TOO MANY TO FAIL?

Evidence of Regulatory Forbearance When the Banking Sector is Weak*

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Abstract

This paper studies bank failures in 21 emerging market countries in the 1990s. By using a competing risk hazard model for bank survival, we show that a government is less likely to take over or close a failing bank if the banking system is weak. This Too-Many-to-Fail effect is robust to controlling for macroeconomic factors, financial crises, the Too-Big-To-Fail effect, domestic financial development, and concerns due to systemic risk and information spillovers. The paper also shows that the Too-Many-to-Fail effect is stronger for larger banks and when there is a large government budget deficit.

Banking is a very important part of a free-market economy. Yet exit from the sector is not governed by market forces alone. An insolvent bank can continue to operate by issuing new deposits to pay old liabilities until government regulators decide to intervene. Hence the timing and the quality of regulatory intervention are important factors in maintaining a healthy financial system and economy.

In principle the government can always close a failing bank as soon as the bank becomes insolvent. In practice, the number of options available to regulators for handling the bank insolvency problem decreases with the severity of the problem (Barth, Caprio, and Levine, 2006; Hoggarth, Reidhill and Sinclair, 2004). When faced with an individual bank with a minor problem, regulatory authorities typically seek to find a private sector solution. They grant time for a bank turn-around and may request that the bank adopt particular measures. When problems are severe for an individual bank, prudent regulation requires a change in bank status through nationalization, liquidation, acquisition, or the sale to a private entity. In times of crisis the government may be forced to intervene through nationalization to reduce disruption in the payments system (Hoggarth, Reidhill and Sinclair, 2004), or to prevent fire sale prices to foreign banks (Acharya and Yorulmazer, 2008), or both.

Regulators appear to practice excessive regulatory forbearance (Hoffman and Santomero, 1998)[1]. They practice regulatory forbearance when prudential regulation dictates a change in bank status. What criteria does the government use when deciding whether to take over or close a weak bank? Does the process depend on the severity of problems in the banking sector? In particular, does the government delay the closing or taking over of a bank if the banking system is weak? These questions have become increasingly important as financial crises become more severe in terms of depth, and global scope.

The 2008 financial crisis provides a timely case study for the Too-Many-to-Fail effect. Regulators arranged for a relatively quick resolution when Bear Stearns experienced difficulty early in the crisis. As the crisis came to a head in October, the sector-wide banking difficulties became evident. This realization ultimately resulted in the U.S. government approving a massive $700 billion in funding for the Troubled Asset Relief Program (TARP). Regulators argue that this sort of "firepower" is necessary because of the scope of the crisis and the number of banks in financial distress. It may be too early to draw conclusions in this instance, but our analysis of the regulatory response to past bank failures in emerging markets is informative, especially since crisis events in the U.S. appear to be similar to those in emerging markets (Reinhart and Rogoff, 2008).

Recent theoretical research argues that the Too-Many-to-Fail phenomenon exists in bank regulation (Acharya and Yorulmazer, 2007; Mitchell, 2001). Regulators may choose not to take over or close a failing bank if there are many weak banks. Alternatively, there may be reasons for aggressive regulatory intervention in failing banks when the banking system is weak, precisely because of concerns about systemic risk[2] (Allen and Gale, 2000). Hence the question of whether there is a Too-Many-to-Fail effect cannot be settled by theoretical arguments only; it requires empirical analysis.

Any empirical study of bank failures—or corporate failures in general—is complicated, both conceptually and econometrically, by the fact that weak banks may be prone to exit the sector through acquisition. Furthermore, the likelihood of a potential bidder to materialize and obtain regulatory approval for an acquisition is unlikely to be independent from the decision to close a failing bank. Therefore an empirical study of bank failures needs to incorporate bank exit through acquisition. This is the first paper to incorporate more than one exit alternative, not just in studying bank failures, but studying corporate failures and bankruptcy in general.

We follow the largest banks in 21 emerging market countries through most of the 1990s. Our main finding is that a government is less likely to take over or less likely to close a failing bank if other banks in that country are weak. This result is robust to controlling for macroeconomic factors, financial crises, the Too-Big-To-Fail effect, domestic financial development, and contagion concerns due to systemic risk and information spillovers. This paper is the first to document the Too-Many-to-Fail channel of regulatory forbearance in a multi-country bank setting.

The magnitude of the Too-Many-To-Fail is economically significant. The rate of bank failure conditional upon past survival—also known as the hazard rate—increases by about 15 to 40 percent as the health of other banks in that country increases from the 25^{th} to 75^{th} percentile. We also find that this effect is greater for large banks and the effect increases with the government's budget deficit.

This paper contributes to the literature on regulatory forbearance. Several single-country studies already suggest that the Too-Many-to-Fail approach exists in banking regulation[3]. Our paper adopts a bank-level, multi-country approach, which allows empirical tests that are difficult to conduct in a single-country setting. This approach allows for us to separate the Too-Many-to-Fail effect from other country-specific factors that tend to be associated with bank failures.

Our paper is also related to the literature on bank failures in emerging markets. In contrast to our paper, most of this literature consists of country-level analyses of banking crises[4]. Two of the exceptions are Bongini et al. (2001) and Bongini et al. (2002), who provide a bank-level analysis of the banking crises in four East Asian countries[5]. In another exception, Brown and Dinc (2005), with which this paper shares data, show that regulators are more likely to take over or close failing banks shortly after elections rather than shortly before elections.

The rest of the paper is organized as follows. The next section presents the data. The second section discusses our methodology. The third section presents the main results. The fourth section provides robustness checks that the Too-Many-To-Fail effect we detect is not a mere reflection of the Too-Big-To-Fail effect. In the fifth section we analyze the most likely drivers of the Too-Many-to Fail effect. The sixth section provides further robustness checks and is followed by concluding remarks.

1. Data

The data are obtained from Brown and Dinc (2005), who identify the 10 largest commercial banks in each of 21 emerging market countries. These banks are followed from January 1, 1994 until one of the following three exit events takes place: (1) failure as manifested through takeover or license suspension/revocation by the regulators; (2) merger with or acquisition by another bank; or (3) reaching December 31, 2000, the end of sample period. Each bank merger is evaluated on a case-by-case basis to decide whether it is in fact, a government takeover of a failing bank. If one of the merger partners is a private bank but the resulting entity is majority-owned by the government, then that merger is considered as a government takeover; hence, the failure of that private bank. If the bank is acquired by another bank, where there is a change of majority ownership, then it is considered a bank acquisition exit event. If the government provides financial support for a bank acquisition, then it is considered a government-assisted acquisition. We recognize that the government can intervene in a failing bank in many ways: by providing liquidity support, limiting operations, or purchasing non-performing assets. We choose to focus on government takeovers and closures of failing banks instead of other limited forms of intervention for the following reasons. First, government takeovers and closures of failing banks are the most costly forms of intervention. Hence the issue of forbearance is likely to be more acute with our chosen forms compared to other limited forms of intervention. Second, the data on limited forms of government intervention are simply not available. Finally and related to the first two reasons, the data quality for limited forms of intervention is likely to be poor. This is because in order to prevent bank runs and other destabilizing market effects, governments actually have an incentive not to be forthcoming about limited forms of intervention[6].

