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Banking Crises and Crisis Dating: Theory and Evidence

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Abstract

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

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I. INTRODUCTION AND SUMMARY

The collapse of the subprime mortgage market in the U.S. in 2007 and ensuing financial instability have spurred 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 differences, both historical (e.g. Bordo, 2008) and as related to the specific mechanics of the shock triggering a crisis (e.g. Gorton, 2008). As pointed out by Allen and Gale (2007), however, the empirical literature on bank fragility has mainly focused on documenting empirical regularities. The definition and measurement of the object of study—what a banking crisis is, when it occurs, and how long it lasts—has been at best loosely derived from theory. As a result, this literature offers many—often contrasting—findings, which vary considerably in terms of samples used, banking crisis definitions and relevant dating.

A large portion of this literature has employed "banking crisis" (BC) indicators based on dating schemes that identify: crisis beginning dates, ending dates, and indicate whether the crisis was "systemic" or not. As we document, these schemes are based primarily on information about government actions undertaken in response to banking distress. A detailed review of the criteria used to identify banking crises shows that virtually all of them depend on information obtained from bank regulators and/or central banks. They do not rely on any theory to identify accounting or market measures that capture the *realization* of systemic bank shocks. In virtually all cases, what is measured is, effectively, a government response to a perceived crisis—not the onset or duration of an adverse shock to the banking industry.

One key implication is that these BC indicators are likely to date banking crisis onsets too late, at least on average. Government responses to banking distress may be lagging because of uncertainty about the actual extent of problems in the industry. In addition, political economy considerations dictate the speed and resolve of the government response.

More importantly, the problem is not limited to one of just systematically late dating. 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 dating the disease's onset when the patient enters a hospital. As stressed by De Nicolò et al. (2004), the researcher will be unable to disentangle the effects of an adverse shock to the banking industry from the effects of the restorative policy response.[1] Disentangling these effects is key to understanding the mechanics of bank fragility: this will be the main contribution of our paper.

Using a simple model of a banking industry, in which an adverse shock to the banking system and a government response are explicitly defined and modeled, we derive measures of systemic bank shocks (SBS). The main objective of the theoretical exercise is to obtain

[1] 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).

measures of an adverse shock to banking that are "empirically relevant", by which we mean measures that can be obtained from available data for a large number of countries and years. The model is just a simple identification tool of theory-based measures of systemic bank shocks (SBS), and is not intended to be a contribution to the banking theory literature.

Our next task is to re-examine the empirical evidence presented in a large empirical literature on the causes and consequences of modern banking crises. We accomplish this using two samples: a country-level dataset and a firm-level dataset, both including a large number of countries and the latter including a large number of banks.

Our contribution is to separately identify binary indicators of SBS shocks and BC indicators. For the BC indicators, we employ four different data series that have appeared in the literature. It is important to note that the existing literature has interpreted an SBS event and a BC event as one and the same. There are two fundamental problems with that approach. First, the two events actually occur on different dates; and second, one event is bad for the industry (an SBS shock), while the other is good for it (government intervention to a perceived problem).

The causal variables that we study are some of those that the existing literature has identified as important determinants of the probability that a country will experience a banking crisis. These include the bank market structure, presence or lack of deposit insurance, and the occurrence of an external shock, (e.g. a currency crisis)[2]. We find that each of these explanatory variables has a different effect on the probability of an adverse shock to the banking industry (represented by SBS indicators) and on the probability of a government intervention (represented by BC indicators). As we hope to make clear, this has led to a great deal of confusion in the interpretation of many empirical results and, we shall argue, to a number of erroneous conclusions.

The rest of the paper proceeds as follows. Section II discusses the criteria used in the literature to date beginnings, severity, and endings of banking crises. We consider four well known crisis dating studies, and it becomes abundantly clear that the dating information is obtained from bank regulators and/or central banks and depends on the implementation of policy. Thus, the key contribution of this section is to show that these classifications record measures of government intervention, not necessarily the realization of adverse shocks to the banking industry.

In section III, we construct BC indicators based on the four major crisis classifications that are employed later in our own empirical work. We show that there are significant discrepancies among the four BC indicators in their dating the beginnings and endings of banking crises, indicating that there is disagreement among researchers in dating the same episodes of financial distress.

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

Section IV presents a theoretical model in which banking problems are produced by the arrival of exogenous shocks to the industry[3]. If a shock is large enough to translate into widespread bank insolvencies, the authorities will respond as soon as they recognize the shock. As noted, the main purpose of this exercise is to identify empirically useful measures of SBS arrivals.

In Section V we begin our empirical analysis employing a large country-level panel dataset similar to those employed by others in this literature. We estimate Logit regressions in which the dependent variable is a BC indicator, and the independent variables are contemporaneous macroeconomic variables identified in the literature as possible determinants of bank fragility. In essence, these are the standard tests searching for the "causes" of banking crises. First, we show that the results obtained are quite different across the BC indicators, either when only beginning crisis dates or all dates are used. Thus, these indicators are not all measuring the same thing and we argue for using BC indicators inclusive of all crises dates. Second, we construct two types of SBS indicators dictated by data availability for the country sample: they index extreme drops of bank real lending and deposits. We show that these indicators consistently and robustly predict all four BC indicators. This provides support for the notion that BC indicators represent lagged government responses to adverse banking shocks. Third, we estimate similar Logit regressions in which the depend variable is an SBS indicator. The results here are much stronger than those obtained with BC indicators, in the sense that many more explanatory variables have the expected sign and are statistically significant.

In Section VI we use the country dataset to assess the impact of bank concentration and deposit insurance on the probability of a systemic bank shock and, separately, on the probability of a government response to bank distress. These regressions are estimated controlling for contemporaneous values of a key set of macroeconomic variables. We obtain two key results. First, more concentrated banking systems significantly increase the probability of a systemic bank shock. However, these variables do not significantly affect the probability of a government response in this sample. In essence, more concentrated banking systems (exhibiting higher interest rate margins) are more likely to experience episodes of systemic bank fragility. As will be discussed, this finding is at odds with what has been reported elsewhere in the literature.

