Banking Crises and Crises Dating: Theory and Evidence*

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Abstract

Many empirical studies of banking crises have employed "banking crisis" (BC) indicators that supposedly date the beginnings and ends of crises. We argue that these BC indicators are constructed using primarily information on government actions undertaken in response to bank distress. We formulate a simple theoretical model of a banking industry which models: the arrival of a systemic bank shock; its turning into a crisis; and the government's policy response. Then we use implications of the theory to construct empirical indicators of systemic bank shocks. We show empirically that our theory based indicators of systemic bank shocks *consistently predict BC indicators,* employing widely-used BC series that have appeared in the literature. The implication is that BC indicators actually measure lagged government responses to crises, rather than the occurrence of crises *per se*. We next re-examine the impact of some key economic factors affecting both the probability of a systemic bank shock and the probability of a government response. These include the bank market structure (competition), the presence of deposit insurance, other external shocks, and currency crises. Disentangling the separate effects of systemic bank shocks and government responses turns out to be crucial in understanding the roots of banking fragility. Key macroeconomic, structural, and institutional features of economies have effects on the likelihood of a government response that are *totally different* from their effects on the likelihood of a banking crisis. Many findings of a large empirical literature need to be re-assessed and/or re-interpreted.

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I. INTRODUCTION

The collapse of the subprime mortgage market in the U.S. in 2007 and the ensuing financial instability have spurred a renewed interest in banking crises. Some have stressed their similarities across countries and historical episodes (e.g. Reinhart and Rogoff, 2008a), while others have emphasized historical differences, as for example related to financial liberalization and the stage of financial development (e.g. Bordo, 2008). As pointed out by Allen and Gale (2007), however, the existing empirical literature on bank fragility has mainly focused on documenting some empirical regularities in the data. The very measurement of the object of study—what a banking crisis is, when it occurs and how long it lasts—has been only loosely informed by or derived from theory. As a result, this literature offers many—often contrasting—findings, which vary considerably both in terms of samples used and of dating of banking crises.[1]

In particular, a large portion of this literature has employed "banking crisis" (BC) indicators based on dating schemes that identify "crisis" beginning dates, ending dates, and an indication as to whether the crisis was "systemic" or not, based primarily on information on government actions undertaken in response of banking distress. A detailed review of the criteria used to identify a banking "crisis" shows that virtually all of them depend on information obtained from the bank regulators and/or central banks. They do not rely on any theory informing the identification of accounting and/or market data for the banking systems that are likely to capture the *realization* of systemic bank shocks eventually *leading to* a crisis. In virtually all cases what is measured is, effectively, a government response to a perceived crisis, not necessarily the onset or the duration of the banking crisis itself.

[1] A partial review of this literature is in Demirgüç-Kunt and Detragiache (2005).

One key implication is that these BC indicators may record the realization of a bank systemic shock leading to a crisis too late on average. Government responses to banking distress may be lagging either because of asymmetric information problems, or because of uncertainty about the actual extent of banking distress—especially when distressed assets are marked to market—and/or because of a variety of political economy considerations dictating the speed and resolve of the intervention of central banks, regulators, and supervisory agencies. This problem is well known in the literature, having been pointed out since the earlier studies of Caprio and Kinglebiel (1996) and Kaminsky and Reinhart (1999), and more recently by Von Hagen and Ho (2007).

Most importantly, though, the problem is not limited to one of just systematically late timing. Equating the dating of a government response to banking distress to the dating of a systemic bank shock is like studying the evolution of a disease by just looking at the therapies implemented by doctors when the patient enters a hospital. As stressed by De Nicolò et al. (2004), the researcher will be unable to disentangle the effects of a negative shock to the banking industry from those of the restorative policy response.[2] Disentangling these effects and obtaining consistent measures of systemic bank shocks is key in understanding the mechanics of bank fragility, and this is where the main contribution of this paper lies.

Using a simple model of a banking industry in which a banking systemic shock, a banking crisis, and a government response to a crisis are explicitly defined and modeled, we

[2] In their analysis of bank systemic risk, De Nicolò et al (2004) used BC-type indicators as controls for "government interventions". They observed that "while the existing classifications of banking crisis and distress track government interventions well, their measurement of crises....as *systemic risk realizations* ...is by construction very sensitive to the classification criterion used." (p. 210).

derive measures of systemic bank shocks. Then, we show that BC indicators constructed on the basis of four major banking crisis classifications used in the literature are systematically biased in that they record the actual realization of a systemic banking shock with lags: these BC indicators actually measure *lagged* government responses to banking distress, rather than the occurrence of crises *per se*.

We then re-examine the impact of several macroeconomic and structural determinants on both the probability of a government response to banking distress and the probability of a systemic bank shock, including bank market structure, deposit insurance, external shocks and currency crises. We find that these determinants have an impact on the probability of government responses to bank distress *significantly different* from that on the probability of systemic bank shocks. Therefore, many results obtained in papers employing BC indicators under the assumption that they track dating and duration of crises as systemic bank shocks need to be re-assessed and re-interpreted. There have been dozens of such papers.

The rest of the paper proceeds as follows. Section II discusses the criteria used for classifying beginnings and duration of banking crises in four major classifications, showing that the dating information is obtained from bank regulators and/or central banks and depends on the implementation of policy. Market and/or accounting data from the banking industry filtered through the lenses of some theory have almost never been employed for this purpose.

Section III presents a theoretical model in which banking crises are produced by the arrival of exogenous shocks to the economy. If a shock is large enough to translate into a systemic bank shock entailing widespread bank insolvencies (crisis), and as soon as the systemic bank shock is recognized by the authorities, they respond to it. We define the crisis recognition date as the date when the government recognizes the negative systemic bank shock. The model makes a number of predictions that can be taken to the data. Importantly, the size of any shock to the economy cannot be influenced by the actions of banks or the government as the sequence of these shocks is assumed to be exogenously given.

Employing a dataset widely used in this literature, in Section IV we construct BC indicators based on four major crisis classifications, documenting their differences and similarities. We also take the predictions of the theory to the data and construct theory-based indicators of systemic bank shocks (SBS). For example, the model predicts, and the data confirm, that before crisis dates identified by BC indicators, total lending will decrease significantly. We show that our SBS indicators consistently predict BC indicators. Thus, BC indicators actually track (lagged) government responses to banking distress.

In Section V we assess the impact of several key potential determinants of the probability of a government response to banking distress and, separately, the probability of a systemic bank shock. We obtain three main findings. First, more concentrated banking systems and larger interest rate margins increase the probability of a systemic bank shock monotonically, while these variables do not affect significantly the probability of a government response to banking distress.

Second, the model predicts that banking "crises" identified by the BC indicators will occur more often in banking systems with formal deposit insurance. The data also provide support for this prediction. However, this finding has previously been interpreted as evidence that deposit insurance results in greater moral hazard, a riskier banking system, and thus, a more common occurrence of banking crises. In the model this obviously cannot be the case. The model predicts that in the presence of formal deposit insurance, the government is more likely to respond to a negative shock of a given size. Indeed, when we use aggregate data, the probability of a systemic bank shock *does not* depend of whether a deposit insurance system is in place. Interestingly, when we use a bank-level dataset with a measure such as the Z-score—an accounting based measure of bank risk exposure that also predicts all the four BC indicators considered —it turns out that the probability of a systemic bank shock in countries where explicit deposit insurance is in place may be even *lower* than in countries that lack such a system.

Lastly, we find that exchange rate depreciations, the worsening of terms of trade, and currency and twin crises have a positive and significant impact on the probability of a systemic bank shock, and we also find evidence, although slightly weaker, of the reverse. By contrast, all these "external" factors do not appear to affect significantly the probability of a government response to bank distress. On the other hand, both the probability of a systemic shock and that of a government response to bank distress are unaffected either by the degree of financial openness or by the degree of flexibility of exchange rate arrangements.

Section VI concludes.

II. Major Classifications of Banking Crises

A variety of classifications of banking crises have been used since the mid 1990s by many researchers.[3] Here we consider four systematic and generally comprehensive classifications, some of them already having been used widely in many empirical analyses.

The first systematic classification of banking crises is due to Caprio and Kinglebiel (CK) (1996, 1999), based on several narratives taken from supervisory and expert sources.[4]

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[3] See Von Hagen and Ho, 2007 for an extensive list.

Specifically, CK classification "...relies upon the assessment of a variety of finance professionals in pulling together characterizations of factors that have caused crises." (1996, p.1), using published sources or interviews with experts familiar with individual episodes. The dates attached to the crises in this classification "...are those generally accepted by finance experts familiar with the countries, but their accuracy is difficult to determine in the absence of the means to mark portfolios to market values" (1996, p. 2). CK noted that it is not easy to date episodes of bank insolvency, especially if an episode does not involve a run on banks and/or on a country's currency, and admit that an episode of banking distress can be detected a period of time after it has started. Similarly, "...it is not always clear when a crisis is over, and in the case of countries in which there are multiple episodes, it may well be that later events are merely a continuation of those occurring earlier."(1996, p. 2). The crisis is defined as systemic, if "...much or all of bank capital has been exhausted."(1996, p.2). Yet, a quantitative limit on the exhaustion of bank capital and its extent across a banking system is not spelled out. In sum, this classification relies mostly on supervisory sources and listings of government measures undertaken in response to a crisis.

Based on CK compilation, Demirgüç-Kunt and Detragiache (2002, 2005) spelled out in more details the criteria used to identify crises start-dates and duration for 94 countries, covering crisis episodes during 1980-2002.[5] This classification and the relevant country dataset have been widely used in empirical analysis. DD defined a *systemic crisis* as

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[4] The use of this classification has been widespread since the crisis compilation reported in the May 1998 issue the IMF World Economic Outlook and have been used to construct early warning forecasting systems by international organizations and private firms since the contributions of Kaminsky and Reinhart (1999) and Demirgüç-Kunt and Detragiache (1997).

[5] Economies in transition, non-market economies, and countries for which data series were mostly incomplete were excluded from this classification.

"...situation in which significant segments of the banking sector become insolvent or illiquid, and cannot continue to operate without special assistance from the monetary or supervisory authorities."(2002, p. 1381) More precisely, episodes of banking distress were classified as systemic when at least one of the following occurred: (i) large scale nationalizations took place, (ii) emergency measures—such as bank holidays, deposit freezes, blanket guarantees to depositors or other bank creditors—were taken to assist the banking system, (iii) the cost of the rescue operations was at least 2 percent of GDP, or (iv) non-performing assets reached at least 10 percent of total assets at the peak of the crisis. However, the dates of the start and the end of a crisis are "...identified ....using primarily information from Lindgren et al. (1996) and Caprio and Klingebiel (1996)." (2002, p.1381)

The first three criteria in the DD classification characterize a banking crisis by dates of *government responses to a systemic bank shock,* rather than the systemic shock that has triggered a crisis. The criterion on a 10-percent non-performing asset ratio is the only one related on an accounting measure. However, it is recorded at the so-called peak of the crisis, but the peak of a crisis is not defined.[6] Yet, it is well known that the recognition of non performing assets occurs typically with a relatively long lag relative to the occurrence of a systemic bank shock.[7]

The second classification we examine is that compiled by Caprio et al. (2005) (CEA henceforth). CEA updated and extended the earlier CK classification covering 126 countries and bank insolvency episodes from the late 1970s to 2005. The authors emphasize that

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[6] "Also, episodes were classified as systemic if non-performing assets reached at least 10 percent of total assets at the peak of the crisis,..." (2002, p. 1381).

[7] See, for example, the discussion in Bordo et al., 2001.