Bankscope provides the balance sheet data. Government takeovers and the ultimate ownership of the banks are determined through manual data collection. Press sources provided in *Factiva* are used to identify the failing banks and determine the exact date of government intervention. The banks that are acquired by other banks are identified using *SDC International M&A* database. The ultimate owner of each bank is determined using *Bankscope, Factiva*, *SDC*, and various Internet sources. Based on the ultimate owner, the sample is split into two groups. The banks in the first group are always 50% or more owned by the central government throughout the sample period. The second group consists of the banks in which government ownership, if any, was less than 50% in at least one year during the sample period. In particular, this group includes banks that were owned by the government at more than the 50% level in 1993 and were subsequently privatized during the sample period. We refer the reader to Brown and Dinc (2005) for the details of the dataset. We also control for several country-level characteristics in this study. Data on deposit insurance and stock market turnover are obtained from the *World Bank Database on Financial Structure*. An index representing the quality of creditor rights is provided by Djankov, McLiesh, and Shleifer (2007). Data on banking crises are sourced from the dataset provided by Demirguc-Kunt and Detragiache (2005), and data on currency crises are sourced from the dataset provided by Kaminsky (2003).

Table 1 reports the number of bank failures in 1994-2000 among the 10 largest banks (as of 1993) in each country. Three findings are worth emphasizing. First, bank failure is very common in the sample countries. Out of 164 private banks, 40 banks, or about 24%, were taken over by the government during the sample period. 32 banks were acquired by other financial institutions of which three were government-assisted. These failures are not just a reflection of the Asian Financial Crisis or another crisis. In total, 12 countries had at least one bank failure among the largest banks during the sample period. Second, the regulatory intervention in failing banks by suspending the banking license of the failing bank, paying the depositors from the deposit insurance, and liquidating the bank is an exception. In 34 of the 40 government action episodes, the government actually took over the bank and continued to operate it. Third and perhaps unsurprisingly given the intervention choice of the government, no government-owned bank in the sample ever lost its banking license.

Given that no government-owned bank failed during the sample period, the analysis in the rest of paper focuses on the bank-years when the banks were private. To summarize, the following entry and exit events are adopted for analysis: bank i enters the study in year t_i, which is the later occurrence of one of the following two 'entry' dates: (a) January 1, 1994, the start of the sample period; and (b) the date the bank is privatized, so that ownership by the central government drops below 50%. Bank i exits the study in year T_i, which is the earliest occurrence of one of the following three 'exit' events: (1) the bank is taken over or has its license suspended/revoked by the government; (2) the bank is acquired by another bank; balance sheet data are no longer available for that bank as a separate entity; or (3) the bank survives until December 31, 2000, the end of the sample period.

Table 2 presents sample statistics for selected balance sheet items of these banks between their entry and exit dates and grouped by the type of bank exits. Banks that are taken over or closed by the government and banks that are acquired by other banks are smaller than the banks that survive to the end of our sample period. Acquired banks also have a lower loan to assets ratio while there is no statistically significant difference for deposits to total assets. Unsurprisingly, banks taken over or closed by the government are undercapitalized and less profitable compared to other banks. The capital ratio, defined as total equity divided by total assets, is only 4.4% for takeover/closure banks while it is 9.3% for banks that survived. Similarly, annual income per asset is lower in failed banks with -1.9%, while the same ratio is 1.7% for banks that survived. Both differences are statistically significant at the one percent level. The negative average income per asset for takeovers has an interesting implication. Unless these banks made very big losses in the year immediately before government intervention, these banks must have incurred losses for several years before the government finally took them over or closed them.

2. Methodology

We adopt a hazard model to study bank failures.[7] In a traditional hazard model, only one type of exit is considered, namely, the bank failure. The hazard rate for this exit, which is defined as the instantaneous rate of bank failure given survival until that time, becomes the basis of estimation. However, there is one more type of exit for a bank from observation: acquisition by another bank. Once a bank is acquired by another bank, the acquired bank drops from observation and it can no longer be known whether or when that bank would fail. Hence, it is desirable to incorporate into the study of bank failures the fact that some banks may exit from observation through acquisition.[8] When multiple states of exits are possible, the resulting hazard analysis is called *competing risk hazard analysis*. When the exit events are independent from each other, the resulting model is easy to estimate econometrically. Unfortunately, such independence cannot be assumed in our context. Not only may a bank be more likely to be acquired if it is weak, the regulators' decision to approve or reject an acquisition may also be related to the bank health. Furthermore, the regulatory decision may also depend on the financial health of other banks, which is the focus of this study. We describe below the competing risk hazard model employed in our analysis.[9]

Recall that, in the traditional hazard analysis with a single type of exit, the *hazard function*, which represents the instantaneous rate of exit at time *t* conditional on having survived until then, is given by

$$\lambda(t|X) = \lim_{h\to 0} \frac{P[t<T<t+h|T>t,X]}{h} \tag{1}$$

where *X* is the observable control variables, which may depend on time *t* as well. The *survivor function* is then

$$S(t|X) = P[t>T|X] = exp\left[-\int_0^t \lambda(u|X)\,du\right] \tag{2}$$

Finally, the likelihood function used in estimation is based on the probability density function for the time to exit; this density function is given by

$$f(t|X) = \lim_{h\to 0} \frac{P[t<T<t+h|X]}{h} = \lambda(t|X)S(t|X) \tag{3}$$

To model competing risks, we consider *type-specific hazard function*, also called *transition intensity*, given by

$$\lambda_j(t|X) = \lim_{h\to 0} \frac{P[t<T<t+h,d=j\,|T>t,X]}{h} \tag{4}$$

$\lambda_j(t|X)$ is the instantaneous rate of exit at time *t* due to type *j* having survived until *t*. We make the standard assumption that at most only one type of exit can occur in any given instant so we have

$$\lambda(t|X) = \sum_j \lambda_j(t|X) \tag{5}$$

The density function for the time to a type *j* exit is given by

$$f_j(t|X) = \lim_{h\to 0} \frac{P[t<T<t+h, d=j|X]}{h} = \lambda_j(t|X)S(t|X) \tag{6}$$