Second, the data suggest that the probability of a government response to bank distress identified by the BC indicators will be higher in banking systems with formal deposit insurance. This finding has been obtained previously in the literature and has been interpreted as evidence that deposit insurance results in greater moral hazard—and thus inherently riskier banking systems. In reality however, all that is occurring is that, in the presence of formal deposit insurance the government is more likely to respond to a negative shock of a given

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

size. This is because, as we find, that the probability of a systemic bank shock *does not* depend on whether a deposit insurance system is in place.

In section VII we examine the impact of external shocks and currency crises on bank fragility. We continue to use the country-level dataset, but we specify Logit regressions with all independent variables *lagged* one period to minimize simultaneity and endogeneity problems. First, we find that exchange rate depreciations, 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 also find evidence of the reverse. By contrast, few of these "external" factors significantly affect the probability of a government response to bank distress. Currency crisis indicators only weakly predict such responses. Second, in this country-level dataset, 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.

We conclude our empirical analysis with Section VIII, where we use the firm-level dataset, one that employs individual bank data in a large number of emerging and developing countries. Importantly, with this dataset we can use SBS indicators which better capture the realization of systemic bank shocks. These are constructed on the basis of sharp declines in bank profitability, taking into account banks' capitalization. As before, we examine whether SBS indicators predict BC indicators, and the main potential determinants of both systemic bank shocks and government responses to these shocks described previously. Tests on this sample are more powerful, as we use random effect Logit regressions that exploit more fully the information contained in banks' heterogeneity. Remarkably, with this finer data set and richer statistical specification all earlier main results are confirmed.

Finally, Section IX concludes.

II. Major Classifications of Banking Crises

A variety of classifications of banking crises have been used since the mid 1990s by many researchers.[4] Here we consider four systematic and generally comprehensive classifications. These classifications are well known in the literature, and some of them have been used in a large number of studies to analyze the determinants of banking crises.

These four classifications are all updates, modifications and/or expansions of the classification of banking crises first compiled by Caprio and Kinglebiel (CK) (1996, 1999). The CK classification is based on several narratives taken from supervisory and expert sources.[5] Specifically, the CK classification "...relies upon the assessment of a variety of

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

[5] The use of this classification has been widespread since the crisis compilation reported in the May 1998 issue the IMF World Economic Outlook. This type of classification has been also 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).

finance professionals in pulling together characterizations of factors that have caused crises" (1996, p. 1). It uses 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. They further 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. We turn now to the four classifications we use in the empirical analysis.

The first classification we examine is due to Demirgüç-Kunt and Detragiache (2002, 2005, hereafter DD). Based on the CK compilation, DD spelled out the criteria used to identify crises start-dates and duration for 94 countries in more details, covering crisis episodes during 1980-2002.[6] DD define a *systemic crisis* as a "...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, (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 of a 10-percent non-performing asset ratio is the only one related to an accounting measure. However, it is recorded at the so-called peak of the crisis, but the peak of a crisis is not defined.[7] 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 (see, for example, the discussion in Bordo et al., 2001).

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

[7] "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).

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 "...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 do not state whether the crisis was systemic or not. They 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 reveals that in 94 percent of the classified cases the information used is one of government responses to address a crisis (in a 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 indicator. In five out of 166 episodes, the beginning of a crisis is defined as a bank run, but neither 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 that 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, 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 occurred, 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 work, however, RR do not identify the duration of a crisis on the grounds 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 based on qualitative information on government responses to banking distress.

Finally, the fourth classification that we consider is that 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 of 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" (Laeven and Valencia, 2008, 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 guarantees, 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" (Laeven and Valencia, 2008, footnote 6, p.5). 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 criteria b) and c) measure government responses to a systemic bank shock, while a) may be an imprecise and lagged gauge of such a realization. As in RR, but differing from DD and CEA, however, there is no estimate of the duration of a crisis.

A full description of the four classifications of banking crises is presented in the Appendix.

In sum, all four classifications are primarily constructed on the basis of information about government actions undertaken in response to banking distress obtained from bank regulators and/or central banks.

III. BC Indicators an d Their Discrepancies

Here, we construct four series of BC indicators that will be used in our own empirical work. As we shall see next, these series are rather different since discrepancies in the dating of crisis onset and duration are pervasive.

The four binary BC indicators, where each indicator is set to 1 if a country-year is classified as a crisis year and 0 otherwise, are: 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 each indicator. The first *excludes* all country-years classified as crisis after the first crisis year. In practice, this kind of indicator identifies crises' *starting dates.* These starting dates have been used extensively in event-type analyses since IMF (1998) and Kaminsky and Reinhart (1999). The second version includes all crisis country-years, beginning with and beyond the starting date. Since the RR and LV classifications do not report crisis durations, for these classifications we have used the duration and country years of the CEA classification, or the DD duration when the CEA duration was not available. In this way, we preserve the starting dates of the original classifications, but we augment them with the applicable duration of either the CEA or DD classifications.

Table 1 reports statistics of these classifications (Panel A), and pair-wise comparisons of crisis dating across classifications (Panel B). The most striking fact is that for many crisis episodes the dating classifications differ considerably both in terms of the starting date and the duration. For example, 15 country years are classified as first crisis years by RR but not by DD, while the reverse is true for 30 country years (Panel B, second line). Alternatively, it can be seen in the last column in Panel B, which shows the ratio of total crisis ranking discrepancies divided by total crisis rankings. This varies between 24.5% and 49.5%. In other words, in terms of dating crises (which is the heart of the matter), the different methods are in disagreement roughly between a quarter and a half of the time. All four classifications only agree on 41 dates of crisis onset.[8]

These widespread discrepancies across banking crisis classifications cast serious doubt about either the robustness or the comparability of many results obtained in a large empirical literature. Indeed, when we turn to our empirical analysis with the four BC indicators, it is not surprising that they often produce significantly different results.

IV. A Simple Banking Model

In this section, we present a simple model of a banking industry and a government deposit insurer, and use its comparative statics to identify measures of systemic bank shocks. The purpose of this theory exercise is very narrow, and we make no pretense of contributing to the theory of the banking firm. Rather, our objective is to identify from first principles, empirically useful measures of adverse shocks to a banking industry.

The banks in the model are Cournot-Nash competitors that raise insured deposits, make risky loans, and hold risk free government bonds. The deposit insurer bails out the banks when they fail. Thus, the economy is composed of a "government" and three classes of agents: entrepreneurs, depositors, and banks. All agents are risk-neutral, and the time is discrete.