"...some judgment has gone into the compilation of the list, in particular in timing the episode of bank insolvency."(p. 307) CEA do not provide a definition of the start and end dates of a banking crisis episode and whether the crisis was systemic or not, but just refer to the corresponding definitions in CK.

In their tables, CEA report an extensive narrative supporting their crisis dating in each country. A simple counting exercise based on such narrative reveals that in 94 percent of the classified cases the information used is one of government responses to address a crisis (in few cases undated statistics on non performing loans are reported), while in the remaining portion there is no explanation of the nature of a crisis. In five out of 166 episodes, the beginning of a crisis is defined as a bank run, but neither a quantification nor a precise dating is reported. Thus, the CEA classification, as the DD classification, identifies banking crises starting dates and duration essentially on the basis of an interpretation of reported government responses to banking distress.

The third classification of banking crises we consider is the one recently compiled by Reinhart and Rogoff (2008b) (RR henceforth). The classification criteria used are essentially those used in Kaminsky and Reinhart (1999), whose classification was, in turn, also based on CK's classification. Kaminsky and Reinhart (1999) originally identified beginning and peak dates of crises for 20 countries for the period from 1970 to mid-1995 at a monthly frequency. In their classification, a banking crisis starts if either of the following occurs: "...(i) bank runs that lead to the closure, merging, or takeover by the public sector of one or more financial institutions, or (ii) if there are no runs, the closure, merging, takeover, or large-scale government assistance of an important financial institution (or group of institutions) that marks the start of a string of similar outcomes for other financial institutions." (p. 476). They clearly recognized the potential drawbacks of equating the date of the realization of a systemic shock leading to a crisis to the dating of a government response. They offered one possible fix to some of these drawbacks by introducing the notion of a crisis "peak", defined as the date when the heaviest government intervention and/or bank closures occur, based on CK and press chronicles (see sources in Table 2, p.478). The updated RR classification is essentially based on the same criteria, using information from Caprio et. al (2005) and a variety of other sources of qualitative and narrative information (see Appendix, pp 79-81). Differing from the earlier Kaminsky and Reinhart's work, however, RR do not identify the duration of a crisis on the ground that it is difficult of even impossible to pinpoint its conclusion precisely (Table A2), In sum, all considerations already made with regard to CEA's classification also apply to RR classification: it is one based on qualitative information on government responses to banking distress.

Lastly, we consider the classification recently constructed by Laeven and Valencia (2008) (LV henceforth), which extends previous classifications both in time and country coverage. LV modify the classification criteria of the earlier crisis database by Caprio et al. (2005) as follows. First, non-systemic crises are excluded on the basis of an identification of distress events that "were not systemic in nature" (p.5) Second, subject to data availability, crises years are identified with either a) deposit runs, defined as a monthly percentage decline in deposits in excess of 5 percent, or with b) the introduction of deposit freezes or blanket guarantee, or with c) liquidity support or bank interventions, defined as the ratio of monetary authorities'' claims on banks as a fraction of total deposits of "at least 5% and at least double the ratio compared to the previous year.". Using these more explicit quantitative measures, LV report that they are "able to confirm" only about two thirds of the crisis dating of the

CEA classification. Yet, as already pointed out, their criterions b) and c) measure government responses to a systemic bank shock, while a) may be an imprecise and lagged gauge of such realization, as depositors runs may be lagging owing to asymmetric information about the status of the banking system, as well as owing to uncertain government responses (or lack thereof) to crises.[8] As in RR, but differing from DD and CEA, however, there is no estimate of the duration of a crisis.

The first two classifications are well known in the literature and have been used in a large number of studies to analyze the determinants of banking crises. The other two more recent classifications will undoubtedly soon be employed for empirical analysis.

Next, we formulate a simple model in which we define a systemic banking shock, a crisis, and a government response to it. In the following empirical sections, we explore the extent to which dating a systemic bank shock by a government response adequately captures the timing of its realization, construct theory-based measures of systemic shocks and assess some of their determinants.

III. Theory

The economy is composed of a "government" and three classes of agents: entrepreneurs, depositors, and banks. All agents are risk-neutral. Time is discrete and the key decision periods are t and $t+1$.

[8] The Northern Rock case may be viewed as a very recent example of a run induced by policy "ambiguity".

Entrepreneurs

There is a continuum of entrepreneurs indexed by their reservation income levels $a \in [0,1]$, and 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, and 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 through simple debt contracts. The contract pays to 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

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

Let a^* denote the value of a that satisfies (1) at equality. The total demand for loans is thus 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:

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

Bonds

One-period bonds are supplied by the government in amounts specified below. For simplicity, we assume that only banks can invest in bonds. 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 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 for this insurance pay a flat rate insurance premium standardized to zero. On the asset side, banks choose the total amount of lending and the amount of funds to invest in bonds.

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 also 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 deposits payments cannot be honored in part or in full. Whenever this occurs, the government will pay depositors all the claims unsatisfied by the banks. As detailed below, these payments will be financed by issuing additional bonds.

A "*banking crisis"* occurs at date $t+1$ when the banking system's total profits are negative. The government's response to a crisis will be triggered when the government is able to ascertain that the banking system is insolvent. We will consider the case in which the government observes date $t+1$ bank profits at $t+2$, i.e. with a lag.

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.

In period $t+1$, P_{t+1} is realized and observed by entrepreneurs and banks. Borrowers pay loans and in turn, banks pay to depositors, if possible.

If bank profits are non-negative, depositors are paid in full. If profits are negative, depositors cannot be paid in full: this is a systemic bank shock leading to a *crisis*. Depositors are paid *pro-rata* from the banks. The government *responds* to the crisis at $t+2$ by issuing bonds and paying depositors any claim unsatisfied by banks.

The previous sequence of actions repeats: borrowers demand and banks supply funds based on $E_{t+1} P_{t+2}$, and deposits, loans and investment in bonds are determined, etc..

Equilibrium

To streamline notation, we describe 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 the other banks.

Banks choose $(L, b, D) \in R_+^3$ 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* profits. As assumed, realized profits are observed by the government with a lag.

The government intervention is described by the indicator function $I^G{}_t(\Pi_{t-1})$:

$I^G{}_t(\Pi_{t-1}) = 1$ if $\Pi_{t-1} < 0$ (crisis), and 0 otherwise.

The government supplies bonds in the amount $B_t^S = \overline{B} - B_t(\Pi_{t-1})$, where $B_t(\Pi_{t-1}) = I_t^G(\Pi_{t-1})\Pi_{t-1}$.

Equilibrium

Given p, an **equilibrium** is an amount of total 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,

c) the government meets its commitment to deposit insurance.

Comparative statics

We illustrate the basic 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 deposit is given by $R^D(Z) = \alpha Z$. The solutions for all the endogenous variables are given by:

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

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

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

The following table summarizes changes in the endogenous variables for a decline in asset quality (p decreases), a decline in the supply of deposits (an increase in α), a decline in the demand for loans (Y decreases), or an increase in the number of banks N.

Summary of comparative statics for the linear case

	Exogenous variables		
	***p* decreases**	***α* increases**	***Y* decreases**
Endogenous variables			
Total Loans	***down***	***down***	***down***
Total Deposits	***down***	***down***	***down***
Bond interest rate	down	up	down
Loan rate	up	up	up
Deposit rate	down	up	up
Loan rate-Deposit rate	***up***	***up***	***up***
Realized profits	down	down	down

A systemic bank shock can be triggered by any of the following: a sharp decline in firms' probability of a good outcome; a sharp decline in firms' demand for loans; or a sharp decline in the demand for deposits. These declines will result in significant drops in both aggregate loans and deposits as well as in a sharp rise in the interest rate margins, the difference between loan and deposit rates. As shown below, we will use these implications of the model to identify in the data measures of systemic bank shocks, which may (but not need to) result in a banking crisis triggering a government response. In turn, the duration of the government response will be determined by the *persistence* of the sequence of negative shocks to the real economy and the banking system.

In sum, the model predicts that a SBS shock is associated with sharp declines in loans, deposits, bank profits, and spikes in interest rate margins. The adequacy of each of these measures in empirically capturing SBSs will depend on the source, timing and magnitude of the underlying shock. Implementation of some of these measures will also depend on data availability.

IV. BC INDICATORS AND SYSTEMIC BANK SHOCKS

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), covering data for 91 countries for the 1980-2002 period.

We proceed in two steps. First, we examine statistics on the four banking crisis classification previously described, pointing out similarities and differences. Second, we construct theory-based indicators of systemic bank shocks (SBS indicators), assess the extent to which these indicators predict BC indicators, and provide evidence on some of the macroeconomic, structural, and institutional determinants of *both* government responses to banking distress and systemic bank shocks.

A. BC indicators

We construct four binary BC indicators, where each indicator is set to 1 if a country-year is classified as a crisis year and 0 otherwise: DD, based on Demirgüç-Kunt and Detragiache(2005); CEA, based on Caprio et al. (2005); RR, based on Reinhart and Rogoff (2008b); and LV, based on Laeven and Valencia (2008).

We consider two versions of these indicators. The first version *excludes* all country-years classified as crisis years after the first one. In practice, these indicators identify crises' *starting dates.* These starting dates have been used extensively in event-type analyses since IMF (1988) and Kaminsky and Reinhart (1999). The relevant indicators have been also used extensively in regression analyses. The second version includes all crisis country-years beyond the starting date, that is, it includes an estimate of the *duration* of a crisis. Since the RR and LV classifications do not report such duration, we have assigned to such classifications the duration and country years of the CEA classification (or the DD duration when the CEA duration was not available) from the relevant starting date.

Table 1 reports statistics of these classifications (Panel A) and a pairwise comparisons of crisis dating across classifications (Panel B). The most striking fact is that for many countries the crisis dating of these classifications differs considerably both in terms of the starting date of a crisis and in terms of their duration. Thus, the application of the different criteria described in section II to identify the dating of systemic banking crises leads to significant discrepancies in crisis dating. For example, 15 country years are classified as crisis years by RR but not by DD, while the reverse is true for 30 country years (Panel B, second line). Total discrepancies among the DD and RR classifications amount to about half of all country years classified by either one or the other dating scheme as a crisis year. Overall, discrepancies are pervasive across all classifications.[9]

Nevertheless, we evaluate the informational content of these classifications using the standard panel logit regression employed by Demirgüç-Kunt and Detragiache (2005) and Beck et al (2006). These regressions include the following explanatory variables: measures of the macroeconomic environment (real GDP growth, the real interest rate, inflation, changes in the terms of trade, and the exchange rate depreciation), a measure of potential vulnerability of a country to a run of the currency (the ratio of M2 to international reserves), a measure of the economic size of a country (real GDP per capita), a measure of financial

[9] All four classifications only agree on 41 dates of crisis onset. Some of these discrepancies have been also noted by Von Hagen and Ho (2007) and Rancière, Tornell and Westermann (2008).

system development (bank credit to private sector to GDP), and real bank credit growth lagged twice, which in this literature has been employed as a proxy measure of credit booms. In these and all other regressions we present later, standard errors are clustered by country.

Table 2 reports results using the version of the classifications that excludes all crisis years except the first, both for samples that maximize country coverage (regressions (1)-(4)) and for the sample common to all classifications (regressions (5)-(8)). It is apparent that real GDP growth and real interest rates are the only variables which 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, either because of differences in country coverage or discrepancies in the classifications. This evidence raises serious concerns about the robustness of several results obtained in the literature based on specific banking crisis classifications and country samples.