Let us denote our sample by $(t_i, \delta_i, d_i, X_i)$, where $i=1,\ldots n$ indexes the number of banks, δ_i is the indicator that becomes one if the bank exits the sample and zero if it reaches the end of our sample period without exiting –hence, it is 'right-censored'--, and d_i denotes the type of the bank's exit, which is unobserved and does not enter into the likelihood function given below if $\delta_i = 0$. The likelihood function then becomes

$$L = \prod_i \left(\left(\lambda_{d_i}(t_i|X_i) \right)^{\delta_i} S(t_i|X_i) \right) \tag{7}$$

Equation (7) has been obtained without any functional assumptions for the hazard function but, without such assumptions, (7) will not be very useful for estimation. We adopt the common exponential form for our type-specific hazard function as given below

$$\lambda_j(t|X) = b_j(t) exp\left[\beta_j X + \mu_j\right] \tag{8}$$

where $b_j(t)$ is the baseline hazard function, β_j are the coefficients to be estimated, and μ_j is the unobserved heterogeneity term, which is discussed in more detail below. There are at least three aspects of (8) that should be emphasized. First, the coefficients β_j to be estimated are indexed by the exit type *j*, which implies that different sets of coefficients are (jointly) estimated for different types of exit in each regression. Second, the baseline hazard $b_j(t)$ is also allowed to be different for different types of exit.

Finally, the hazard function (8) includes unobserved heterogeneity term μ_j, which is akin to 'random effects', as in Han and Hausman (1990) and Sueyoshi (1992), among others. This term serves two purposes. First, Heckman and Singer (1984) show that including unobserved heterogeneity and estimating it nonparametrically increases the accuracy of coefficient estimates for the structural equations even if the distribution of the unobserved heterogeneity is not accurately estimated. Second, this term permits us to allow dependence between different types of exits. In other words, by *not* requiring μ_j and μ_l to be independent for $j \neq l$, we allow the banks that are more likely to be acquired by other banks for reasons unobserved by the econometrician to be more (or less) likely to be taken over or closed by the government.[10]

Heckman and Singer (1984) argue for modeling the unobserved heterogeneity as a discrete distribution and for estimating the jump points and their associated probabilities together with structural coefficients. Following McCall (1994), Dolton and van der Klaauw (1999), Deng et al. (2000), and Fallick and Ryu (2007), among others, we also adopt this framework. More precisely, we assume that

$$\mu_j \in \{\mu_{j1}, \dots, \mu_{jk}\} \text{ with } P[\mu_j = \mu_{jk}] = \pi_{jk} \text{ and } \sum_{jk} \pi_{jk} = 1 \tag{9}$$

Hence, our type-specific hazard function in (8) becomes

$$\lambda_j(t|X) = \sum_k \left(\pi_{jk} b_j(t) exp[\beta_j X + \mu_{jk}]\right) \tag{10}$$

while the survivor function can be obtained as

$$S(t|X) = exp\left[-\int_0^t \sum_{jk} \left(\pi_{jk} b_j(u) exp[\beta_j X + \mu_{jk}]\right) du\right] \tag{11}$$

The likelihood function can then be obtained by plugging (10) and (11) into (7).

Notice that (9) has too many free parameters so it requires some normalization. In estimation, we normalize μ_{j1} for all *j*, adopt discrete unobserved heterogeneity with K=2, and fit a fourth order polynomial for the natural log functions of the baseline hazard $b_j(t)$, separate for each *j*. In our model, we consider only two different types of exit for banks, namely, (i) a takeover or closure by the government, or (ii) acquisition by another bank, so *j*=1,2. Finally, our explanatory variables *X* depend on time and include measures of financial health for other banks, as discussed in the next section.

3. Regression Results

The focus of our analysis is the government takeover or closure of failing banks. However, as described in the Methodology section, a bank may also exit from the sample when it is acquired by another bank. An acquisition exit may (or may not) be related to bank health and need not be independent from a government takeover or closure decision. Our hazard analysis explicitly incorporates the exit through being acquired as a competing risk to the main focus of the analysis. For each regression, two sets of coefficients are (jointly) estimated: one for each exit type as the coefficients for each type of exit are allowed to be different. Throughout our analysis, we report marginal effects (in percentage points) on the hazard evaluated at the sample mean. A positive effect indicates an increase in the probability of exit (by that type) given that the bank has survived to the current point in time. As the government action need not be independent across the banks within a country, the errors are clustered at the country level –and robust to heteroscedasticity.

The main regression results are reported in Table 3. Each column reports the results of a single regression, which jointly-estimates the coefficients of variables for two types of bank exit:

government takeover and acquisition by another entity. To control for size, all the regressions include *Total Assets/GDP*, which is the bank's total assets normalized by the GDP of the country where it is located. Two variables in the regression control for the bank's financial health: *Capital Ratio*, defined as the book value of the shareholder equity divided by total assets and *Income*, defined as the operating income divided by total assets. Brown & Dinc (2005) find that governments are less likely to take over or close a failing bank before elections so we include a *Before Election* dummy variable. This variable takes the value of one if the bank exits in the latter half of the electoral cycle, or in the case of no exit, the end of bank's accounting year if it falls within the latter half of the electoral cycle. All these variables, with the exception of the *Before Election* dummy variable, are as of year t-1.

The first regression in Table 3 serves as a benchmark and does not include measures of financial health for other banks. For government takeover/bank closure, there is no evidence that size is a factor for this sample when the macroeconomic factors are not controlled for. On the other hand, the bank financial health plays a large role, as expected. The marginal effect of *Capital Ratio* on the hazard is negative and statistically significant at the one percent level, which indicates that banks with larger capital bases are less likely to fail given that they have survived to the current point in time. The regression also confirms that political concerns play a major role in the government decision to take over a failing bank as the marginal effect for the *Before Election* dummy is negative and statistically significant.

The primary finding for acquisitions is that larger banks are less likely to be acquired. This effect is statistically significant at the five percent level. However, we do not find any evidence that weak banks are any more likely to be acquired. Similarly, we do not find any role for the electoral cycle or the country's income level for bank acquisitions. While the coefficients of these factors may not be individually significant in explaining bank acquisitions, they are jointly significant at the one percent level.

The second regression in Table 3 is one of our main regressions. It includes a measure of financial health for other banks, *Capital Ratio_Other Banks*, which is the average of capital ratio measure of other banks in that country, weighted by bank total assets. While the regression sample contains only private banks, these measures are constructed using all the banks in the initial sample (government and private) to capture the financial health of the banking sector in that country. As discussed before, this variable should not have a statistically significant effect if the government decision to take over or close a failing bank is based only on that bank's health. On the other hand, if there is regulatory delay in taking over or closing a bank when the other banks in the system are weak, *Capital Ratio_Other Banks* will have a positive and statistically significant effect.