Entrepreneurs

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

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

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

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

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

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

Bonds

One-period bonds are supplied by the government in amounts specified below. For simplicity, we assume that only banks can invest in bonds.[9] 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 $R^D(Z_t) = \alpha_t Z_t$, 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 pay a flat rate insurance premium standardized to zero. On the asset side, banks choose the total amount of lending and the amount of bonds. In both loan and deposit markets banks are symmetric Cournot-Nash competitors. Banks are perfectly diversified in the sense that for any positive measure of entrepreneurs financed, $P_{t+1} \in (0,1)$, is also the fraction of borrowers whose project turns out to be successful at date $t+1$. Banks observe the realization of P_{t+1} at date $t+1$. Hence, as for the entrepreneurs, banks make their date t decisions on the basis of their conditional expectations $E_t P_{t+1}$.

Government

The government supplies a fixed amount of bonds to the market, denoted by $\bar{B}$. The government also guarantees deposits. It will *intervene* whenever bank deposits payments cannot be honored in part or in full. When this occurs, the government will pay depositors all the claims unsatisfied by banks and all banks will be bailed out. These payments will be

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

financed by issuing additional bonds, which will be purchased by banks who collect new deposits at date $t+1$.[10]

The realization of a systemic banking shock occurs at date $t+1$ and, by definition, occurs when the banking system's profits are negative. The government's response to such a shock will be triggered when the government is able to ascertain that the banking system has become insolvent. By further assumption, the government observes date $t+1$ bank profits at $t+2$.

Sequence of events

In period t**,** suppose realized bank profits are non-negative. Banks collect deposits, entrepreneurs demand, and banks supply funds based on $E_t P_{t+1}$. Deposits, bank loans, and investment in bonds are determined for period t. *In period* $t+1$, P_{t+1} is realized and observed by entrepreneurs and banks. Borrowers pay loans and in turn, banks pay depositors, if possible. If bank profits are non-negative, depositors are paid in full. If profits are negative, depositors cannot be paid in full, and by definition, this is a systemic bank shock. Depositors are paid *pro-rata* by the banks. The government *responds* to the crisis at $t+2$ by issuing bonds and paying depositors any claim unsatisfied by banks.

Equilibrium

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

The bank problem

Let D_i denote total deposits of bank i, $Z \equiv \sum_{i=1}^{N} D_i$ denote total deposits, and $D_{-i} \equiv \sum_{j \neq i} D_j$ denote the sum of deposits chosen by all banks except bank i. Let $L_{-i} \equiv \sum_{j \neq i} L_j$ denote the sum of loans chosen by all banks except bank i. Each bank chooses deposits, loans, and bond holdings b so as to maximize expected profits, given the choices of other banks. Thus, a bank chooses $(L,b,D) \in R_+^3$ to maximize:

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

subject to

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

---

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

The government's policy function

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

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

Comparative Statics

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

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

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

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

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

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

We can see from this table that a systemic bank shock can be triggered by any of the following shocks to the technology (p and Y) or to either preferences or wealth (α): a decline in firms' probability of a good outcome, represented by a decline in p ; a decline in firms' demand for loans due to a decline in Y ; or a decline in consumers' demand for deposits, prompted by a decline in α .

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

Thus, the model allows us to identify a systemic bank shock with a severe decline in loans, deposits, bank profits, and significant increases in interest rate margins. Empirically, the adequacy of each of these measures in capturing systemic bank shocks will depend, *inter alia*, on the *timing* of the underlying shock. And of course, the use of any of these measures will also depend on data availability. Thus, in our empirical investigation we will use these properties of the model to create empirical measures of systematic banking shocks that can be constructed with the two different samples we use.

V. Evidence from Cross-Country Data: Benchmark Specifications

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

We proceed in three steps. *First,* we estimate benchmark Logit regressions in which the dependent variable is one of the four BC indicators discussed above. The point of this exercise is to show how sensitive results are to each of the four indicators, when we use a set of explanatory variables that has been commonly employed in the literature.[11]

Second, we construct our theory-based indicators of systemic bank shocks (SBS indicators) for this sample and include *lagged* SBS indicators as an additional explanatory variable in the same regressions. This gives an assessment of the extent to which SBS indicators *predict* BC indicators. These tests are critical to our argument that BC indicators are measures of (lagged) government interventions in response to bank distress.

Third and finally, we estimate the *same* Logit regressions but now substitute the SBS indicators as the dependent variables. The goal here is to compare the overall explanatory power of the regressions with SBS and BC indicators, and assess their similarities and differences.

[11] Our objective is not to replicate original results. By exactly matching the explanatory variables and the sample dating, with minor exceptions we can replicate all results in the main studies referenced.

A. Logit Regressions with BC Indicators as Dependent Variables

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

In Table 2, we first report results using the version of the four BC indicators that excludes all crisis years except the first. This is done for comparative purposes, since this exclusion has been made in many studies 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). Also, we employ two different samples. The first sample (columns 1 – 4) employs all available data in each regression. The second sample (columns 5 – 8) employs only data points that are common to all four BC indicators. A comparison of the results obtained with these two samples can be useful to identify differences in results due to either country or crisis coverage.

It is apparent from Table 2 that real GDP growth and real interest rates are the only variables that enter significantly (negatively and positively respectively) in all eight regressions. For all other explanatory variables, there is at least one specification that yields results different from all the others. These differences in results occur not only between specifications *within* the same sample, but also comparing results of the same regressions *between* samples.[12]

We should stress that the use of BC indicators constructed by excluding crisis years after the first one seems unwarranted to us. As we have shown in section II, the BC classifications actually index a variety of government measures to address banking distress. Therefore, deleting observations of years during which a government implements measures in response to continued banking distress significantly reduces the informational content of these classifications. Moreover, excluding these observations requires taking a stand on the duration of a crisis. As documented in Table 1 of section III, excluded observations account for a sizeable portion of the sample, ranging from 10 to 15 percent of available country years,

[12] For example, the inflation rate (infl) has been found as significantly associated with banking crises in Demirgüç-Kunt and Detragiache (2005), but here it is only significant in five of eight cases. For another example, the vulnerability to a currency run variable (m2res) is only statistically significant in three out of eight cases, compared with its significance in all regressions considered by Demirgüç-Kunt and Detragiache (2005).

inducing sample biases difficult to control.[13] For these reasons, in the sequel we focus on BC indicators including all crisis years observations.