In addition, we view the use of BC indicators constructed by excluding crisis years after the first one as unwarranted. 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). Yet, as we have shown in section II, these classifications actually index a variety of government measures to address banking distress. Therefore, deleting observations of years during which a government continues to implement measures in response to continued banking distress significantly reduces the informational content of these classifications. Last but not least, excluding these observations requires necessarily to take a stand on the duration of a crisis As documented in Table 1, 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, in the sequel we focus on BC indicators including all crisis years observations.

Table 3 reports regressions both for samples that maximize country coverage (regressions (1)-(4)) and for the sample common to all classifications (regressions (5)-(8)). Again, real GDP growth and to a lesser extent, the real interest rate appear the only variables which enter significantly in most regressions. *Prima facie*, these results suggest that the lack of explanatory power of many standard macroeconomic variables in these regressions may be in part due to the variety of approaches in addressing banking distress adopted by governments.

B. Theory-based SBS indicators and BC indicators

Are BC indicators reasonable proxy measures of timing and duration of banking crises? We address this question using theory-based indicators of systemic bank shocks (SBS). We construct two types of SBS indicators. The first one measures sharp decreases in total loans. Specifically, we construct two indicator variables, SBSL25 and SBSL10, which 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 respectively. The second indicator measures a sharp decrease in total bank deposits. 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.

If BC indicators are contemporaneous to systemic bank shock realizations, then BC indicators would be reasonable proxy indicators of banking crises, and *SBS indicators should not predict BC indicators.* As shown in Table 4, however, *this is not the case*. SBS *lending* indicators predict BC indicators in all specifications. By contrast, as shown in Table 5, lagged SBS *deposit* indicators are positively associated with BC indicators, but the relevant coefficients are (weakly) significant only in two out of eight specifications. This is not surprising, as depositors may either react to a systemic bank shock with a lag due to information asymmetries, or not react at all if implicit or explicit guarantees on deposits are either already in place or swiftly introduced as a response to perceived systemic risk.

In sum, these findings show that BC indicators systematically record systemic bank shocks with a lag. This is because these indicators index the (lagged) start and duration of *government responses to banking distress.* As noted and worth stressing again, the lack of robust evidence on their macroeconomic determinants (apart from GDP growth and to some extent the real interest rate) is not surprising in light of the variety and differences across countries of the policies used to address systemic bank distress.

As we show next, this has important implications for the relevance and interpretations of the results of a large literature. This literature has essentially focused on studying the determinants of government responses to banking distress (systemic bank shocks), rather than of "banking crises" as realizations of systemic bank shocks.

V. SYSTEMIC BANK SHOCKS AND GOVERNMENT RESPONSES

What is the impact of the benchmark explanatory variables we have considered on the probability that a systemic bank shock occurs? Table 6 reports the results of the benchmark panel logit regression with our SBS indicators as explanatory variables.

Two important facts emerge. First, the impact of most variables appears more relevant, the levels of significance are generally higher, and the overall explanatory power of the regressions generally stronger, than the regressions with the BC indicators. In particular, the impact of the "external" variables appears significant in most regressions, consistent with the role of external shocks in triggering shocks to domestic banking systems emphasized in some of the literature, on which we turn to momentarily in more detail.

Second, and most importantly, some of the same explanatory variables may have a significant impact on both SBS and BC indicators, but with *opposite* signs. For example, the real interest rate and the inflation rates are *negatively and contemporaneously* associated with the probability of a systemic bank shock (Table 6, regressions (1) and (2)), but are *positively and contemporaneously* associated with government responses (Table3, regressions (5), (6) and (8)).

Moreover, a systemic bank shock is less likely in more financially developed countries (the coefficient of bank credit to the private sector to GDP is *negative* and significant) but government responses to systemic bank shocks may be more likely in such countries (the private sector bank credit to GDP coefficient is *positive* and significant in Table 3, regressions (1) and (5)). Both these facts may not be surprising, as more financially developed economies may be the ones in which banking systems are less fragile and institutions dealing with bank distress are stronger.

These are first examples showing the importance of disentangling systemic bank shocks and government responses in understanding bank fragility, as the SBS and BC indicators measure very different things: a systemic bank shock and the government response to it. As we will see momentarily, these examples abound in the context of our re-examination and re-interpretation of the evidence on the relationship between bank concentration, competition and bank fragility, the role of deposit insurance, and the interplay between currency and banking crises, to which we now turn. .

A. Bank Market Structure and Competition

In an extensive set of logit regressions based on the DD classification, Beck et al. (2006) conclude that banking "crises" are less likely in more concentrated banking systems

Table 7 reports the results of our baseline specification using concentration variables identical to those used by these authors: the average C3 concentration ratio (the asset share of the largest three banks in the total banking sector) and an average of the Herfindhal index. It is evident that a negative and significant relationship between concentration measures and the probability of a government response to banking distress is totally absent, both when a C3 ratio and the more appropriate Herfindhal index are used. Thus, Beck et al (2006) results are not robust both within their classification and across different banking crisis classifications. In fact, these results actually say that the *government response to banking distress does not depend necessarily on the market structure of a banking system*.

However, the results are totally different when we use our SBS indicators as dependent variables. As shown in Table 8, in all but one specifications using a C3 concentration ratio, and in all specification using the more appropriate Herfindhal index, *systemic bank shocks* (*crises) are indeed more likely to occur in more concentrated banking systems.*

These results are consistent with the implications of the models by Boyd, De Nicolò and Jalal (2006), which extend the model by Boyd and De Nicolò (2005) to allow banks to invest in multiple assets, and that by De Nicolò and Loukoianova (2007), which introduces heterogeneous banks that differ in terms of monitoring technology and bankruptcy costs. Empirically, the positive relationship between bank concentration, market power and bank fragility implied by these models is supported by substantial evidence of the adverse impact of concentration on theory-based measures of bank fragility in large panels of bank-level data reported in these papers.

In a recent contribution, however, Martinez-Peira and Repullo (2008) extend the model by Boyd and De Nicolò (2005) by allowing imperfect correlation of loan defaults for identical banks that invest only in loans. For some parameter values, they show there can be a non-linear relationship between measures of competition and bank systemic risk, which translates into an inverted U-shaped (concave) relationship between measures of bank concentration and/or bank margins and measures of bank systemic risk. Thus, bank fragility may increase when either bank concentration or margins decline (competition increases) beyond a certain threshold. Yet, these predictions, while theoretically plausible, do not appear of relevance in our data. As shown in Table 9, in none of the regressions there is evidence of a quadratic relationship between bank concentration, interest rate margins and the probability of a systemic bank shock: the quadratic terms in these regressions are negative but not statistically significant *and* the implied thresholds for bank concentration and margins obtained with the estimated coefficients are *outside the range* of these variables in the data, indicating the empirical irrelevance of non-linear effects.

B. Deposit Insurance

In logistic regressions of the kind illustrated thus far, Demirgüç-Kunt and Detragiache (2002) find—and Barth, Caprio and Levine (2004) and Beck et al.(2006) confirm—that banking "crises" are more likely in countries where a deposit insurance system is in place. This findings has been interpreted as consistent with the standard moral hazard incentives created by guarantees such as deposit insurance. Yet, it is well known that this argument is valid only in a partial equilibrium context and absent sufficiently strong countervailing measures 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 10 reports the results of logistic regressions, in which we retain the Herfindhal index, with the BC indicators as dependent variables. Indeed, there is some evidence of a positive and significant relationship between the BC indicators and the variable indexing whether a deposit insurance system is in place, although it is not statistically significant for two BC indicators. However, this result simply says that *government 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 a government to intervention in the presence of explicit deposit guarantees.

Yet, and again, results are different when we use our SBS indicators as dependent variables. As shown in regressions (5)-(8) of Table 10, 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 further, in Table 11 we report logit regressions where we have added an index of "moral hazard" associated with design features of deposit insurance systems, and a variable indexing the quality of institutions, as used in Beck et al (2006). Again, there is no evidence that deposit insurance systems with more "moral hazard"-inducing features induce a higher probability of a government response to banking distress. Moreover, and perhaps not surprisingly, the probability of a government response to banking distress is lower in countries with better institutions, maybe because better institutions include stronger supervisory and regulatory bodies likely to *prevent* banking distress. By contrast, as shown in regressions (5)-(8), the moral hazard index and the quality of institutions do not appear to have any explanatory role for the probability of a systemic bank shock.

C. Currency and "twin" crises

In analyzing the joint incidence of banking and currency crises ("twin" crises), Kaminsky and Reinhart (1999) found that the occurrence of a banking crisis is a predictor for a currency crisis—although feedback effects can be present— and indicators of real, rather than monetary, activity best predict the occurrence of both crises. As observed in Demirgüç-Kunt and Detragiache (2005), however, their analysis was based on a relatively small sample of 20 countries—with mostly fixed exchange rate arrangements—and the impact of several potential determinants was not examined jointly.

Eichengreen and Rose (1998) and Arteta and Eichengreeen (2002) have also examined the impact of "external" shocks on banking crises and one of their findings is that exchange rate arrangements do not appear to have a significant impact on banking "crises". By contrast, Domac and Martinez-Peira (2003) find that banking "crises" are less likely in countries with a fixed exchange rate arrangement for a sample of developing economies. Apart from significant differences in country samples, in all these studies banking "crises" have been equated to government responses to bank distress using some BC indicator of the type analyzed previously.

Here we re-examine the role of "external" factors in determining the four measures of government responses to banking distress as well as of our measures of systemic bank shocks. To this end, we refine the specification of the logit regressions used thus far —which has been adopted primarily for comparison purposes—as follows. First, we use lagged values of all explanatory variables. This specification is more satisfactory since it delivers an interpretation of these regressions as "forecasting" regressions, where both simultaneity biases and endogeneity issues are likely to be 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 currency crises indicators of a type widely used in the literature. We constructed indicators of currency crises based on monthly data using the algorithm implemented in Frankel and Wei (2004). These indicators equal to 1 if the sum of exchange rate depreciation and loss of international reserves passes the 35 percent (crisis35), the 25 percent (crisis25) and the 15 percent (crisis15) thresholds respectively. We also constructed an indicator of "twin" systemic currency and bank shocks, which equals to 1 if *both* the sum of exchange rate depreciation and loss of international reserves passes the 25 percent threshold and real credit growth is lower that the 25th percentile of the entire cross country distribution.[10]

Third, we introduce two additional explanatory variables: a measure of financial openness, given by the sum of countries' external assets and liabilities over GDP estimated by Lane and Milesi-Ferretti (2005), and the index of the degree of flexibility of exchange rate arrangements constructed by Reinhart and Rogoff (2004).

Table 12 illustrates the results for the BC indicators as dependent variables. Note that all considerations regarding the relatively poor explanatory power of the regressions with contemporaneous explanatory variables described previously apply to these regressions. The only variable that enters negatively and significantly across all specifications is real GDP growth, as government responses may be triggered by banking distress which is contemporaneous if not caused by a sharp decline in real activity. All other variables do have barely a significant and uniform impact on these BC indicators. In particular, this is true for the variables proxying financial openness and the flexibility of exchange rate arrangements, which do not enter significantly in any regression. These variables have been pointed out in the literature as potentially important determinants of banking fragility, but they do not appear to be significant determinants of government responses to banking distress. .