Capital Ratio_Other Banks has a positive and statistically significant effect for the government takeover or closure. This indicates that, controlling for individual bank-level factors, the government is more likely to take over or liquidate a failing bank if the remaining banks have high capital ratios—a Too-Many-to-Fail effect. We do not find a similar effect for bank exit through acquisitions by other banks.

It is important to study the robustness of the aforementioned results to common macroeconomic factors. The main concern is whether the health of other banks just proxies for the general health of the economy. Though if that were the case, there would be a negative coefficient indicating a slower rate of failure, not a positive coefficient as we found. Nevertheless, in regression 3 we control for five different macroeconomic variables: GDP per capita, GDP growth rate, currency depreciation, inflation rate, and real interest rate.[11] We also include the total IMF loans to that country, normalized by that country's GDP, to control for any influence by IMF. It is also important to check whether the Too-Many-to-Fail effect we detect is a mere reflection of financial crises. To control for this effect, we include country-year *Banking Crisis* dummy variable constructed with the data from Demirguc-Kunt & Detragiache (2005).[12] All macroeconomic variables are as of year t - 1.

Regression 3 in Table 3 reports the results of the regressions that include these macroeconomic variables. Our main variable of interest in the analysis, *Capital Ratio_Other Banks*, continues to have positive and statistically significant effects in all the regressions. These results indicate that the Too-Many-to-Fail effect does not occur because the financial health measures employed in the analysis proxy for some common macroeconomic factor.

Other bank-level risk indicators may also have predictive power in a government takeover or closure of failing banks, so it is important to check whether the financial health measures for other banks in the country are robust to controlling for those bank-level factors. Unfortunately, there is a lack of data about one factor likely to determine bank failures—non-performing loans. Data on non-performing loans are available for fewer than half of the bank-years in the sample. Without those data, we turn our attention to other factors that may play a role in determining bank failure.

Equity reserves may provide a cushion for adverse times so banks with greater reserves are less likely to fail. Loans are illiquid while the deposits are liquid, so a bank with a high proportion of loans may be more likely to fail. Similarly, the risks taken by a bank may be reflected in the difference between the interest paid by the bank to depositors and the interest charged to its borrowers. Each regression reported in Table 4 controls for these factors but, none of them seem to have a statistically significant impact once we control for the bank's capital ratio and income. On the other hand, *Capital Ratio_Other Banks* continues to have a positive and statistically significant effect. These results imply that the Too-Many-to-Fail effect shown above is not a proxy for some common bank-level risk factor.

4. Too-Many-to-Fail and Too-Big-To-Fail

It is important to verify that the Too-Many-To-Fail effect we demonstrate is not just a reflection of the Too-Big-To-Fail effect discussed in the literature. Our sample include only the largest ten banks in a country and our regressions always include a size variable so our analysis already suggests some robustness in this direction. However, given the importance of Too-Big-To-Fail in banking, it is still desirable to study this issue in detail. Instead of our usual size variable, we create four different dummy variables for the top three banks based on assets, loans, deposits, or employee expenses in that country in that year.[13] While these tests do not, of course, constitute a proof or repudiation of any potential Too-Big-To-Fail effect in these countries, they will capture non-parametrically any Too-Big-To-Fail effect within our sample of already large banks. These four variables are, naturally, correlated with one another but they are also different that they are likely to capture different effects. For example, the dummy variables constructed using loans will capture the government concern for the borrowers upon the failure of largest lenders, while the dummy variable based on the deposits will reflect the government concern for the burden of a large bank failure on the deposit insurance fund. Similarly, the dummy variable constructed using employee expenses will incorporate the government aversion to large layoffs upon the failure of large banks.

Table 5 reports these regressions. In all the regressions, regardless of which of the four different bank-specific characteristics we use, the dummy variable for the largest three banks has a negative and statistically significant coefficient. Our main variable of interest *Capital*

Ratio_Other Banks continues to have positive and statistically significant coefficient. These results cannot conclude that the Too-Big-To-Fail effect did or did not exist in these countries but they do imply that the Too-Many-To-Fail effect demonstrated in this paper is separate and not just a reflection of any possible Too-Big-To-Fail effect.

5. Understanding the Too-Many-to-Fail Effect

In this section we study the potential economic drivers of the Too-Many-to Fail effect. In doing so, we employ a number of interaction effects. For a nonlinear model such as the one used in this paper, the study of interaction effects is not as straightforward as it would be in a linear regression. In a linear regression, the interaction effect is completely captured by the coefficient of the interaction term; hence, the interaction effect remains constant for all the values of explanatory variables. But, as Ai and Norton (2003) show, the interaction effect cannot be completely captured by the coefficient of the interaction term in a non-linear regression; instead, it also depends on other coefficients and the values of explanatory variables at which it is evaluated. In Appendix A, we derive the interaction effect for the hazard model used in this paper.

A. <u>The Role of Government Fiscal Health</u>

A potential explanation may be that the government itself may have incentives to delay the ultimate reckoning in bank failures, as found in the S&L crisis by Kane (1989) and Kroszner and Strahan (1996) among others. In particular, the takeover or closure of a bank causes the government to incur costs of a financial clean up in the short run. We hypothesize that the Too-Many-to-Fail effect may be weaker for governments that run a budget surplus or a small deficit.

To test this hypothesis, we study the interaction effect between *Capital Ratio_Other Banks* and a *High Budget Balance* dummy variable. The *High Budget Balance* dummy variable takes the value one if that country's budget balance in that year, as a ratio to its GDP, is greater than the sample median. In our sample, the median is a budget deficit equal to 1.49% of GDP so *High Budget Balance dummy* is one for countries with a budget surplus or a small deficit.

Table 6 provides the regression results with the *High Budget Balance* dummy and the interaction of that variable with *Capital Ratio_Other Banks*. The interaction effect is evaluated at the sample mean of all other explanatory variables. The first regression includes *High Budget Balance* but no interaction term to serve as a benchmark. *High Budget Balance* does not have a statistically significant effect when no interaction term is included. The second regression includes the interaction term. It shows that the interaction effect is negative and statistically significant at the sample mean.

B. <u>The Exposure of Other Banks to the Failing Bank</u>

Prudential regulation suggests that there are legitimate reasons why government regulators may choose forbearance and delay intervention when the banking system is weak. One reason is that the failure of an initial bank may trigger failures of other banks if the other banks have loaned large sums to the initial bank through the interbank market (Allen and Gale, 2000). In turn, regulators might delay the takeover of the failing bank to avoid triggering subsequent industry upheavals and bank failures. To test whether these concerns are behind the Too-Many-to-Fail delay, we control for the total interbank borrowing by a given bank normalized by the country's GDP. The results of the regression analysis reported in regression 2, Table 6.