Accordingly, in Table 3 we report regressions of exactly the same type as those in Table 2, but with BC indicators including all crisis dates. Now, real GDP growth appears to be the only variable that enters significantly in all (or even most) regressions. *Prima facie*, these results suggest that the lack of explanatory power of many standard macroeconomic variables in these regressions may be due to the considerable differences, documented earlier, in the BC classification schemes.

B. SBS indicators Predict BC indicators

For this sample, our choice of SBS indicators is dictated by data availability. Aggregate bank profits are unavailable in our dataset, while interest rates spreads are available only for a very limited number of country-years, and may not be measured in the same way across countries. That leaves changes in loan and deposit levels, which are available for almost all nations.

We construct two types of SBS indicators, one based on aggregate bank loans and the other based on aggregate bank deposits. For loans, we construct two indicator variables, SBSL25 and SBSL10, which represent sharp decreases in lending growth. They are equal to one if real domestic lending growth is lower than the 25% and 10%-percentile of the entire distribution of real domestic bank credit growth across countries. The second indicators represent sharp decreases in total bank deposits as a fraction of GDP. Analogously, we construct two indicator variables, SBSD25 and SBSD10, equal to one if the growth rate of the deposit-to-GDP ratio is lower than the 25% and 10% percentile of its distribution across countries respectively.[14]

Table 4 replicates the results in Table 3, the only change being that there are two additional explanatory variables, the SBS lending indicators. Now, if BC indicators are contemporaneous to systemic bank shock realizations, then *SBS indicators should not predict BC indicators.* As shown in Table 4, however, *this is not the case*. *Lagged* SBS *lending* indicators predict the BC indicators in all specifications. This is true both with the 25th percentile cut-off (columns 1 – 4), and the 10th percentile cut-off (columns 5 – 8).

Table 5 shows the same regressions as in Table 4, except that we include the SBS deposit indicators instead of the loan indicators. As shown in Table 5, SBS lagged *deposit* indicators are always positively associated with BC indicators, However, the relevant coefficients are (weakly) significant in only two 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 in place. Indeed, as illustrated

[13] As pointed out by Boyd et al. (2005), this procedure can be particularly troublesome for countries where multiple crises have occurred.

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

below, SBS lending indicators *predict* SBS deposit indicators, suggesting complex dynamics not included the our simple model .

In sum, these findings indicate 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 earlier, 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 interpretation of results in a large literature. This literature has essentially focused on studying the determinants of government responses to banking distress – which is what the BC indicators are capturing - rather than on the realizations of systemic shocks to the banking sector.

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C. Logit Regressions with SBS Indicators as Dependent Variables

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 dependent variables.

Two important facts emerge. First, the impact of many explanatory variables appears more in line with expectations when SBS indicators are dependent. The levels of significance is generally higher, and the overall explanatory power of the regressions is stronger, than in the regressions with the BC indicators as dependent variables. For example, the impact of the "external" variables now enters significantly in most regressions, consistent with the role of external shocks in triggering shocks to domestic banking systems. For example, the terms of trade change variable, *totch,* is positive and statistically significant in all eight specifications in Table 6. The exchange rate depreciation variable, *depr,* enters positively in all specifications in Table 6, and is statistically significant in six of eight cases.

Second, (and arguably more important), most explanatory variables have a significant impact on SBS indicators, but not on BC indicators. Recall that real GDP growth appears to be the only variable that enters significantly in all (or even most) regressions with BC indicators as dependent variables. By contrast, as shown in Table 6, the real interest rate and the inflation rates are *negatively and contemporaneously* associated with the probability of a systemic bank shock (regressions (1) (2) and(5)). Moreover, a systemic bank shock is less likely in more financially developed countries. That is, the coefficient of real GDP per capita, *rgdppc,* is negative in seven out of 8 cases, and statistically significant in six.

Finally, the last two regressions show the strong predictive power of SBS lending indicators for SBS deposit indicators. Indeed, SBS lending indicators *predict* SBS deposit indicators in Logit regressions with SBS deposit indicators as the dependent variable, suggesting complex dynamics that are not modeled in our simple static model.

Overall, this evidence indicates the importance of disentangling systemic bank shocks and government responses to such shocks. . The SBS and BC indicators measure very different things: a systemic bank shock and the government response to bank distress, respectively. The importance and economic significance of these differences is illustrated next.

VI. MARKET STRUCTURE AND DEPOSIT INSURANCE

Here, we re-examine and re-interpret the evidence on the relationships between bank competition and banking fragility and between deposit insurance and banking fragility. In both these literatures, researchers have employed BC indicators as dependent variables and interpreted the results as if they were systemic banking shocks. We argue that this has produced a considerable mis-interpretation of results. To facilitate comparisons, we continue to use the country-sample used thus far.

A. Bank Market Structure and Competition

In an extensive set of logit regressions using the DD crisis classification dataset, Beck et al. (2006) conclude that banking crises are less likely in more concentrated banking systems. Table 7 reports the results of our baseline *logit* specification adding bank concentration measures identical to those used by Beck et.al (2006). The average C3 concentration ratio, *concenmean* represents the asset share of the largest three banks in the country. The variable *avgherf* is an inter-temporal average of the Hirschman-Herfindhal index for each country.[15] Interestingly, our tests indicate that there is no evidence of any significant relationship between the bank concentration measures and the probability of a government response to banking distress. That conclusion is supported by all eight specifications in Table 7. Thus, the Beck et al (2006) results are seemingly not robust to either: the definition of a BC event, changes in sample composition, or the choice of other explanatory variables.

In Table 8 we report the results of estimates of the same equations as in Table 7, but with our SBS indicators as dependent variables. In all but one specification using a C3 concentration ratio, and in all specifications using the (arguably more appropriate) Herfindhal index, *systemic bank shocks are more likely to occur in more concentrated banking systems.*

Properly interpreted, these results are not necessarily inconsistent with those reported by Beck et al (2006) because the dependent variables are completely different. However, the results presented in Table 8 are perfectly consistent with the implications of the models by Boyd and De Nicolò (2005), Boyd, De Nicolò and Jalal (2006 and 2009) and De Nicolò and Loukoianova (2007), as well as the empirical evidence reported in these papers.[16]

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[15] Our baseline specification differs slightly from the one used by Beck et al (2006). However, we have been able to essentially replicate their results using their identical specification and sample, and so on.