As shown in Table 13, however, different results are obtained for the SBS indicators as dependent variables. First, all results obtained previously continue to hold when we condition the probability of a systemic bank shock on the (lagged) values of explanatory

[10] We also dropped the twice-lagged value of real credit growth, since in the literature we have reviewed the choice of this lag for this variable appears somewhat ad-hoc, being not derived from a systematic statistical analysis of the lag structure of *all* possible predictors in the regressions.

variables. Lower real GDP growth, higher real interest rates and higher inflation predict a higher probability of a systemic bank shock. Higher bank concentration continues to be positively and significantly associated with a higher probability of a systemic bank shocks in all regressions, while the indicator of quality of institutions does not enter significantly in any regression.[11]

Importantly, the variables associated with "external" shocks significantly predict the probability of a systemic bank shock, but this appears to be independent of both the extent to which countries are financially open and the degree of flexibility of their exchange rate arrangements. A worsening of the terms of trade as well as the occurrence of a currency crisis or a twin crisis both predict an increase in the probability of a systemic bank shock. Thus, *the positive impact of currency and twin crises on the probability of systemic bank shocks is significant.* As we have shown in Table 12, this could not be detected by a researcher identifying BC indicators with banking "crises", since *government responses to banking distress are not predicted by currency crisis indicators*.[12] On the other hand—and this time similarly to what obtained with the BC indicators—financial openness and the flexibility of exchange rate arrangements do not have any significant impact on the probability of a systemic bank shock.

Finally, there is also evidence of a negative and significant impact of a systemic bank shock on the probability of a currency crisis. This indicates that the effects of adverse

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[11] Interestingly, the SBS *deposit* indicators are positively and significantly predicted by the proxy measure of bank development, suggesting depositors may be more prone to "run" in relatively more developed banking systems, perhaps owing to lower informational asymmetries.

[12] 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.

domestic and external shocks are mutually reinforcing, as originally conjectured in Kaminsky and Reinahrt (1999). As shown in Table 14, indicators of systemic bank shocks have a significant predictive power on the probability of a currency crisis in most specifications. If we replace the SBS indicators with the BC indicators in the same regressions (which we do not report for the sake of brevity) no effect is found. Again, a researcher using BC indicators as measures of systemic bank shock would fail to detect this evidence.

D. Evidence from bank-level data

In this sub-section we partially replicate the exercise conducted above using the bank level dataset employed in Boyd, De Nicolò and Jalal (2006) and De Nicolò and Loukoianova (2007), which covers bank level data for about 120 countries for the 1993-2003 period. Although the period covered is shorter than the one of the previous dataset, it has two key advantages: we can take the bank market structure fully into account, and we can use another theory-based measure of systemic bank shocks, the Z-score (averaged out all banks in a country). The Z-score is given by the sum of returns on assets and capitalization, divided by an estimate of earnings volatility. This measure is both a proxy measure of a bank's probability of failure and of systemic bank shocks realizations. In fact, consistent with the implications of our model's comparative statics exercise, it can capture a systemic bank shock through a sharp drop in banking system profits (and capitalization).

As shown in panel A of Table15, in all specifications the average Z-score predicts the BC indicators, confirming that these are indeed indicators of lagged government responses to banking distress. In Panel B, we report a Z-score (bank fixed effects) regression with lagged explanatory variables. Consistent with our previous findings, the Z-score is negatively associated with the Herfindhal index, and exchange rate depreciation significantly increases systemic bank risk. Differing from previous evidence using aggregate data, however, the Z-score of banks in countries with deposit insurance are *higher* than those in country lacking a system of explicit depositors protection. This suggests that the presence of explicit systems may prompt more effective regulation and supervision in controlling banks' risk taking. This result is the opposite of what obtained by Barth, Caprio and Levine (2004), who have used BC indicators as dependent variables.

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 understand bank fragility and its determinants. We have demonstrated this to be the case showing that the impact of key macroeconomic variables, bank market structure, deposit insurance, external shocks and currency crises on systemic bank shocks and government responses to bank distress differs significantly.

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 has been raised as an open and unresolved 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, as was indeed found. 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. Therefore, BC indicators actually represent lagged government responses to crises, rather than the occurrence of crises.

It should be stressed again that 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, obviously, would be expected to have very different determinants and effects than the former.

Then, we re-examined the impact of several key factors potentially at the roots of banking crises. What our results suggest is quite troubling for many previous studies. For example, previous research has concluded that, *ceteris paribus,* more concentrated banking systems are less likely to experience crises than others, (Beck et al, 2006). By contrast, our results suggest, that more concentrated banking systems are more likely to experience banking crises, but government responses to banking distress do not appear to depend on market structure. Previous methodology simply could not disentangle these two effects.

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.

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, as the conclusions of many studies are potentially affected by our findings. Understanding bank fragility and the identification of policies capable of reducing its potential welfare costs is still a field in its infancy. Progress will be undoubtedly achieved by theoretical developments capable of delivering consistent measurement.

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Table 1. 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 with Start Date BC indicators (crisis dates after the first crisis date excluded)

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 US$ exchange rate depreciation; 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. Standard errors are clustered by country. Robust p-values are reported in brackets, with *** p<0.01, ** p<0.05, * p<0.1.

COEFFICIENT	(1) DDs	(2) CEAs	(3) RRs	(4) LVs	(5) DDs	(6) CEAs	(7) RRs	(8) LVs
rgdpgr	-0.109***	-0.121***	-0.130***	-0.102***	-0.139***	-0.139***	-0.150***	-0.144***
	[0.000214]	[0.000253]	[0.0000366]	[0.00157]	[0.0000169]	[0.0000464]	[0.0000500]	[0.0000136]
rint	0.000417**	0.000353**	0.000646**	0.000301**	0.000452**	0.000469***	0.000607***	0.000389**
	[0.0116]	[0.0284]	[0.0158]	[0.0361]	[0.0123]	[0.00883]	[0.00833]	[0.0141]
infl	0.000526*	0.000465*	-0.000955	0.000352	0.000605**	0.000624**	-0.0006	0.000478**
	[0.0662]	[0.0560]	[0.409]	[0.102]	[0.0490]	[0.0218]	[0.615]	[0.0465]
totch	0.000415	-0.00448	-0.00358	-0.00729	-0.000893	-0.00446	-0.0032	-0.00427
	[0.956]	[0.516]	[0.649]	[0.267]	[0.895]	[0.520]	[0.692]	[0.491]
depr	0.122	0.217	0.296	0.383	-0.0406	0.041	0.07	0.22
	[0.758]	[0.544]	[0.637]	[0.239]	[0.923]	[0.916]	[0.930]	[0.519]
m2res	0.00117	0.00114*	0.00125**	0.00108	0.000953	0.00108	0.00129*	0.000796
	[0.103]	[0.0975]	[0.0138]	[0.104]	[0.182]	[0.118]	[0.0653]	[0.257]
rgdpcp	-0.0000408**	-0.0000314	-0.0000359	-0.0000264	-0.0000409*	-0.0000521	-0.0000406	-0.0000901***
	[0.0325]	[0.198]	[0.145]	[0.174]	[0.0631]	[0.128]	[0.188]	[0.00672]
privcrd_gdp	0.00129***	-0.0753	-0.045	-0.0942	0.00114***	-0.0419	-0.0407	-0.0228**
	[0.0000312]	[0.429]	[0.347]	[0.360]	[0.00168]	[0.430]	[0.398]	[0.0416]
L2.rdomcredgr	0.0127**	0.0124**	0.0137**	0.00511	0.0134**	0.00814	0.0142**	0.00953*
	[0.0453]	[0.0405]	[0.0144]	[0.355]	[0.0292]	[0.198]	[0.0295]	[0.0997]
Constant	-2.724***	-2.752***	-2.994***	-2.695***	-2.548***	-2.706***	-2.850***	-2.516***
	[0]	[0]	[0]	[0]	[0]	[0]	[0]	[0]
Observations	1459	1267	1522	1406	1153	1153	1153	1153
# of countries	91	80	91	87	78	78	78	78
Pseudo-R2	0.0918	0.115	0.105	0.0977	0.109	0.135	0.122	0.153

Table 3. Logit Regressions with BC indicators (all observations with crisis dating)

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 US$ exchange rate depreciation; 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. 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)
COEFFICIENT	DD	CEA	RR	LV	DD	CEA	RR	LV
rgdpgr	-0.0674***	-0.0867***	-0.0840***	-0.0839***	-0.0768***	-0.0867***	-0.0874***	-0.0905***
	[0.000424]	[0.0000158]	[0.00000208]	[0.0000375]	[0.000102]	[0.0000205]	[0.00000237]	[0.0000111]
rint	0.000151	0.000122	0.000295*	0.000114	0.000137	0.000125	0.000295*	0.000104
	[0.162]	[0.228]	[0.0700]	[0.277]	[0.202]	[0.215]	[0.0663]	[0.313]
infl	0.000126	0.0000951	-0.000924	0.0000811	0.000113	0.000104	-0.000891	0.0000719
	[0.496]	[0.526]	[0.116]	[0.614]	[0.547]	[0.488]	[0.127]	[0.654]
totch	-0.00102	-0.00148	-0.002	-0.00222	-0.000708	-0.00144	-0.00209	-0.00241
	[0.799]	[0.649]	[0.625]	[0.526]	[0.861]	[0.657]	[0.607]	[0.487]
depr	0.392	0.4	0.774**	0.46	0.361	0.377	0.688*	0.434
	[0.196]	[0.187]	[0.0390]	[0.129]	[0.245]	[0.212]	[0.0707]	[0.157]
m2res	0.00206*	0.00119	0.00191**	0.00148	0.00195*	0.00114	0.00172*	0.00139
	[0.0508]	[0.194]	[0.0401]	[0.107]	[0.0627]	[0.215]	[0.0612]	[0.130]
rgdpcp	-0.0000147	-0.0000205	-0.0000184	-0.0000244	-0.00000842	-0.0000204	-0.0000131	-0.0000237
	[0.479]	[0.513]	[0.570]	[0.266]	[0.683]	[0.510]	[0.687]	[0.258]
privcrd_gdp	0.00111***	-0.186	-0.101	-0.15	0.000911***	-0.187	-0.121	-0.152
	[0.000801]	[0.242]	[0.399]	[0.272]	[0.00639]	[0.230]	[0.302]	[0.227]
L2.rdomcredgr	0.00204	-0.0025	-0.00307	-0.0015	0.00312	-0.00241	-0.00287	-0.000851
	[0.593]	[0.437]	[0.375]	[0.699]	[0.398]	[0.449]	[0.401]	[0.823]
Constant	-1.355***	-0.991***	-1.482***	-1.179***	-1.257***	-0.962***	-1.335***	-1.076***
	[0]	[0.00000660]	[0]	[1.31e-09]	[0]	[0.0000117]	[0]	[3.16e-08]
Observations	1707	1529	1707	1633	1497	1497	1497	1497
# of countries	91	81	91	87	79	79	79	79
Pseudo-R2	0.0399	0.0718	0.07	0.0758	0.0408	0.0709	0.0651	0.0757