The use of interbank deposits as a control variable is not without its own disadvantages. Such borrowing tends to have short maturities, often overnight, while our data come from balance sheets so it has an annual frequency. Low observation frequency relative to the maturities of deposits may not allow us to detect other banks' reaction to one bank's deteriorating financial health. Another disadvantage is that we have no data on the identity of the lending banks. Some of the lending banks may in fact be government-owned banks directed to support the failing bank through interbank deposits. Such disguised government support may reflect the politicians' or regulators' hope that the failing bank may later regain its financial health on its own or their desire to wait until a more opportune time to intervene. Nevertheless, we still believe that it is informative to study the role of interbank exposure in regulatory forbearance.

We find no evidence that the exposure of other banks to a failing bank in the system causes regulators to show forbearance and delay major intervention. *Interbank Deposits/GDP* has a negative but statistically insignificant coefficient while the effect of our measure of other banks' financial health remains statistically significant.

C. Information Spillovers

Another regulatory concern might be that a failing bank potentially reveals information about the whole banking system and that this information might cause runs on other banks (Lang and Stulz, 1992; Slovin et al., 1999). Such fears of contagion may delay regulatory intervention. Although there is only rare evidence of such contagion (Calomiris and Mason, 1997, 2003), it is still important to study whether such regulatory concerns are behind the Too-Many-to-Fail effect.

As a measure of publicly available information about the bank, we use a variable for the presence of a debt rating. If the bank is rated, a regulatory intervention is less likely to carry new information about the financial health of banking in that country. It is also less likely to create concerns about runs on other banks due to information spillovers. In fact, Berger et al. (2000)

show that supervisory reports, when stale, tend to generate little information about a bank over what the market already knows and that any such information is short-lived.

Regression 3 in Table 6 reports the results of regressions that include the indicator variable *Rated*, which takes the value of one if the bank was issued a debt rating by Moody's in the previous year. The effect of this variable is never statistically significant, but *Capital Ratio_Other Banks* continues to have positive and statistically significant effect. To be specific, concerns about information spillovers do not appear to lead to the Too-Many-to-Fail effect demonstrated in this paper.[14]

D. Other Interaction Effects

In regressions reported in Table 7, we explore whether the magnitude of the Too-Many-To-Fail effect changes with some bank-level characteristics. We start by studying whether the Too-Many-to-Fail effect is stronger for larger banks. In the first regression, we use the base specification with a dummy variable for large banks instead of the continuous size variable. The *Large Banks* dummy variable takes the value one if *Total Assets/GDP* is greater than the sample median. We also include an interaction between the dummy variable for *Large Banks* and *Capital Ratio_Other Banks*. The interaction effect is positive and statistically significant at the one percent level, which implies that the Too-Many-To-Fail effect is indeed stronger for larger banks.

We also explore whether the Too-Many-to-Fail effect is stronger for weaker banks. The second and third regressions show negative interaction effects when we include variables for bank strength: a dummy variable for *High Capital Ratio* and a dummy variable for *High Income*. The *High Capital Ratio* dummy variable takes the value one if that bank's capital ratio is greater than the sample median. The *High Income* dummy variable takes the value one if that bank's operating income (as a percentage of total assets) is greater than the sample median. Both interaction effects are negative and statistically significant at the five percent level or better, which indicates that the Too-Many-To-Fail effect is stronger for weaker banks.

6. Robustness

A. Alternative Measures Of Financial Health For Other Banks

We start by studying the robustness of the Too-Many-to-Fail effect reported above to different measures of financial health for other banks. The first regression in Table 8 uses *Liquid Reserves_Other Banks* instead of *Capital Ratio_Other Banks*. Carletti, Hartmann, and Spagnolo (2004) motivate *Liquid Reserves_Other Banks* as a measure of banking system liquidity. It is constructed using the average of the liquid equity reserves of other banks in that country, weighted by bank total assets. This variable also has a positive effect that is statistically significant at one percent level. The second regression uses *Income_Other Banks*, which is the average of income of other banks in that country, weighted by bank total assets. This variable also has a positive effect that is statistically significant at the one percent level. Finally, *Capital Ratio_Other Banks*, our main measure of other banks' financial health, may be endogenous to the system if it includes the capital ratio of the banks that fail later in the sample period. To check the robustness of our measure to this concern, we construct *Capital Ratio_No Fail Banks* by excluding banks that failed at any point in time. *Capital Ratio_No Fail Banks* also has a positive effect that is statistically significant at the five percent level. These results indicate that the Too-Many-to-Fail effect found in previous sections is robust to using different measures for the financial health of other banks.

B. Alternative Specifications

We check the robustness of our results to different definition of bank failure and bank acquisition. The results are reported in Table 9. We first replace the bank failure with the first sign of problems, which is defined as the first year of negative income. We then consider only the acquisitions by foreign banks as the exit through being acquired. *Capital Ratio_Other Banks* has a positive and statistically significant coefficient in both regressions, which indicate that our results are robust to different definition of bank exit.

C. Domestic Financial Development

It may be a concern that our measures of financial health for other banks may be capturing the level of domestic financial development and other institutional factors. In order to check the robustness of our findings, we use the following country-year-level control variables: a creditor rights index, the presence of a formal deposit insurance scheme, and stock market turnover. The results are presented in Table 7. None of these factors seem to play a statistically significant role in the government's decision to take over or close a failing bank. However, *Capital Ratio_Other Banks* continues to have positive and statistically significant effect, which indicates that the Too-Many-to-Fail effect remains robust to controlling for financial development and other institutional factors.

7. Conclusion

We study banking in major emerging economies throughout the latter part of the 1990s to demonstrate regulatory forbearance towards failing banks when the banking sector is weak. This Too-Many-To-Fail effect is unlikely to be limited to emerging markets. It was present in the U.S. Savings and Loan crisis of the 1980s and the Japanese banking crisis of the 1990s[15]. To the extent that the current U.S crisis is similar to emerging market crises[16], as argued by Reinhart and Rogoff (2008), we expect to see a U.S regulatory response characterized by Too-Many-To-Fail concerns. In fact, the $700 billion Troubled Asset Relief Program (TARP)—that aims to support weak banks—appears to be motivated by the large number of weak banks and the widespread nature of the problems in the banking sector.

Regulatory decisions do not depend only on the characteristics of the bank in question. This finding has implications for recent policy debates on bank regulation. The finding suggests that Basel II's focus on bank characteristics without proper emphasis on regulatory incentives may be misplaced. The direct bank-level, multi-country evidence presented in this paper strengthens the arguments that designing bank regulation without due concern for regulatory incentives is not likely to be very productive (Barth, Caprio, and Levine, 2006). Instead, market monitoring of banks may be a welcome augmentation for mitigating the negative impact of regulatory incentive issues (Flannery and Sorescu, 1996; Berger et al., 2000; and Peria and Schmukler, 2001).