[16] Martinez-Peira and Repullo (2008) extended 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. Yet, this prediction does not appear of relevance in our data. When we estimated regressions of the type reported in Table 8 with the addition of a quadratic term for concentration, there was no evidence of a non-linear

(continued…)

B. Deposit Insurance

In logistic regressions of the kind employed 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 with a deposit insurance system is in place. This finding has been interpreted as consistent with the standard moral hazard incentives created by deposit insurance and other government guarantees. Yet, it is well known that this argument is valid only in a partial equilibrium context and absent sufficiently strong countervailing regulations limiting banks' risk-taking, (such as capital requirements). In a general equilibrium context, and allowing contracts in nominal terms because of a non-trivial role for money, this simple moral hazard argument does not necessarily hold (e.g. Boyd, Chang and Smith 2002 and 2004).

Table 9 , columns 1 – 4, reports the results of logistic regressions with the BC indicators as dependent variables, in which we retain the Herfindhal index as a control. In addition, we include the indicator variable *di* which takes on the value 1.0 if a government deposit insurance system is in place, zero otherwise. The indicator variable is obtained from Demirgüç-Kunt and Detragiache (2002). Indeed, there is evidence of a positive and significant relationship between the BC indicators and the deposit insurance variable, although it is not statistically significant for one BC indicator (Equations (3)). However, this result essentially suggests 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 intervene in the presence of explicit deposit guarantees.

But, again, results are different when we use our SBS indicators as dependent variables. As shown in regressions (5)-(8) of Table 9, in all specifications *the probability of a systemic bank shock does not depend on whether there is a deposit insurance system in place*. To explore this issue further, in Table 10 we report logit regressions where we have added an index of "moral hazard" associated with design features of deposit insurance systems, *princom,* and a variable indexing the quality of institutions, *kk_compo*, as used in Beck et al (2006). Since *princom* is never statistically significant in columns 1 – 4, there is no evidence that more generous deposit insurance systems induce a higher probability of a government response to banking distress. However, the variable *kk_compo* is negative and statistically significant in all four tests (columns 1 – 4), suggesting that the probability of a government response to banking distress is lower in countries with better institutions. Possibly, this is because better institutions include stronger supervisory and regulatory bodies likely to *prevent* banking distress.

relationship between bank concentration and probability of a systemic bank shock. For brevity these results are not reported but are available upon request.

By contrast, as shown in regressions (5)-(8), the moral hazard index does not appear to have any explanatory role for the probability of a systemic bank shock. Moreover, the quality of institutions variable, *kk_compo*, does not seem to have much affect either, although it is negative and significant in one specification.

VII. Currency and "Twin" Crises

There is a substantial literature on external shocks to an economy and their effects on the incidence of banking crises. In all the studies we have seen, the relationship between bank fragility and external shocks has been empirically assessed equating a banking crisis with one of the BC indicators. Findings have differed markedly across studies also because of the use of significantly different country samples.

For example, 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, while indicators of real, rather than monetary, activity best predict the occurrence of both kinds of crises. As observed in Demirgüç-Kunt and Detragiache (2005), however, their analysis was based on a relatively small sample of 20 countries. They investigated mostly fixed exchange rate arrangements and the impact of several potential determinants of both kinds of crises was not examined jointly.

Eichengreen and Rose (1998) and Arteta and Eichengreeen (2002) have also examined the impact of "external" shocks on banking crises. One of their main findings is that exchange rate arrangements do not appear to have a significant impact on banking "crises". 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.

Here we re-examine the role of "external" factors in determining the four measures of government responses to banking distress (BC indicators) as well as of our two measures of systemic bank shocks (SBS indicators). As before, our focus is on illustrating the key differences in the results obtained by using BC indicators and SBS indicators. We present an extended set of Logit regressions where we simultaneously take into account indicators of currency crises and external shocks.

To this end, we refine the specification of the logit regressions in the previous sections — which has been adopted to facilitate broad comparisons with the results of previous studies. First, we use lagged values of all explanatory variables. This specification is more satisfactory than using contemporaneous variables, since it delivers an interpretation of these regressions as "forecasting" equations, where both simultaneity biases and endogeneity issues are likely to be less relevant.[17] Second, we replace the measure of exchange rate

[17] Von Hagen and Ho (2007) adopt the same specification for similar reasons.

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 described below. Third, motivated by the contrasting results in the literature concerning the role of financial openness and exchange rate arrangements, 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).

Fourth and finally, we constructed indicators of currency and "twin" crises, both based on monthly data, using the algorithm implemented in Frankel and Wei (2004). We then employ them as explanatory variables in Logit regressions with BC and SBS indicators as dependent variables, The task here is to assess whether there is a significant two-way relationship between banking fragility, government responses to it, and currency crises. The currency crisis indicators equal 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.[18]

A. BC and SBS Indicators as Dependent Variables

Table 11 illustrates the results for the BC indicators as dependent variables. Note that the relatively poor explanatory power of the regressions obtained with the previous specification using contemporaneous explanatory variables applies here as well. The only variable that enters negatively and significantly across *all* specifications is lagged real GDP growth, although lagged real interest rates also enter positively and significantly in six out of eight regressions. No other variables have a significant and uniform impact on the BC indicators for all, or even for a majority, of specifications.

With regard to the variables associated with external shocks, four results stand out. First, changes in terms of trade do not appear to have any impact on government responses to bank distress, as the relevant variable (*totch)* does not enter significantly in any regression. Second the sign of the proxy for financial openness (*finopen)* is *negative* in all regressions, but significant in only two out of eight regressions. Third, the flexibility of exchange rate arrangements (*erclassrr)* does not enter significantly in any regression. These variables have been mentioned in the literature discussed above as potentially important determinants of banking fragility. However, they do not appear to be significant determinants of government responses to banking distress as represented by BC indicators.

[18] We also dropped the twice-lagged value of real credit growth, since 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.