Table 4. Logit Regressions: BC Indicators and SBS *lending* indicators

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 US$ exchange rate depreciation; 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. 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)
COEFFICIENT	DD	CEA	RR	LV	DD	CEA	RR	LV
rgdpgr	-0.0674***	-0.0871***	-0.0841***	-0.0837***	-0.0672***	-0.0869***	-0.0840***	-0.0837***
	[0.000438]	[0.0000149]	[0.00000274]	[0.0000405]	[0.000437]	[0.0000190]	[0.00000325]	[0.0000426]
rint	0.000178	0.000158	0.000312*	0.000139	0.000177	0.000174	0.000345**	0.000156
	[0.123]	[0.150]	[0.0586]	[0.213]	[0.119]	[0.109]	[0.0490]	[0.162]
infl	0.000167	0.00015	-0.000845	0.00012	0.000161	0.000163	-0.000906	0.000137
	[0.387]	[0.333]	[0.124]	[0.470]	[0.405]	[0.289]	[0.122]	[0.406]
totch	-0.00126	-0.00194	-0.00221	-0.00247	-0.00102	-0.00169	-0.00179	-0.00224
	[0.759]	[0.560]	[0.597]	[0.486]	[0.803]	[0.618]	[0.673]	[0.530]
depr	0.337	0.324	0.706*	0.405	0.341	0.298	0.706*	0.378
	[0.269]	[0.283]	[0.0516]	[0.182]	[0.273]	[0.327]	[0.0565]	[0.216]
m2res	0.00198*	0.00108	0.00182**	0.00139	0.00204*	0.00114	0.00187**	0.00144
	[0.0533]	[0.233]	[0.0455]	[0.121]	[0.0540]	[0.220]	[0.0464]	[0.118]
rgdpcp	-0.0000115	-0.0000171	-0.0000149	-0.0000217	-0.000013	-0.0000174	-0.0000149	-0.0000216
	[0.579]	[0.585]	[0.643]	[0.318]	[0.529]	[0.573]	[0.640]	[0.316]
privcrd_gdp	0.00116***	-0.165	-0.0904	-0.136	0.00113***	-0.164	-0.0884	-0.135
	[0.000385]	[0.243]	[0.417]	[0.272]	[0.000497]	[0.239]	[0.414]	[0.268]
L2.rdomcredgr	0.00322	-0.000809	-0.0016	-0.000377	0.00218	-0.00209	-0.00274	-0.00127
	[0.383]	[0.789]	[0.637]	[0.920]	[0.560]	[0.502]	[0.413]	[0.740]
L.SBSL25	**0.412*** **	**0.576*** **	**0.519*** **	**0.428*** **				
	[0.00388]	**[0.000126]**	**[0.000126]**	**[0.00733]**				
L.SBSL10					**0.365** **	**0.785*** **	**0.771*** **	**0.632*** **
					[0.0469]	**[0.0000272]**	**[0.0000261]**	**[0.000901]**
Constant	-1.485***	-1.181***	-1.655***	-1.318***	-1.402***	-1.104***	-1.603***	-1.272***
	[0]	[0.000000135]	[0]	[0]	[0]	[0.000000847]	[0]	[0]
Observations	1707	1529	1707	1633	1707	1529	1707	1633
# of countries	91	81	91	87	91	81	91	87
Pseudo-R2	0.0448	0.0818	0.0777	0.0812	0.042	0.0825	0.0802	0.0827

Table 5. Logit Regressions: BC Indicators and SBS *deposit* indicators

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 US$ exchange rate depreciation; 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. 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)
COEFFICIENT	DD	CEA	RR	LV	DD	CEA	RR	LV
rgdpgr	-0.0674***	-0.0869***	-0.0840***	-0.0840***	-0.0674***	-0.0872***	-0.0840***	-0.0842***
	[0.000431]	[0.0000168]	[0.00000224]	[0.0000390]	[0.000430]	[0.0000168]	[0.00000234]	[0.0000384]
rint	0.000152	0.000123	0.000294*	0.000115	0.000151	0.000122	0.000293*	0.000115
	[0.155]	[0.226]	[0.0683]	[0.274]	[0.155]	[0.229]	[0.0674]	[0.274]
infl	0.00013	0.0000982	-0.000916	0.0000839	0.00013	0.0000997	-0.000912	0.0000868
	[0.477]	[0.512]	[0.115]	[0.600]	[0.477]	[0.506]	[0.113]	[0.588]
totch	-0.000946	-0.00141	-0.00197	-0.00216	-0.00104	-0.0015	-0.00201	-0.00226
	[0.813]	[0.662]	[0.632]	[0.533]	[0.794]	[0.638]	[0.622]	[0.510]
depr	0.393	0.401	0.773**	0.462	0.388	0.393	0.767**	0.453
	[0.191]	[0.185]	[0.0388]	[0.127]	[0.197]	[0.195]	[0.0394]	[0.135]
m2res	0.00201*	0.00114	0.00189**	0.00143	0.00202**	0.00113	0.00187**	0.00141*
	[0.0524]	[0.199]	[0.0381]	[0.106]	[0.0453]	[0.174]	[0.0335]	[0.0877]
rgdpcp	-0.0000142	-0.0000202	-0.0000183	-0.0000241	-0.000014	-0.0000195	-0.0000179	-0.0000234
	[0.492]	[0.518]	[0.571]	[0.271]	[0.499]	[0.533]	[0.580]	[0.284]
privcrd_gdp	0.00110***	-0.181	-0.1	-0.146	0.00111***	-0.179	-0.0991	-0.144
	[0.000844]	[0.247]	[0.403]	[0.274]	[0.000759]	[0.242]	[0.402]	[0.272]
L2.rdomcredgr	0.00266	-0.00188	-0.00284	-0.00097	0.00261	-0.00143	-0.00254	-0.000525
	[0.485]	[0.572]	[0.402]	[0.803]	[0.496]	[0.654]	[0.451]	[0.891]
L.SBSD25	**0.152**	**0.143**	**0.0542**	**0.128**				
	[0.415]	**[0.425]**	**[0.763]**	**[0.485]**				
L.SBSD10					**0.212**	**0.340***	**0.182**	**0.338***
					[0.343]	**[0.0922]**	**[0.482]**	**[0.0949]**
Constant	-1.396***	-1.030***	-1.497***	-1.215***	-1.381***	-1.035***	-1.505***	-1.223***
	[0]	[0.00000217]	[0]	[1.16e-09]	[0]	[0.00000355]	[0]	[5.50e-10]
Observations	1707	1529	1707	1633	1707	1529	1707	1633
# of countries	91	81	91	87	91	81	91	87
Pseudo-R2	0.0405	0.0723	0.07	0.0762	0.0405	0.0734	0.0704	0.0774

Table 6. Logit Regressions with SBS indicators

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 US$ exchange rate depreciation; 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. Standard errors are clustered by country. Robust p-values are reported in brackets, with *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

COEFFICIENT	(1) SBSL25	(2) SBSL10	(3) SBSD25	(4) SBSD10	(5) SBSL25	(6) SBSL10	(7) SBSD25	(8) SBSD10
rgdpgr	-0.119***	-0.0948***	0.0280*	0.0168	-0.125***	-0.0976***	0.0281*	0.0097
	[0.000000706]	[0.00119]	[0.0836]	[0.403]	[6.32e-09]	[0.000305]	[0.0553]	[0.615]
rint	-0.000308**	-0.000220*	0.0000618	0.0000411	-0.000345***	-0.000186	-0.0000245	-0.0000141
	[0.0226]	[0.0688]	[0.627]	[0.735]	[0.00578]	[0.168]	[0.874]	[0.915]
infl	-0.000582**	-0.000566**	-0.000119	-0.000258	-0.000632***	-0.000517**	-0.000253	-0.000352
	[0.0250]	[0.0225]	[0.660]	[0.400]	[0.00938]	[0.0427]	[0.419]	[0.307]
totch	0.0118***	0.00720*	0.0116**	0.0178**	0.0126***	0.00868**	0.0106***	0.0169***
	[0.00344]	[0.0658]	[0.0297]	[0.0133]	[0.000342]	[0.0221]	[0.00443]	[0.000728]
depr	1.238***	1.615***	0.392	0.876**	1.292***	1.566***	0.592	1.003**
	[0.00274]	[0.000224]	[0.291]	[0.0302]	[0.000660]	[0.000255]	[0.117]	[0.0137]
m2res	0.00128**	-0.000229	0.00174**	0.00164*	0.00133***	-0.000285	0.00214***	0.00182*
	[0.0139]	[0.710]	[0.0145]	[0.0971]	[0.00972]	[0.669]	[0.00703]	[0.0711]
rgdpcp	-0.0000527***	0.00000223	-0.0000212**	-0.0000580***	-0.0000553***	-0.00000181	-0.0000202*	-0.0000622***
	[0.0000839]	[0.940]	[0.0477]	[0.00149]	[0.0000860]	[0.950]	[0.0535]	[0.00105]
privcrd_gdp	-0.000925***	-5.120***	0.000578***	-0.00276**	-0.000335	-5.087***	0.000748***	0.000379
	[0.000444]	[0.0000900]	[0.00461]	[0.0132]	[0.178]	[0.0000401]	[0.000158]	[0.203]
L2.rdomcredgr	-0.00608	0.00584	-0.0150***	-0.00954**				
	[0.151]	[0.213]	[0.000239]	[0.0369]				
Constant	-0.692***	-1.126***	-1.242***	-2.287***	-0.740***	-1.136***	-1.399***	-2.367***
	[2.19e-08]	[7.49e-08]	[0]	[0]	[1.11e-09]	[4.83e-08]	[0]	[0]
Observations	1707	1707	1707	1707	1894	1894	1894	1894
# of countries	91	91	91	91	91	91	91	91
Pseudo-R2	0.122	0.228	0.0351	0.0712	0.124	0.224	0.0222	0.0634

Table 7. Logit Regressions: BC Indicators and Bank Concentration Measures

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 US$ exchange rate depreciation; 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 C# 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.

COEFFICIENT	(1) DD	(2) CEA	(3) RR	(4) LV	(5) DD	(6) CEA	(7) RR	(8) LV
rgdpgr	-0.101***	-0.123***	-0.104***	-0.118***	-0.0850***	-0.109***	-0.0954***	-0.104***
	[0.000203]	[0.00000400]	[0.000160]	[0.0000241]	[0.000134]	[0.00000292]	[0.0000634]	[0.00000997]
rint	0.00574*	0.00544	0.00475	0.00186	0.00501	0.00503	0.0049	0.0017
	[0.0952]	[0.317]	[0.171]	[0.574]	[0.160]	[0.367]	[0.166]	[0.590]
infl	0.00695	0.0058	0.00334	0.0025	0.00527	0.00518	0.00338	0.00212
	[0.195]	[0.280]	[0.269]	[0.503]	[0.161]	[0.343]	[0.260]	[0.518]
totch	-0.000587	-0.00268	-0.00273	-0.00247	0.00254	0.0000405	-0.000178	0.000608
	[0.897]	[0.536]	[0.562]	[0.555]	[0.575]	[0.992]	[0.969]	[0.878]
depr	0.333	0.468	0.724	0.449	0.534	0.74	0.807	0.574
	[0.682]	[0.480]	[0.231]	[0.477]	[0.319]	[0.199]	[0.159]	[0.285]
m2res	0.00270*	0.00129	0.00213**	0.00131	0.00188*	0.000912	0.00182**	0.000987
	[0.0784]	[0.197]	[0.0401]	[0.181]	[0.0682]	[0.250]	[0.0302]	[0.238]
rgdpcp	-0.0000255	-0.0000199	-0.0000372	-0.0000435*	-0.0000212	-0.00000921	-0.000038	-0.0000405
	[0.210]	[0.490]	[0.290]	[0.0865]	[0.362]	[0.779]	[0.352]	[0.134]
privcrd_gdp	0.000741*	-0.229	-0.0953	-0.166	0.00117***	-0.18	-0.0871	-0.13
	[0.0990]	[0.320]	[0.502]	[0.423]	[0.00123]	[0.297]	[0.511]	[0.420]
L2.rdomcredgr	0.00176	-0.00348	-0.00275	-0.00298	0.00287	-0.00165	-0.00224	-0.00156
	[0.789]	[0.568]	[0.622]	[0.655]	[0.583]	[0.728]	[0.657]	[0.770]
concen_mean	**-1.363**	**0.238**	**-0.59**	**-0.183**				
	[0.103]	**[0.756]**	**[0.460]**	**[0.799]**				
avgherf					**-0.118**	**1.114**	**-0.375**	**0.361**
					[0.848]	**[0.221]**	**[0.635]**	**[0.672]**
Constant	-0.333	-1.274*	-1.032	-0.865	-1.335***	-1.605***	-1.433***	-1.209***
	[0.619]	[0.0577]	[0.127]	[0.187]	[0.0000103]	[0.000747]	[0.000790]	[0.00224]
Observations	1093	977	1093	1047	1205	1057	1205	1143
# of countries	71	63	71	68	79	69	79	75
Pseudo-R2	0.0781	0.122	0.111	0.125	0.06	0.12	0.0986	0.113

Table 8. Logit Regressions: SBS Indicators and Bank Concentration Measures

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 US$ exchange rate depreciation; 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 C# 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.