Whether it is through acquisition, nationalization, or liquidation, prudential regulation suggests a change in bank status when the banking system weakens. The results presented in this paper can be interpreted as evidence of neglect by the government. We provide a note of caution on this interpretation. We focus on two drastic and costly forms of government intervention: government takeovers and bank closures. There are many other forms of intervention that the government can use: liquidity support, purchase of non-performing assets, and other short term aid. We do not consider limited forms of government intervention because, to the best of our knowledge, there is no reliable dataset on these types of actions[17]. Our findings may not extend to these limited forms of government intervention.

The econometric methodology that we use to study bank failure may be of independent interest for other bank failure studies and for bankruptcy studies in general. Many weak banks exit the sector not just through government actions: takeover or liquidation, but through acquisition. To the extent that acquisitions are not independent of government action—and there are many reasons why they may not be—bank failure studies must allow for exit through acquisitions. We hope that the competing risk method will become a standard approach in this regard.

The results presented in this paper lead to several questions for further research. Does the Too-Many-to-Fail effect lead to bank herding ex ante? A banker may be more likely to take risks or lend to the same sectors (e.g. real estate) if he knows that his bank is less likely to be closed or taken over when subsequent problems appear to be system wide[18]. How costly is the Too-Many-to-Fail effect? How costly is regulatory forbearance in general? We leave these interesting questions for future research.

Appendix A

In an effort to explain the timing of bank failures, we estimate several interaction effects. For linear models, the coefficient for an interaction term can be easily interpreted as the interaction effect. For example, let us allow a continuous variable y to depend on two continuous variables x_1, x_2, their interaction, and a vector of additional independent variables $\boldsymbol{X}$ including a constant term. Hence the following data generating process.

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_{12} x_{i1} x_{i2} + \boldsymbol{X}_{i,-(1,2,12)} \beta_{,-(1,2,12)} + u_i \tag{A1}$$

The interaction effect of the independent variables is the cross-derivative of the expected value of y_i.

$$\frac{\partial^2 E[y|x_1, x_2, \boldsymbol{X}]}{\partial x_1 \partial x_2} = \beta_{12} \tag{A2}$$

In this paper, we present a competing risk proportional hazard model for bank failure. This model is nonlinear in the estimated coefficients. In nonlinear models, the interaction effect is not equal to the coefficient for the interaction term. Following Ai and Norton (2003), we present the correct way to recover interaction effect estimates and standard errors for nonlinear models using continuous variables. We then present the correct way to recover interaction effect estimates and standard errors in our model using one continuous variable and one binary variable.

Consider the following type-specific hazard.

$$\lambda_j(t|X) = b_j(t) exp\left(\beta_{j1} x_1 + \beta_{j2} x_2 + \beta_{j12} x_1 x_2 + \boldsymbol{X}_{j,-(1,2,12)} \beta_{j,-(1,2,12)} + \epsilon_j\right) \tag{A3}$$

Let x_1 and x_2 be continuous variables. The interaction effect is given by the cross derivative of the type-specific hazard.

$$\mu_{12} = \lambda_j(t|X) * \left[\left(\beta_{j1} + \beta_{j12} x_2\right)\left(\beta_{j1} + \beta_{j12} x_1\right) + \beta_{j12}\right] \tag{A4}$$

Note that the interaction effect is conditional on the explanatory variables. The interaction effect is estimated by

$$\hat{\mu}_{12} = \lambda_j(t|X) * \left[\left(\hat{\beta}_{j1} + \hat{\beta}_{j12}x_2\right)\left(\hat{\beta}_{j1} + \hat{\beta}_{j12}x_1\right) + \hat{\beta}_{j12}\right] \qquad \text{(A5)}$$

The continuity of the type-specific hazard and the consistency of the estimated coefficients ensure the consistency of the interaction effect estimator. The standard error of the estimated interaction effect is found by applying the Delta method. Hence the asymptotic variance of the estimated interaction effect is itself estimated consistently by

$$\hat{\sigma}_{12} = \frac{\partial}{\partial\beta'}[\hat{\mu}_{12}]\hat{\Omega}_{\beta}\frac{\partial}{\partial\beta}[\hat{\mu}_{12}] \qquad \text{(A6)}$$

where Ω_β is the covariance for β.

In the paper, we present the following type-specific hazard

$$\lambda_j(t|M,X) = b_j(t)exp\left(\beta_{j1}x_1 + \beta_{jM}M + \beta_{j1M}x_1M + \boldsymbol{X}_{j,-(1,M,1M)}\beta_{j,-(1,M,1M)} + \epsilon_j\right) \qquad \text{(A7)}$$

M is a dummy variable and can one of take two values: zero or one. The interaction effect is given by the finite difference of the derivative of the type-specific hazard with respect to x_1

$$\mu_{12} = \left(\beta_{j1} + \beta_{j1M}\right) * \lambda_j(t|M=1,X) - \beta_{j1} * \lambda_j(t|M=0,X) \qquad \text{(A8)}$$

In the paper, we present the interaction effect and the standard errors given the hazard at the sample mean. We also provide the t statistic for each estimate to test the hypothesis that the interaction effect equals zero**.**

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[1] Kasa and Spiegel (2008) argue that excessive regulatory forbearance may come about as a result of a pre-commitment to a relative closure rule in bank failure resolution. They argue that this policy, as opposed to an absolute closure rule, permits a low number of closures when there are severe problems in the banking sector.

[2] For models of the Too-Many-to-Fail effect in non-banking contexts, see Roland and Verdier (1994) for privatization and Perotti (1998) for monetary stabilization. Although our paper is not an empirical test of any particular model, we use the insights from theoretical models as motivation for our tests.

[3] See Kane (1989), Barth (1991), White (1991), and Kroszner and Strahan (1996) argue for the Savings and Loan crisis in the United States; Hoshi and Kashyap (2001) and Amyx (2004) for the Japanese banking crisis; and, in a non-banking setting, Berglof and Bolton (2002) for the implementation of corporate bankruptcy laws in Hungary and the Czech Republic.

[4] See, e.g., Barth et al., 2006; Beck et al., 2006; Caprio and Klingebiel, 2002; Claessens et al. 2005; and Demirguc-Kunt and Detragiache, 2002.

[5] In a firm-level study of the East Asian financial crisis, Aguiar and Gopinath (2005) show that foreign firms provided liquidity through acquisitions. This finding suggests that remedies to liquidity problems in a country may not be limited to government intervention in the banking sector.