Last, government responses to bank distress appear to be positively associated with currency crises, although the relevant coefficients are significant in only two out of the four regressions 1-4. On the other hand, the "twin" crisis indicator appears to have no impact on the dependent variables in any of the four regressions 5-8. A researcher using a BC indicator as a proxy of bank distress would reach the conclusion that the impact of a currency crisis on bank distress would be mixed and none for twin crises. But this conclusion would be unwarranted.

As shown in Table 11, very different results are obtained with the SBS indicators as dependent variables. When we look at the domestic variables we have used as controls, most of the results obtained previously continue to hold when we condition the probability of a systemic bank shock on the lagged values of explanatory variables. Lower real GDP growth, higher real interest rates and higher inflation predict a higher probability of an SBS lending shock indicator. Real interest rates and inflation, although they have positive coefficients, are not significant determinants of SBS deposit indicators. Furthermore, higher bank concentration continue to be positively and significantly associated with a higher probability of a systemic bank shocks in all cases, while the indicator of quality of institutions does not enter significantly in any regression, as before.[19]

Importantly, both currency and "twin" crises predict the probability of a systemic bank shock, and significantly so in all regressions except Equations 4-5. Moreover, financial openness appears to have an independent impact on the probability of systemic bank shocks, but only in three out of eight regressions. The degree of flexibility of exchange rate arrangements seems unimportant. Finally, a worsening of the terms of trade turns out to be an important determinant of the probability of systemic bank shocks. The sign associated with changes in the terms of trade is negative in all regressions, and strongly significant in six out of eight.

In sum, *the positive impact of currency and twin crises on the probability of systemic bank shocks is significant.* As noted, this could hardly be detected by a researcher identifying BC indicators with banking "crises", since *government responses to banking distress are very weakly predicted by currency crisis indicators and not predicted by "twin" crisis indicators*.[20]

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

[20] 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.

B. Currency Crises as Dependent Variables

Do the realizations of systemic bank shocks have any impact on the probability of a currency crisis? This question has been raised in several contributions in the literature, but results using BC indicators as *explanatory* variables have been typically mixed.

As shown in Table 12, the evidence of a positive and significant impact of a systemic bank shock on the probability of a currency crisis is strong using our SBS indicators as explanatory variables. Indicators of systemic bank shocks have a significant predictive power on the probability of a currency crisis in most specifications. Thus, the effects of adverse domestic and external shocks are mutually reinforcing, as originally conjectured in Kaminsky and Reinahrt (1999). However, 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 shocks would fail to detect this evidence.

VIII. Evidence from Bank-Level Data

In this section we replicate some of the key tests conducted above using the bank-level dataset employed in Boyd, De Nicolò and Jalal (2006, 2009) and De Nicolò and Loukoianova (2007). This dataset includes bank accounting data for about 120 emerging and developing countries for the 1993-2004 period.

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

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

Next, we first define SBS indicators for this sample. Then we assess whether our SBS indicators predict BC indicators, and finally examine the role of the key determinants of bank fragility examined previously in explaining both BC and SBS indicators.

A. Measures of Systemic Bank Shocks

As observed in Boyd, De Nicolò and Jalal (2009), the best empirical measure of actual failure in banking may be a binary indicator indicating whether a sample bank "survived" or "failed". Yet, such data are difficult to obtain since actual bank failures are quite uncommon occurrences and failing banks are usually rescued by government.
However, consistent with the implications of our model's comparative statics exercise, we can define two measures capturing extreme adverse realizations of bank profits. Specifically, we construct two SBS indicators based on the overall distribution of the sum of profits and equity capital standardized by assets: FAIL5 and FAIL10, corresponding to the 5th and 10th percentile of the entire distribution of this sum across time and countries. Thus, these measures can capture a systemic bank shock through a sharp drop in the sum of the profits and the capital of the banking system, standardized by total assets

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

Our baseline specification includes standard macroeconomic variables as controls: GDP per capita (gdppc), GDP growth (growth), the inflation rate (infl), and exchange rate depreciation (depr). In all regressions below, we also control for bank size with the log of assets (lasset), to account for banks of different size operating in markets of different size.

B. SBS indicators Predict BC indicators

As before, we use *lagged* SBS indicators as an additional explanatory variable in the Logit regressions with BC indicators as the dependent variables. As noted, assessing the extent to which SBS indicators predict BC indicators is critical to our argument that BC indicators are measures of (lagged) government interventions undertaken in response to bank distress.

As shown in Table14, in all specifications the SBS indicators predict the BC indicators with high significance, suggesting yet again that these BC indicators capture lagged government responses to banking distress.

Notably, some key macroeconomic variables predict BC indicators with a significance stronger than what was obtained with country data, perhaps because of the more precise information content derived from heterogeneity in bank-level data. As before, higher GDP growth predicts a lower probability of government response to bank distress Importantly, inflation enters positively and significantly in all regressions on BC indicators. By contrast, recall that in the regressions based on country data we found that the effect of inflation on BC indicators was at best mixed.

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

C. Market Structure, Deposit Insurance and External Shocks

Mirroring what was done previously, the last set of regressions compares Logit regressions with BC and SBS indicators as dependent variables, focusing on the impact on these indicators of measures of bank concentration, the existence of an explicit deposit insurance system, selected variables indexing the external environment and currency crises. Table 15 reports the relevant regressions with BC indicators as dependent variables (Equations (1)-(4)), and with SBS indicators as dependent variables (Equations (5) and (6)).

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

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

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

All in all, the evidence obtained with this bank-level dataset supports all previous findings, and specifically, the key differences between BC and SBS indicators. It also provides some indication that the use of bank-level data may be more informative in assessing the determinants of bank fragility.

VI. Conclusion

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

We found overwhelming evidence that widely employed schemes for dating banking crises (BC indicators) measure lagged government responses to banking crises, not crises *per se.* Whether, and to what extent, mixing the realization of banking shocks and the restorative policy response has been problematic for empirical research and has been an open 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. We concluded that our indicators of systemic bank shocks consistently predict BC indicators constructed on the basis of four different major banking crisis classifications used extensively in the literature.

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

Our results are quite troubling for many previous studies. 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 systematic banking shocks; however, 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.