COEFFICIENT	(1) SBSL25	(2) SBSL10	(3) SBSD25	(4) SBSD10	(5) SBSL25	(6) SBSL10	(7) SBSD25	(8) SBSD10
rgdpgr	-0.130***	-0.135***	0.0465**	0.0293	-0.120***	-0.109***	0.0545***	0.0355
	[0.0000216]	[0.0000161]	[0.0122]	[0.241]	[0.0000131]	[0.000916]	[0.00172]	[0.131]
rint	-0.00798*	-0.00720**	-0.00151	-0.00341*	-0.00921*	-0.00670*	-0.00103	-0.00299
	[0.0839]	[0.0409]	[0.629]	[0.0870]	[0.0692]	[0.0513]	[0.726]	[0.112]
infl	-0.00616	-0.00752***	-0.00302	-0.00495**	-0.0018	-0.00663**	-0.00235	-0.00461**
	[0.248]	[0.00511]	[0.290]	[0.0243]	[0.790]	[0.0348]	[0.386]	[0.0279]
totch	0.0194***	0.0149**	0.0146	0.0266***	0.0181***	0.0136**	0.0158*	0.0268***
	[0.00148]	[0.0240]	[0.135]	[0.00986]	[0.00142]	[0.0260]	[0.0935]	[0.00756]
depr	2.798***	3.415***	1.672***	2.363***	2.446***	3.305***	1.633***	2.576***
	[0.0000635]	[0.000000164]	[0.000407]	[0.0000100]	[0.000275]	[6.14e-08]	[0.000618]	[0.000000884]
m2res	0.00131	-0.000145	0.00126*	0.00105	0.00181**	-0.000329	0.00165***	0.00168
	[0.154]	[0.870]	[0.0694]	[0.453]	[0.0257]	[0.668]	[0.00924]	[0.137]
rgdpcp	-0.0000299**	0.0000313	-0.0000202*	-0.0000780***	-0.0000181	0.0000503**	-0.0000142	-0.0000568***
	[0.0371]	[0.230]	[0.0833]	[0.000381]	[0.222]	[0.0392]	[0.269]	[0.00770]
privcrd_gdp	-0.000355	-5.297***	0.00102***	-0.00138	-0.000645**	-5.794***	0.000835***	-0.00125
	[0.304]	[0.0000488]	[0.000392]	[0.266]	[0.0238]	[0.0000101]	[0.0000619]	[0.276]
L2.rdomcredgr	-0.0140**	0.00192	-0.0125**	-0.00632	-0.0134**	0.00231	-0.0142***	-0.006
	[0.0115]	[0.748]	[0.0352]	[0.370]	[0.0114]	[0.646]	[0.00755]	[0.314]
concen_mean	**1.656*****	**1.917****	**1.045***	**1.206**				
	[0.00437]	**[0.0310]**	**[0.0694]**	**[0.140]**				
avgherf					**1.460*****	**1.562*****	**0.866****	**1.587*****
					[0.0000475]	**[0.00135]**	**[0.0250]**	**[0.00121]**
Constant	-2.212***	-2.952***	-2.130***	-3.266***	-1.539***	-1.936***	-1.705***	-3.120***
	[0.00000294]	[0.000419]	[0.0000145]	[0.00000843]	[0]	[0.0000105]	[0]	[0]
Observations	1093	1093	1093	1093	1205	1205	1205	1205
# of countries	71	71	71	71	79	79	79	79
Pseudo-R2	0.189	0.344	0.0636	0.144	0.178	0.313	0.0672	0.157

Table 9. Logit Regressions: SBS Indicators, Bank Concentration and Interest Rate Margins

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 US$ exchange rate depreciation; 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 and avgherf2 are the average and squared Herfindhal indexes respectively; margin and margin2 are the level and squared level of interest rate margins. Standard errors are clustered by country. Robust p-values are reported in brackets, with *** p<0.01, ** p<0.05, * p<0.1.

COEFFICIENT	SBSL25	SBSD25	SBSL25	SBSD25	SBSL25	SBSD25
rgdpgr	-0.119***	0.0539***	-0.151***	0.0105	-0.151***	0.0109
	[0.000]	[0.002]	[0.004]	[0.678]	[0.004]	[0.674]
rint	-0.00920*	-0.0011	-0.0012	-0.0249	-0.0013	-0.0263
	[0.055]	[0.682]	[0.803]	[0.204]	[0.786]	[0.220]
infl	-0.00201	-0.00242	0.000232	-0.0185	0.000389	-0.019
	[0.766]	[0.339]	[0.966]	[0.402]	[0.944]	[0.417]
totch	0.0181***	0.0156*	0.0139	0.01	0.0139	0.00989
	[0.002]	[0.093]	[0.104]	[0.336]	[0.107]	[0.346]
depr	2.478***	1.632***	0.904	0.833	0.902	0.86
	[0.000]	[0.001]	[0.316]	[0.288]	[0.321]	[0.289]
m2res	0.00170**	0.00153**	0.00125	0.00276***	0.00128	0.00276***
	[0.039]	[0.020]	[0.193]	[0.000]	[0.184]	[0.000]
rgdpcp	-0.0000125	-0.00000835	-0.0000344**	-0.00000336	-0.0000313	0.00000188
	[0.411]	[0.520]	[0.050]	[0.818]	[0.102]	[0.899]
privcrd_gdp	-0.000488	0.000991***	-0.00376	0.000780***	-0.00371	0.000749***
	[0.124]	[0.000]	[0.335]	[0.000]	[0.322]	[0.000]
L2.rdomcredgr	-0.0134**	-0.0142***	-0.00601	-0.0186**	-0.00592	-0.0181**
	[0.012]	[0.008]	[0.332]	[0.021]	[0.339]	[0.020]
avgherf	**3.008****	**2.662****				
	[0.032]	**[0.036]**				
avgherf2	**-1.527**	**-1.827**				
	[0.264]	**[0.149]**				
margin			**11.73*****	**7.832***	**18.02***	**20.25**
			[0.000]	**[0.051]**	**[0.097]**	**[0.115]**
margin2					**-33.64**	**-68.37**
					[0.510]	**[0.327]**
Constant	-1.813***	-2.001***	-1.616***	-1.563***	-1.855***	-2.007***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Observations	1205	1205	715	715	715	715
# of countries	79	79	81	81	81	81
Pseudo-R2	0.18	0.0696	0.161	0.0547	0.162	0.0574

Table 10. Logit Regressions: BC Indicators, SBS Indicators and Deposit Insurance

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 US$ exchange rate depreciation; 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)
COEFFICIENT	DD	CEA	RR	LV	SBSL25	SBSL10	SBSD25	SBSD10
rgdpgr	-0.0871***	-0.118***	-0.0980***	-0.112***	-0.119***	-0.110***	0.0546***	0.036
	[0.000148]	[0.00000276]	[0.0000569]	[0.0000110]	[0.0000156]	[0.00107]	[0.00169]	[0.134]
rint	0.00546	0.00597	0.00537	0.00227	-0.00936*	-0.00662*	-0.000987	-0.00277
	[0.128]	[0.256]	[0.129]	[0.451]	[0.0679]	[0.0572]	[0.739]	[0.154]
infl	0.00568	0.00601	0.00374	0.00257	-0.00165	-0.00665**	-0.00231	-0.00440**
	[0.132]	[0.250]	[0.210]	[0.413]	[0.811]	[0.0276]	[0.395]	[0.0408]
totch	0.00219	-0.000736	-0.000612	-0.000135	0.0182***	0.0133**	0.0158*	0.0264***
	[0.624]	[0.867]	[0.895]	[0.974]	[0.00144]	[0.0291]	[0.0938]	[0.00697]
depr	0.523	0.762	0.801	0.586	2.434***	3.327***	1.631***	2.603***
	[0.338]	[0.223]	[0.177]	[0.301]	[0.000319]	[4.63e-08]	[0.000587]	[0.00000116]
m2res	0.00197*	0.00116	0.00191**	0.00119	0.00179**	-0.000283	0.00167***	0.00179
	[0.0554]	[0.125]	[0.0212]	[0.134]	[0.0271]	[0.712]	[0.00880]	[0.110]
rgdpcp	-0.0000306	-0.0000252	-0.0000451	-0.0000560**	-0.0000163	0.0000467**	-0.0000155	-0.0000643***
	[0.172]	[0.438]	[0.278]	[0.0429]	[0.300]	[0.0469]	[0.285]	[0.00253]
privcrd_gdp	0.00114***	-0.219	-0.102	-0.156	-0.000647**	-5.741***	0.000831***	-0.00119
	[0.00127]	[0.195]	[0.465]	[0.334]	[0.0229]	[0.0000175]	[0.0000496]	[0.290]
L2.rdomcredgr	0.00295	-0.000858	-0.00196	-0.00115	-0.0134**	0.00242	-0.0142***	-0.00556
	[0.568]	[0.855]	[0.687]	[0.828]	[0.0114]	[0.628]	[0.00785]	[0.342]
avgherf	**0.189**	**1.898****	**-0.0661**	**0.986**	**1.416*****	**1.731*****	**0.904****	**1.893*****
	[0.766]	**[0.0298]**	**[0.933]**	**[0.242]**	**[0.000249]**	**[0.000589]**	**[0.0273]**	**[0.0000349]**
di	**0.568***	**1.325*****	**0.549**	**1.105*****	**-0.101**	**0.334**	**0.0775**	**0.584**
	[0.0719]	**[0.00185]**	**[0.203]**	**[0.00423]**	**[0.685]**	**[0.275]**	**[0.789]**	**[0.164]**
Constant	-1.552***	-2.188***	-1.651***	-1.667***	-1.509***	-2.079***	-1.732***	-3.364***
	[0.00000484]	[0.00000165]	[0.0000959]	[0.0000227]	[0]	[0.00000852]	[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 11. Logit Regressions: BC Indicators, SBS Indicators Deposit Insurance Features and Quality of Institutions

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 US$ exchange rate depreciation; 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; princomp is the "moral hazard" index; kk_compo is the indicator of quality of institutions. Standard errors are clustered by country. Robust p-values are reported in brackets, with *** p<0.01, ** p<0.05, * p<0.1.