[6] For example, the U.S. Federal Reserve established new channels for liquidity support to banks instead of using the usual discount window after the 'sub-prime' crisis so that the banks obtaining such support would remain undisclosed. In addition, government intervention may also take place through loans from government-owned banks, which would make that type of intervention very difficult to distinguish from normal interbank lending.

[7] Shumway (2001) shows the superiority of hazard models to single-period models in forecasting bankruptcy. Studies that use hazard models in analyzing bank failures include Lane et al. (1986), Whalen (1991), Molina (2002), and Brown and Dinc (2005).

[8] We thank a referee for suggesting this addition.

[9] See Kalbfleisch and Prentice (2002, Ch. 8) and Lancaster (1990, Section 5.5) for a textbook treatment of competing risk hazard models; our exposition largely follows the former. See also the references below for economic applications.

[10] For the importance of allowing dependence, see Honore and Tamer (2006).

[11] It should also be noted that, to the extent that country-wide macroeconomic factors are correlated with the financial health of other banks, potential multicollinearity problems will make it difficult to obtain a statistically significant coefficient for our measure of other banks' health.

[12] In an earlier version, we also checked the robustness of the Too-Many-to-Fail effect to the existence of a currency crisis in that country, as opposed to a banking crisis, using the data from Kaminsky (2003) and obtained similar results.

[13] We also constructed our dummy variables for top five banks instead of three and obtained similar results.

[14] It is important to be clear about what these results do and do not imply. In particular, they do not imply that regulators are not concerned about systemic risks in banking. In fact, their preferred method of intervention in a failing bank, namely the government takeover as opposed to the closing of the bank, may be motivated by concerns about systemic risks. Our results only imply that such concerns are not behind the Too-Many-to-Fail delay demonstrated in this paper.

[15] See Kane (1989), Barth (1991), White (1991), and Kroszner and Strahan (1996) argue for the Savings and Loan crisis in the United States; Hoshi and Kashyap (2001) and Amyx (2004) for the Japanese banking crisis; and, in a non-banking setting, Berglof and Bolton (2002) for the implementation of corporate bankruptcy laws in Hungary and the Czech Republic.

[16] Reinhart and Rogoff (2008) show remarkable similarities between emerging markets and developed countries in the events leading up to, and the impact on the government's budget subsequent to a financial crisis.

[17] Any such dataset is likely to be incomplete because regulators have an incentive not to disclose information about these limited forms of intervention in order to prevent bank runs. Even during the onset of the subprime crisis in the U.S., the Federal Reserve Bank introduced a policy to provide liquidity support to weak banks without disclosing their identity. This policy shift was made in order to supplement its usual discount window through which it could provide liquidity support to a bank only by disclosing the bank's identity.

[18] Acharya and Yorulmazer (2007) provide evidence that suggests that this type of herding exists.

Table 1. Bank Failures by Country

The table provides the number of bank failures among the largest 10 banks (as of the end of 1993) in each of the 21 sample countries during the sample period 1994-2000. Each bank is followed from January 1, 1994 until the first occurrence of one of the three exit events: 1) take-over or license revocation / liquidation by the government; 2) acquisition by another bank; or 3) surviving to January 1, 2001. The table splits the sample based on ownership. Banks that are *always government-owned* are the banks that were always owned by the central government at least at the 50 percent level throughout 1994-2000. *Private Banks* are the remaining banks. The banks that were owned by the government in 1993 but were later privatized are included among the Private Banks unless one of the three exit events occurred first.

		Always Government-Owned		Private Banks			
COUNTRY	**Total Number of Banks (1993)**	**Total Number**	**License Revoked or Liquidated**	**Total Number**	**Taken Over by the Government**	**License Revoked or Liquidated**	**Acquisition**
Southeast Asia							
Indonesia	10	5	--	5	5	--	--
Malaysia	10	2	--	8	--	--	2
Singapore	10	--	--	10	--	--	--
South Korea	10	2	--	8	5	--	--
Taiwan	10	3	--	7	--	--	--
Thailand	10	2	--	8	4	--	1
Total	**60**	**14**	**0**	**46**	**14**	**0**	**3**
Latin America							
Argentina	10	2	--	8	--	--	2
Brazil	10	1	--	9	3	--	1
Chile	10	1	--	9	--	--	3
Colombia	10	2	--	8	1	--	2
Mexico	10	2	--	8	3	--	1
Peru	10	1	--	9	1	--	5
Venezuela	10	1	--	9	4	--	1
Total	**70**	**10**	**0**	**60**	**12**	**0**	**15**
Rest of the World							
Czech Republic	10	--	--	10	4	2	2
Hungary	10	1	--	9	1	--	3
India	10	9	--	1	--	--	--
Israel	10	2	--	8	--	--	2
Poland	10	3	--	7	--	--	6
Russia	10	2	--	8	2	4	--
South Africa	10	1	--	9	--	--	1
Turkey	10	4	--	6	1	--	--
Total	**80**	**22**	**0**	**58**	**8**	**6**	**14**
Overall Total	**210**	**46**	**0**	**164**	**34**	**6**	**32**

Table 2. Sample Statistics

The table provides sample statistics for the banks in the sample. *Government Takeover/Closure* represents the banks that were taken over by the government or had their licenses revoked by the government during the sample period. *Acquisition* represents banks that were sold or acquired during the sample period. *N* denotes the number of bank-years. *Capital ratio* is the book value of shareholder equity divided by total assets. All variables are book values. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively, in a two-sided test of the mean of the type of exit with the mean of banks that survived.

		Exit Type	**Exit Type**		
Variable Name		**Government Takeover/ Closure**	**Acquisition**	**Banks that Survived**	**All Banks**
Assets/GDP	Mean	5.586**	3.255***	7.932	6.979
	se.	0.580	0.298	0.444	0.337
	sd.	6.868	2.695	10.171	9.207
	N	140	82	525	747
Total Loans/Assets	Mean	0.569	0.540**	0.580	0.574
	se.	0.014	0.018	0.007	0.006
	sd.	0.171	0.165	0.152	0.158
	N	140	82	525	747
Total Deposits/Assets	Mean	0.766	0.748	0.746	0.750
	se.	0.013	0.014	0.007	0.006
	sd.	0.149	0.120	0.163	0.157
	N	138	79	520	737
Capital Ratio	Mean	0.044***	0.090	0.093	0.083
	se.	0.014	0.004	0.002	0.003
	sd.	0.163	0.032	0.055	0.087
	N	140	82	525	747
Operating Income/Assets	Mean	-0.019***	0.015	0.017	0.010
	se.	0.017	0.002	0.001	0.003
	sd.	0.196	0.020	0.025	0.088
	N	137	79	521	737