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

We believe that many empirical results of a large literature need to be re-interpreted and the role of some cross-country determinants of bank fragility need to be reassessed. Understanding bank fragility and the identification of policies capable of reducing its potential welfare costs is still a field in its infancy.

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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 year excluded)

Dependent variables are the BC indicators with crisis dates after the first crisis year excluded: DDs, CEAs, RRs and LVEs. Full sample regressions (1)-(4) include all available observations. Common Sample regressions (5)-(8) include only observations common to all crisis classifications. Explanatory variables: *rgdpgr* is the GDP growth rate; *rint* is the real interest rate; *infl* is the percentage change in the GDP deflator; *totch* is the change in the terms of trade; *depr* is the exchange rate depreciation vs. the US$; *m2res* is the ratio of M2 to foreign exchange reserves; *rgdpcp* is real GDP per-capita; *privcrd_gdp* is bank credit to the private sector to GDP; *L2.domcredgr* is real domestic bank credit growth to the private sector lagged twice. Standard errors are clustered by country. Robust p-values are reported in brackets, with *** p<0.01, ** p<0.05, * p<0.1.

	Full sample				Common Sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
COEFFICIENT	DDs	CEAs	RRs	LVs	DDs	CEAs	RRs	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)

Dependent variables are the BC indicators with all crisis dates: DD, CEA, RR and LVE. Full sample regressions (1)-(4) include all available observations. Common Sample regressions (5)-(8) include only observations common to all crisis classifications. Explanatory variables: *rgdpgr* is the GDP growth rate; *rint* is the real interest rate; *infl* is the percentage change in the GDP deflator; *totch* is the change in the terms of trade; *depr* is the exchange rate depreciation vs. the US$; *m2res* is the ratio of M2 to foreign exchange reserves*; rgdpcp* is real GDP per-capita; *privcrd_gdp* is bank credit to the private sector to GDP; *L2.domcredgr* is real domestic bank credit growth to the private sector lagged twice. Standard errors are clustered by country. Robust p-values are reported in brackets, with *** p<0.01, ** p<0.05, * p<0.1.

	Full sample				Common Sample			
	(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: Do SBS *Lending* Indicators Predict BC Indicators?

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
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: Do SBS *Deposit* indicators Predict BC Indicators?

Dependent variables are the BC indicators with all crisis dates: DD, CEA, RR and LVE. All regressions are full sample regressions including all available observations for each classification. Explanatory variables: *rgdpgr* is the GDP growth rate; *rint* is the real interest rate; *infl* is the percentage change in the GDP deflator; *totch* is the change in the terms of trade; *depr* is the exchange rate depreciation vs. the US$; *m2res* is the ratio of M2 to foreign exchange reserves; *rgdpcp* is real GDP per-capita; *privcrd_gdp* is bank credit to the private sector to GDP; *L2.domcredgr* is real domestic bank credit growth to the private sector lagged twice. *L.SBD25* and *L.SBSD10* are lagged SBS deposit indicators. Standard errors are clustered by country. Robust p-values are reported in brackets, with *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
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 as Dependent Variables

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

	(1)	(2)	(3)	(4)	(5)	(6)
COEFFICIENT	SBSL25	SBSL10	SBSD25	SBSD10	SBSD25	SBSD10
rgdpgr	-0.119***	-0.0948***	0.0280*	0.0168	0.0328*	0.02
	[0.000000706]	[0.00119]	[0.0836]	[0.403]	[0.0681]	[0.337]
rint	-0.000308**	-0.000220*	0.0000618	0.0000411	0.000066	0.0000972
	[0.0226]	[0.0688]	[0.627]	[0.735]	[0.563]	[0.411]
infl	-0.000582**	-0.000566**	-0.000119	-0.000258	-0.000115	-0.000255
	[0.0250]	[0.0225]	[0.660]	[0.400]	[0.686]	[0.445]
totch	0.0118***	0.00720*	0.0116**	0.0178**	0.0117**	0.0183**
	[0.00344]	[0.0658]	[0.0297]	[0.0133]	[0.0299]	[0.0130]
depr	1.238***	1.615***	0.392	0.876**	0.299	0.790*
	[0.00274]	[0.000224]	[0.291]	[0.0302]	[0.432]	[0.0676]
m2res	0.00128**	-0.000229	0.00174**	0.00164*	0.00156***	0.00158*
	[0.0139]	[0.710]	[0.0145]	[0.0971]	[0.00850]	[0.0735]
rgdpcp	-0.0000527***	0.00000223	-0.0000212**	-0.0000580***	-0.0000119	-0.0000482***
	[0.0000839]	[0.940]	[0.0477]	[0.00149]	[0.232]	[0.00433]
privcrd_gdp	-0.000925***	-5.120***	0.000578***	-0.00276**	0.000740***	-0.00234**
	[0.000444]	[0.0000900]	[0.00461]	[0.0132]	[0.000143]	[0.0327]
L2.rdomcredgr	-0.00608	0.00584	-0.0150***	-0.00954**	-0.0114***	-0.00923**
	[0.151]	[0.213]	[0.000239]	[0.0369]	[0.00459]	[0.0386]
L.SBSL25					1.149***	
					[0]	
L.SBSL10						1.195***
						[4.39e-09]
Constant	-0.692***	-1.126***	-1.242***	-2.287***	-1.661***	-2.526***
	[2.19e-08]	[7.49e-08]	[0]	[0]	[0]	[0]
Observations	1707	1707	1707	1707	1707	1707
# of countries	91	91	91	91	91	91
Pseudo-R2	0.122	0.228	0.0351	0.0712	0.0771	0.0988

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

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
COEFFICIENT	DD	CEA	RR	LV	DD	CEA	RR	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

Dependent variables are the SBS lending indicators, *SBL25* and *.SBSL10*, and the SBS deposit indicators, *SBSD25* and SBSD10. Explanatory variables: *rgdpgr* is the GDP growth rate; *rint* is the real interest rate; *infl* is the percentage change in the GDP deflator; *totch* is the change in the terms of trade; *depr* is the exchange rate depreciation vs. the US$; *m2res* is the ratio of M2 to foreign exchange reserves; *rgdpcp* is real GDP per-capita; *privcrd_gdp* is bank credit to the private sector to GDP; *L2.domcredgr* is real domestic bank credit growth to the private sector lagged twice; *concen_mean* is the average C3 concentration ratio; *avgherf* is the average Herfindhal index. Standard errors are clustered by country. Robust p-values are reported in brackets, with *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
COEFFICIENT	SBSL25	SBSL10	SBSD25	SBSD10	SBSL25	SBSL10	SBSD25	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: BC Indicators, SBS Indicators and Deposit Insurance