COEFFICIENT	(1) DD	(2) CEA	(3) RR	(4) LV	(5) SBSL25	(6) SBSL10	(7) SBSD25	(8) SBSD10
rgdpgr	-0.0813***	-0.108***	-0.0902***	-0.104***	-0.116***	-0.116***	0.0619***	0.0442*
	[0.000454]	[0.0000528]	[0.000420]	[0.0000731]	[0.0000438]	[0.000871]	[0.00106]	[0.0718]
rint	0.00668**	0.00937**	0.00765*	0.00382	-0.00897	-0.00679*	-0.00037	-0.00241
	[0.0498]	[0.0462]	[0.0564]	[0.243]	[0.103]	[0.0523]	[0.911]	[0.235]
infl	0.00686*	0.00929*	0.00544	0.00404	-0.00175	-0.00688**	-0.00172	-0.00403*
	[0.0573]	[0.0534]	[0.101]	[0.238]	[0.804]	[0.0213]	[0.554]	[0.0699]
totch	0.0033	0.00143	0.00134	0.00155	0.0189***	0.0153**	0.0159*	0.0253***
	[0.463]	[0.734]	[0.770]	[0.691]	[0.000978]	[0.0132]	[0.0834]	[0.00727]
depr	0.364	0.531	0.73	0.46	2.471***	3.396***	1.531***	2.545***
	[0.514]	[0.436]	[0.226]	[0.431]	[0.000211]	[6.08e-08]	[0.000991]	[0.00000150]
m2res	0.00178*	0.000957	0.00175**	0.00101	0.00178**	-0.000232	0.00152***	0.00172
	[0.0539]	[0.157]	[0.0151]	[0.152]	[0.0235]	[0.766]	[0.00717]	[0.109]
rgdpcp	0.0000106	0.0000493*	0.0000132	0.0000124	-0.000000571	0.00004	0.0000122	-0.0000317
	[0.717]	[0.0819]	[0.800]	[0.650]	[0.978]	[0.256]	[0.531]	[0.204]
privcrd_gdp	0.00129***	-0.146	-0.115	-0.109	-0.000585**	-5.852***	0.000877***	-0.000994
	[0.0000134]	[0.217]	[0.359]	[0.315]	[0.0493]	[0.0000149]	[0.00000194]	[0.392]
L2.rdomcredgr	0.0039	0.00124	-0.000637	0.000661	-0.0114**	0.00321	-0.0130**	-0.00455
	[0.445]	[0.798]	[0.895]	[0.902]	[0.0214]	[0.524]	[0.0157]	[0.435]
avgherf	**-0.0373**	**1.249**	**-0.481**	**0.613**	**1.239*** **	**1.727*** **	**0.764***	**1.815*** **
	[0.951]	**[0.141]**	**[0.527]**	**[0.413]**	**[0.00257]**	**[0.000759]**	**[0.0785]**	**[0.000119]**
di	**-0.574**	**-0.188**	**1.249**	**-0.73**	**-0.137**	**0.972**	**-0.0148**	**-0.421**
	[0.674]	**[0.896]**	**[0.226]**	**[0.641]**	**[0.861]**	**[0.195]**	**[0.982]**	**[0.760]**
princom	**0.205**	**0.258**	**-0.169**	**0.331**	**-0.000698**	**-0.12**	**0.000577**	**0.183**
	[0.442]	**[0.353]**	**[0.452]**	**[0.259]**	**[0.996]**	**[0.433]**	**[0.996]**	**[0.455]**
kk_compo	**-0.631***	**-1.295*** **	**-0.920***	**-1.023*** **	**-0.262**	**0.0984**	**-0.438***	**-0.38**
	[0.0571]	**[0.000482]**	**[0.0667]**	**[0.000696]**	**[0.238]**	**[0.738]**	**[0.0710]**	**[0.269]**
Constant	-1.129*	-1.786**	-2.210***	-1.075	-1.536***	-2.329***	-1.785***	-3.030***
	[0.0785]	[0.0141]	[0.000427]	[0.147]	[0.000395]	[0.000181]	[0.00000592]	[0.00000474]
Observations	1189	1057	1189	1143	1189	1189	1189	1189
# of countries	78	69	78	75	78	78	78	78
Pseudo-R2	0.0788	0.192	0.122	0.166	0.181	0.324	0.073	0.167

Table 12. Logit Regressions: BC Indicators, Currency and Twin Crises

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; rgdpcp is real GDP per-capita; priverd_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.; 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. Standard errors are clustered by country. Robust p-values are reported in brackets, with *** p<0.01, ** p<0.05, * p<0.1.

COEFFICIENT	DD	CEA	RR	LV	DD	CEA	RR	LV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
L.rgdpgr	-0.0746***	-0.105***	-0.107***	-0.104***	-0.0745***	-0.106***	-0.109***	-0.106***
	[0.00300]	[0.0000753]	[0.000000794]	[0.0000924]	[0.00331]	[0.0000648]	[0.000000741]	[0.0000882]
L.rint	0.00629**	0.00648	0.00727**	0.00689*	0.00735*	0.00768	0.00847**	0.00719*
	[0.0433]	[0.152]	[0.0385]	[0.0925]	[0.0503]	[0.108]	[0.0217]	[0.0749]
L.infl	0.00529**	0.00554	0.00389	0.00614	0.00611**	0.0068	0.00474*	0.00652*
	[0.0329]	[0.173]	[0.129]	[0.116]	[0.0284]	[0.132]	[0.0732]	[0.0918]
L.rgdpcp	0.00000546	0.0000630**	0.0000165	0.0000197	0.00000467	0.0000619**	0.0000158	0.0000188
	[0.895]	[0.0325]	[0.770]	[0.489]	[0.910]	[0.0345]	[0.776]	[0.509]
L.privcrd_gdp	0.00100***	-0.135	-0.0971	-0.0995	0.000953***	-0.146	-0.105	-0.105
	[0.00169]	[0.305]	[0.408]	[0.423]	[0.00276]	[0.281]	[0.385]	[0.405]
L.avgherf	0.0688	0.816	-0.256	-0.0559	0.0493	0.717	-0.423	-0.0136
	[0.916]	[0.452]	[0.754]	[0.947]	[0.938]	[0.504]	[0.595]	[0.986]
L.kk_compo	-0.434	-1.266***	-0.629	-0.948***	-0.442	-1.271***	-0.662	-0.927***
	[0.308]	[0.00187]	[0.284]	[0.00435]	[0.296]	[0.00149]	[0.250]	[0.00497]
L.finopen	**-0.426***	**-0.246**	**-0.385**	**-0.36**	**-0.429***	**-0.251**	**-0.407**	**-0.361**
	[0.0869]	**[0.350]**	**[0.153]**	**[0.176]**	**[0.0853]**	**[0.309]**	**[0.147]**	**[0.181]**
L.erclassrr	**0.0178**	**0.0344**	**-0.0215**	**-0.0138**	**0.0138**	**0.0181**	**-0.0312**	**-0.0226**
	[0.631]	**[0.477]**	**[0.632]**	**[0.692]**	**[0.707]**	**[0.719]**	**[0.486]**	**[0.523]**
L.totch	**0.00307**	**-0.000513**	**-0.000575**	**0.000662**	**0.00321**	**-0.000805**	**-0.00165**	**0.000254**
	[0.423]	**[0.884]**	**[0.879]**	**[0.864]**	**[0.441]**	**[0.823]**	**[0.678]**	**[0.951]**
L.crisis25	**0.322**	**0.501***	**0.422***	**0.32**				
	[0.196]	**[0.0685]**	**[0.0977]**	**[0.232]**				
L.stwins2525					**0.289**	**0.299**	**0.359**	**0.163**
					[0.330]	**[0.318]**	**[0.212]**	**[0.585]**
Constant	-1.192**	-1.815**	-0.974	-0.89	-1.097**	-1.529**	-0.716	-0.763
	[0.0268]	[0.0228]	[0.142]	[0.128]	[0.0373]	[0.0485]	[0.272]	[0.187]
Observations	1057	933	1057	1023	1083	959	1083	1049
# of countries	61	54	61	59	63	56	63	61
Pseudo-R2	0.0706	0.164	0.118	0.146	0.071	0.157	0.119	0.142

Table 13. Logit Regressions: SBS Indicators and Lagged Currency Crises Indicators

All explanatory variables are lagged one year (prefix L.): 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 US$ exchange rate depreciation; 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.; 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.. Standard errors are clustered by country. Robust p-values are reported in brackets, with *** p<0.01, ** p<0.05, * p<0.1.

COEFFICIENT	SBSL25	SBSL10	SBSL25	SBSL10	SBSD25	SBSD10	SBSD25	SBSD10
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
L.rgdpgr	-0.105***	-0.0895***	-0.104***	-0.101***	-0.0637***	-0.0723**	-0.0512***	-0.0716**
	[0.00000143]	[0.000191]	[0.000000584]	[0.000101]	[0.00148]	[0.0472]	[0.00622]	[0.0471]
L.rint	0.00885***	0.00848***	0.0104***	0.00906***	0.0025	0.00038	0.00309	0.000683
	[0.00664]	[0.00000661]	[0.0000509]	[0.0000235]	[0.593]	[0.852]	[0.451]	[0.749]
L.infl	0.0105***	0.00788***	0.0108***	0.00848***	0.00126	0.0000359	0.00133	0.0000185
	[0.00000848]	[0.0000102]	[0.00000112]	[0.0000392]	[0.730]	[0.985]	[0.680]	[0.992]
L.rgdpcp	-0.00000358	-0.0000183	-0.00000673	-0.0000274	-0.00000935	-0.0000849**	-0.00000658	-0.0000861**
	[0.870]	[0.698]	[0.751]	[0.583]	[0.597]	[0.0124]	[0.712]	[0.0156]
L.privcrd_gdp	-0.0000902	-1.094	-0.000349	-0.899	0.00140***	0.00248***	0.00139***	0.00227***
	[0.828]	[0.211]	[0.381]	[0.253]	[6.02e-09]	[3.24e-10]	[0]	[3.00e-09]
L.avgherf	1.525***	1.437***	1.415***	1.473***	1.540***	2.359***	1.515***	2.243***
	[0.000108]	[0.000701]	[0.000388]	[0.00108]	[0.000631]	[0.000236]	[0.000379]	[0.000321]
L.kk_compo	-0.36	-0.251	-0.388*	-0.23	-0.215	-0.13	-0.165	-0.0849
	[0.110]	[0.364]	[0.0650]	[0.392]	[0.311]	[0.723]	[0.437]	[0.822]
L.finopen	**0.0472**	**0.210****	**-0.0441**	**0.0174**	**0.112**	**0.341*****	**0.0372****	**0.0543**
	[0.519]	**[0.0154]**	**[0.310]**	**[0.712]**	**[0.313]**	**[0.00809]**	**[0.0140]**	**[0.230]**
L.erclassrr	**-0.00283**	**0.0245**	**0.00398**	**0.0292**	**0.0295**	**0.0721*****	**0.0325**	**0.0817*****
	[0.909]	**[0.350]**	**[0.862]**	**[0.276]**	**[0.223]**	**[0.00972]**	**[0.180]**	**[0.00375]**
L.totch	**-0.0175*****	**-0.0191*****	**-0.0215*****	**-0.0197*****	**-0.00568**	**-0.0120****	**-0.00815**	**-0.0146****
	[0.00140]	**[0.00219]**	**[0.000523]**	**[0.00247]**	**[0.270]**	**[0.0481]**	**[0.106]**	**[0.0148]**
L.crisis25	**1.057*****	**0.760*****			**0.253**	**0.448***		
	[7.73e-10]	**[0.00517]**			**[0.207]**	**[0.0662]**		
L.stwins2525			**0.999*****	**0.321**			**1.092*****	**0.909*****
			[0.0000637]	**[0.261]**			**[0.00000730]**	**[0.00216]**
Constant	-2.014***	-3.157***	-1.666***	-2.733***	-1.885***	-3.897***	-1.949***	-3.559***
	[0]	[0]	[1.61e-08]	[5.72e-09]	[0.000000290]	[0]	[4.62e-08]	[0]
Observations	1057	1057	1083	1083	1057	1057	1083	1083
# of countries	61	61	63	63	61	61	63	63
Pseudo-R2	0.181	0.21	0.162	0.189	0.0679	0.17	0.0831	0.169

Table 14. Logit Regressions: Currency Crises and Lagged SBS Indicators

All explanatory variables are lagged one year (prefix L.): 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 US$ exchange rate depreciation; 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.; kk_compo is the indicator of quality of institutions; finopen is financial openness; erclassrr is the index of flexibility of exchange rate arrangements. Standard errors are clustered by country. Robust p-values are reported in brackets, with *** p<0.01, ** p<0.05, * p<0.1.

