8551	8551
Number of banks	1846	1812	1846	1846	1846	1846