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
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 10. Logit Regressions: BC Indicators, SBS Indicators Deposit Insurance Features and Quality of Institutions

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
COEFFICIENT	DD	CEA	RR	LV	SBSL25	SBSL10	SBSD25	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 11. Logit Regressions: BC Indicators, Currency and Twin Crises

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

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 12. Logit Regressions: SBS Indicators, Currency and Twin Crises

Dependent variables are the SBS lending indicators, *SBL25* and *.SBSL10*, and the SBS deposit indicators, *SBSD25* and *SBSD10*. 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; *rgdpcp* is real GDP per-capita; *privcrd_gdp* is bank credit to the private sector to GDP; *avgherf* is the average Herfindhal index.; *kk_compo* is the indicator of quality of institutions; *finopen* is financial openness; *erclassrr* is the index of flexibility of exchange rate arrangements; *totch* is the change in the terms of trade; *crisis 25* and *stwins2525* are indicators of currency and twin crises respectively. Standard errors are clustered by country. Robust p-values are reported in brackets, with *** p<0.01, ** p<0.05, * p<0.1.

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 13. Logit Regressions: Currency Crises as Dependent Variables

Dependent variables are the currency crisis indicators constructed according to the alghoritm proposed by Frankel and Wei (2004): *crisis 35*, *crisis 25* and *crisis15*. 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; *rgdpcp* is real GDP per-capita; *privcrd_gdp* is bank credit to the private sector to GDP; *avgherf* is the average Herfindhal index.; *kk_compo* is the indicator of quality of institutions; *finopen* is financial openness; *erclassrr* is the index of flexibility of exchange rate arrangements; *totch* is the change in the terms of trade. *SBL25* and *.SBSD25* are lending and deposit SBS indicators 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	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 14. Bank Level Data, Random Effect Logit Regressions: SBS Indicators Predict BC Indicators

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

COEFFICIENT	DD	DD	CEA	CEA	RR	RR	LV	LV
	(1)	(2)	(3)	(4)	(5)	(6)	(8)	(9)
L.gdppc	0.000***	0.000***	0.000**	0.000**	0.000***	0.000***	0.000***	0.000***
	[0.000]	[0.000]	[0.026]	[0.023]	[0.000]	[0.000]	[0.000]	[0.000]
L.growth	-0.164***	-0.164***	-0.130***	-0.130***	-0.102***	-0.101***	-0.131***	-0.132***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
L.infl	0.045***	0.045***	0.009***	0.009***	0.024***	0.024***	0.012***	0.012***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
L.depr	0.004	0.004	-0.010***	-0.010***	0.012***	0.012***	-0.008***	-0.008***
	[0.271]	[0.227]	[0.000]	[0.000]	[0.001]	[0.001]	[0.004]	[0.005]
L.lasset	0.349***	0.339***	0.330***	0.321***	0.342***	0.333***	0.410***	0.403***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
L.FAIL5	0.819***		0.765***		0.609***		0.681***	
	[0.000]		[0.000]		[0.001]		[0.000]	
L.FAIL10		0.772***		0.694***		0.673***		0.593***
		[0.000]		[0.000]		[0.000]		[0.000]
Constant	-7.356***	-7.265***	-6.067***	-5.983***	-8.448***	-8.375***	-8.405***	-8.344***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Observations	13479	13479	13130	13130	13479	13479	13428	13428
Number of banks	3172	3172	3082	3082	3172	3172	3163	3163

Table 15. Bank Level Data, Random Effect Logit Regressions:: Determinants of BC and SBS Indicators

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

	BC Indicators				SBS Indicators	
COEFFICIENT	DD (1)	CEA (2)	RR (3)	LV (4)	FAIL5 (5)	FAIL10 (6)
L.gdppc	0.000***	0.000***	0.000***	0.000***	0.000**	0
	[0.000]	[0.000]	[0.000]	[0.000]	[0.022]	[0.653]
L.growth	-0.200***	-0.175***	-0.155***	-0.153***	-0.038**	-0.002
	[0.000]	[0.000]	[0.000]	[0.000]	[0.021]	[0.908]
L.infl	0.050***	0.052***	0.002***	0.051***	0	0
	[0.000]	[0.000]	[0.000]	[0.000]	[0.383]	[0.696]
L.lasset	0.370***	0.357***	0.447***	0.491***	0.524***	0.688***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
L.hhib	1.388***	1.157**	3.467***	2.367***	2.223***	2.215***
	[0.002]	[0.022]	[0.000]	[0.000]	[0.000]	[0.000]
L.di	0.059	0.970***	0.735***	0.680***	0.048	0.243
	[0.702]	[0.000]	[0.000]	[0.000]	[0.813]	[0.184]
L.kk_compo	-1.919***	-2.830***	-1.720***	-1.960***	-0.479*	-0.184
	[0.000]	[0.000]	[0.000]	[0.000]	[0.080]	[0.481]
L.finopen	-1.059***	-1.029***	-1.026***	-0.942***	0.073	0.105
	[0.000]	[0.000]	[0.000]	[0.000]	[0.516]	[0.320]
L.erclassrr	-0.190***	-0.257***	-0.264***	-0.238***	-0.059***	-0.048**
	[0.000]	[0.000]	[0.000]	[0.000]	[0.005]	[0.015]
L.totch	-0.005	0.004	0.016***	0.011**	0.002	-0.002
	[0.266]	[0.348]	[0.002]	[0.026]	[0.744]	[0.725]
L.crisis25	-0.239**	-0.271**	-0.247*	-0.127	0.522***	0.475***
	[0.043]	[0.032]	[0.052]	[0.300]	[0.002]	[0.002]
Constant	-6.145***	-6.329***	-8.096***	-9.186***	-11.922***	-13.380***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Observations	8527	8391	8527	8527	8527	8527
Number of banks	1846	1812	1846	1846	1846	1846

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			