COEFFICIENT	crisis35	crisis35	crisis25	crisis25	crisis15	crisis15
	(1)	(2)	(3)	(4)	(5)	(6)
L.rgdpgr	-0.0715***	-0.0838***	-0.0761***	-0.0899***	-0.0737***	-0.0870***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
L.rint	0.00580*	0.00588**	0.00521***	0.00509***	0.00154	0.00118
	[0.054]	[0.048]	[0.008]	[0.008]	[0.660]	[0.748]
L.infl	0.00498**	0.00515**	0.00419***	0.00421***	0.00609*	0.00566*
	[0.044]	[0.042]	[0.007]	[0.008]	[0.059]	[0.064]
L.rgdpcp	-0.0000750**	-0.0000763**	-0.0000401*	-0.0000410*	-0.00000752	-0.00000858
	[0.032]	[0.031]	[0.084]	[0.078]	[0.723]	[0.679]
L.privcrd_gdp	-0.00364	-0.00352	-0.00444	-0.00433	-0.00100**	-0.00114**
	[0.398]	[0.378]	[0.163]	[0.138]	[0.023]	[0.014]
L.avgherf	0.0344	0.106	0.266	0.281	0.864	0.805
	[0.960]	[0.876]	[0.661]	[0.648]	[0.166]	[0.197]
L.kk_compo	-0.356	-0.365	-0.393	-0.393	-0.523*	-0.514*
	[0.283]	[0.268]	[0.223]	[0.223]	[0.064]	[0.064]
L.finopen	**-0.128**	**-0.117**	**0.0834**	**0.0857**	**-0.0938**	**-0.0976**
	[0.567]	**[0.592]**	**[0.495]**	**[0.491]**	**[0.463]**	**[0.459]**
L.erclassrr	**-0.0112**	**-0.00997**	**0.0213**	**0.0216**	**0.0276**	**0.0276**
	[0.811]	**[0.835]**	**[0.560]**	**[0.562]**	**[0.416]**	**[0.423]**
L.totch	**-0.00523**	**-0.0044**	**-0.00376**	**-0.00314**	**-0.00508**	**-0.00482**
	[0.437]	**[0.503]**	**[0.482]**	**[0.559]**	**[0.267]**	**[0.297]**
L.SBSL25	**0.420***		**0.414****		**0.329***	
	[0.053]		**[0.036]**		**[0.076]**	
L.SBSD25		**0.258**		**0.435****		**0.607*****
		[0.249]		**[0.037]**		**[0.009]**
Constant	-1.089*	-1.044	-0.948**	-0.913*	-0.124	-0.107
	[0.090]	[0.111]	[0.041]	[0.054]	[0.773]	[0.807]
Observations	1057	1057	1057	1057	1057	1057
R-squared	.	.	.	.	.	.
# of countries	61	61	61	61	61	61
Pseudo-R2	0.14	0.137	0.12	0.121	0.107	0.113

Table 15. Evidence from bank-level data

Explanatory variables: czz is the Z-score, gdppc is real GDP per capita; growth is the GDP growth rate; infl is CPI inflation; depr is the US$ exchange rate depreciation; hhhib is the 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.

Panel A: Logit Regressions

COEFFICIENT	DD	CEA	RR	LV
	(1)	(2)	(3)	(4)
L.czz	**-0.00346*****	**-0.00387*****	**-0.00338****	**-0.00429*****
	[0.004]	**[0.003]**	**[0.012]**	**[0.006]**
gdppc	0.000101	0.000127*	0.000123	0.000136*
	[0.184]	[0.096]	[0.114]	[0.072]
growth	-0.0391	-0.0377	-0.0544	-0.0571*
	[0.240]	[0.248]	[0.105]	[0.069]
infl	0.00676	0.000635	-0.0178	0.000712
	[0.516]	[0.586]	[0.286]	[0.615]
depr	-0.0271**	-0.0219**	-0.0283**	-0.0276***
	[0.044]	[0.024]	[0.018]	[0.008]
Constant	-1.539**	-1.538**	-1.651**	-1.778***
	[0.012]	[0.012]	[0.013]	[0.005]
Observations	12148	11701	12148	12097
# of countries	66	60	66	65
Pseudo-R2	0.0823	0.0738	0.082	0.101

Panel B: Fixed effects regression

COEFFICIENT	Z-score
	(5)
L.gdppc	-0.000948
	[0.554]
L.growth	0.133
	[0.342]
L.infl	0.00102
	[0.714]
L.depr	-0.105*
	[0.053]
L.di	**8.575****
	[0.041]
L.hhib	**-13.08****
	[0.014]
Constant	42.03***
	[0.000]
Observations	9165
# of countries	66

Table A1. "Systemic" Banking Crises and Crisis Dating in Different Classifications.

Country	DD (2002,2005)		Caprio et al.(2005) Non-Systemic		Caprio et al.(2005) Systemic		RR (2008)	LV (2008)
	Start date	Duration	Start date	Duration	Start date	Duration	Start date	Start date
Algeria	1990	3			1990	3	1990	1990
Argentina	1980	3			1980	3	1980	1980
							1985	
	1989	2			1989	2	1989	1989
	1995	1			1995	1	1995	1995
	2001	2			2001	2	2001	2001
Australia			1989	4				
Bangladesh					1987	10	1987	1987
Benin	1988	3			1988	3	1988	1988
Bolivia	1986	3			1986	3		1986
							1987	
	1994	4			1994	9	1994	1994
							1999	
	2001	2						
Botswana					1994	2		
Brazil								
	1990	1			1990	1	1990	1990
	1994	6			1994	6		1994
							1995	
Burkina Faso	1988	7			1988	7	1988	1988
Burundi	1994	4			1994	9	1994	1994
Cameroon	1987	7			1987	7	1987	1987
	1995	4			1995	4	1995	1995
Canada			1983	3				
CAR					1980	13		1976
	1988	12					1988	
					1995	5		1995
Chad					1980	8		1983
	1992	1			1992	2		1992
Chile							1980	1976
	1981	7			1981	3		1981
Colombia	1982	4			1982	6	1982	1982
								1998
	1999	2						
Congo, DRS					1980	8		1983
							1982	
					1991	2		1991
	1994	9			1994	3		
Congo, Rep.	1992	11			1992	11	1992	1992
								1994
Costa Rica							1987	1987
	1994	4			1994	3	1994	1994
Cote d'Ivoire	1988	4			1988	4	1988	1988
Denmark			1987	6				
Dominican Republic								2003
Ecuador					1980	3	1980	1982
	1995	8						
					1996	6	1996	
							1998	1998
Egypt, Arab Rep.					1980	3	1980	1980
			1991	5				
El Salvador	1989	1			1989	1	1989	1989

Table A1. Continued.

Country	DD (2002,2005)		Caprio et al.(2005) Non-Systemic		Caprio et al.(2005) Systemic		RR (2008)	LV (2008)
	Start date	Duration	Start date	Duration	Start date	Duration	Start date	Start date
Finland	1991	4			1991	4	1991	1991
France			1993	1				
Gabon			1995	8				
Gambia, The			1985	8				
Ghana	1982	8			1982	8	1982	1982
	1997	6	1997	6				
Greece			1991	5				
Guatemala			1991	12				
Guinea	1985	1			1985	1	1985	1985
	1993	2			1993	2	1993	1993
Guinea-Bissau	1994	4						
					1995	2	1995	1995
Guyana	1993	3						1993
Honduras								
India	1991	4						
			1993	10				1993
Indonesia	1992	4						
			1994	1				
	1997	6			1997	6	1997	1997
Israel					1980	4		1977
	1983	2						
Italy	1990	6	1990	6				
Jamaica			1994	1				
	1996	5			1996	5		1996
Japan	**1992**	**11**			1992	11	1992	1997
Jordan	1989	2	1989	2				1989
Kenya					1985	5	1985	1985
					1992	4	1992	
	1993	3						
			1996	1				
					1997	6		
Korea								
	1997	6			1997	6	1997	1997
Lebanon	1988	3			1988	3	1988	1988
Lesotho			1988	15				
Liberia	1991	5			1991	5	1991	1991
Madagascar	1988	4			1988	1	1988	1988
Malaysia	1985	4	1985	4				
	1997	5			1997	5	1997	1997
Mali	1987	3			1987	3	1987	
Mauritania	1984	10			1984	10		1984
Mauritius			1996	1				
Mexico					1981	11	1981	1981
	1982	1						
	1994	4			1994	7	1994	1994
Nepal	1988	4			1988	1	1988	1988

Table A1. Continued

Country	DD (2002,2005)		Caprio et al.(2005) Non-Systemic		Caprio et al.(2005) Systemic		RR (2008)	LV (2008)
	Start date	Duration	Start date	Duration	Start date	Duration	Start date	Start date
New Zealand			1987	4				
Niger	1983	4			1983	14	1983	1983
Nigeria	1991	5			1991	5		1991
			1997	1				
Norway	1987	7			1990	4		1991
Panama	1988	2			1988	2	1988	1988
Papua New Guinea	1989	4	1989	14				
Paraguay	1995	5			1995	6	1995	1995
			2001	2				
Peru	1983	8			1983	8	1983	1983
Philippines	1981	7					1981	1983
					1983	5		
							1997	1997
	1998	5			1998	5		
Portugal	1986	4						
Senegal	1983	6						
					1988	4	1988	1988
Sierra Leone	1990	4			1990	7	1990	1990
Singapore			1982	1				
South Africa	1985	1						
			1989	13				
Sri Lanka	1989	5			1989	5	1989	1989
Swaziland	1995	1			1995	1	1995	1995
Sweden	1990	4						
					1991	4	1991	1991
Taiwan			1983	2				
			1995	1				
	1997	2			1997	2	1997	
Tanzania					1986	17		
							1987	1987
	1988	4						
Thailand	1983	5			1983	5	1983	1983
							1996	1997
	1997	6			1997	6		
Togo					1993	3	1993	1993
Tunisia	1991	5	1991	5				1991
Turkey	1982	1			1982	4		1982
	1991	1						
	1994	1	1994	1				
	2000	3			2000	3		2000
Uganda	1994	4			1994	3	1994	1994
United Kingdom			1980	23				
United States	1980	13						
			1988	4				1988

Table A1. Continued

Country	DD (2002,2005)		Caprio et al.(2005) Non-Systemic		Caprio et al.(2005) Systemic		RR (2008)	LV (2008)
	Start date	Duration	Start date	Duration	Start date	Duration	Start date	Start date
Uruguay	1981	5			1981	4	1981	1981
	2002	1			2002	1	2002	2002
Venezuela			1980	8				
	1993	5					1993	
					1994	2		1994
Zambia					1995	1	1995	1995
Number of crises	83		33		78		69	85
Number of crisis/years in % of total years	15.3		7.6		16.1			
Average duration of crisis	4.4		5.6		4.9			