Table 3. Too Many To Fail: Regulatory Reluctance When the Banking System is Weak

The table presents the results of a competing risk proportional hazard model for bank failure, where there are two types of bank exit: takeovers or closures of banks by the government and the acquisition of the bank by another bank. The model allows for correlated bank exit types. Each column represents a single regression and the coefficients for both types of exits in a column are jointly estimated. For each variable, we report the marginal effect evaluated at the sample mean. A positive effect (in percentage points) denotes an increasing hazard of bank exit through that type of exit event. *Total Assets/GDP* is the bank's total assets normalized by the country's GDP. *Capital Ratio* is total equity divided by total assets. *Income* is operating income divided by total assets. *Capital Ratio_Other Banks* is the weighted average (by total assets) of capital ratio of other banks in that country. All are book values and as of year t - 1. *Before Election* is a dummy variable that takes one if the bank fails in the latter half of the electoral cycle or, in the case of no exit, the end of bank's accounting year falls within the latter half of the electoral cycle. *GDP per Capita* is GDP for a given year divided by the population in that year. *GDP Growth* is the rate of growth in the country's GDP. *Currency Depreciation* is the decrease in the local currency's exchange rate against U.S. dollars; it is negative if the local currency appreciates. *Inflation Rate* is the logarithm of one plus the consumer price inflation. *Real Interest Rate* is the nominal lending rate minus the rate of consumer price inflation. *IMF Loans/GDP* is total IMF loans outstanding to the country, normalized by the country's GDP. All variables are as of t- 1. p-values of a Wald test that all coefficients are jointly zero are reported for each type of bank exit and then for both types of bank exit. Heteroscedasticity-robust standards errors, corrected for clustering at the country level, are in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Government Takeover/Closure	Acquisition	Government Takeover/Closure	Acquisition	Government Takeover/Closure	Acquisition
Total Assets/GDP	-1.856	-1.349***	-1.826	-1.362***	-2.115***	-1.038*
	(1.450)	(0.387)	(1.406)	(0.383)	(0.473)	(0.561)
Capital Ratio	-0.499***	-0.017	-0.722***	-0.017	-0.401***	-0.014
	(0.178)	(0.108)	(0.202)	(0.118)	(0.082)	(0.161)
Income	0.050	-0.106	-0.147	-0.147	-0.139	-0.137
	(0.195)	(0.119)	(0.184)	(0.184)	(0.097)	(0.095)
Before Election	-4.388**	-0.107	-4.993**	-0.109	-3.333**	-0.800
	(1.966)	(1.415)	(2.300)	(1.454)	(1.406)	(0.795)
Capital Ratio_Other Banks			1.235***	-0.006	1.873***	0.427
			(0.414)	(0.703)	(0.389)	(0.440)
GDP per Capita					-1.191***	0.030
					(0.401)	(0.777)
GDP Growth					0.387***	0.050
					(0.054)	(0.179)
Currency Depreciation					8.473***	1.364
					(2.768)	(2.832)
Inflation Rate					-1.102	-2.528
					(2.194)	(1.862)
Real Interest Rate					-0.010	1.601
					(3.950)	(4.074)
IMF Loans/GDP					2.128***	6.119
					(0.502)	(0.843)
Banking Crisis					0.485	-1.842
					(1.029)	(1.218)
p-value	0.000	0.003	0.000	0.004	0.000	0.000
Observations	763		763		523	
p-value (all)	0.000		0.000		0.000	

Table 4. Too Many To Fail: Additional Bank-Level Factors

The table presents the results of a competing risk proportional hazard model for bank failure, where there are two types of bank exit: takeovers or closures of banks by the government and the acquisition of the bank by another bank. The model allows for correlated bank exit types. Each column represents a single regression and the coefficients for both types of exits in a column are jointly estimated. For each variable, we report the marginal effect evaluated at the sample mean. A positive effect (in percentage points) denotes an increasing hazard of bank exit through that type of exit event. *Total Assets/GDP* is the bank's total assets normalized by the country's GDP. *Capital Ratio* is total equity divided by total assets. *Income* is operating income divided by total assets. *Capital Ratio_Other Banks* is the weighted average (by total assets) of capital ratio of other banks in that country. All are book values and as of year *t* - 1. *Before Election* is a dummy variable that takes one if the bank fails in the latter half of the electoral cycle or, in the case of no exit, the end of bank's accounting year falls within the latter half of the electoral cycle. Macro and crisis control variables include *GDP per Capita*, *GDP Growth*, *Banking Crisis*, *Currency Depreciation*, *Inflation Rate*, *Real Interest Rate* and *IMF Loans/GDP*. *Equity Reserves* represents the equity reserves of the bank, normalized by total assets. *Loans* represents the total net loans divided by total assets. *Lending Margin* is the spread between the average interest rate charged on loans and the average interest rate paid on deposits. All variables are as of *t*- 1. *p*-values of a Wald test that all coefficients are jointly zero are reported for each type of bank exit and then for both types of bank exit. Heteroscedasticity-robust standards errors, corrected for clustering at the country level, are in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Government Takeover/Closure	Acquisition	Government Takeover/Closure	Acquisition	Government Takeover/Closure	Acquisition
Total Assets/GDP	-2.717***	-1.054*	-2.283***	-0.953	-2.200***	-1.107*
	(0.492)	(0.575)	(0.766)	(3.759)	(0.497)	(0.598)
Capital Ratio	-0.797***	-0.034	-0.443	-0.018	-0.550***	-0.025
	(0.155)	(0.157)	(0.753)	(0.326)	(0.155)	(0.164)
Income	-0.227	-0.146	-0.094	-0.136	-0.024	-0.105
	(0.274)	(0.146)	(1.314)	(0.820)	(0.155)	(0.112)
Before Election	-3.267**	-0.788	-3.335*	-0.859	-2.174**	-0.849
	(1.477)	(0.854)	(1.962)	(1.799)	(1.008)	(0.830)
Capital Ratio_Other Banks	2.332***	0.445	1.930***	0.588	1.831***	0.368
	(0.460)	(0.514)	(0.531)	(3.466)	(0.239)	(0.474)
Equity Reserves	0.327	0.021				
	(0.246)	(0.135)				
Loans			1.509	0.350		
			(1.941)	(2.872)		
Lending Margin					0.959	-1.942
					(0.607)	(1.462)
Macro & Crisis Control	Yes	Yes	Yes	Yes	Yes	Yes
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Observations	520		523		513	
p-value (all)	0.000		0.000		0.000	

Table 5. Too Many To Fail vs. Too Big To Fail

The table presents the results of a competing risk proportional hazard model for bank failure, where there are two types of bank exit: takeovers or closures of banks by the government and the acquisition of the bank by another bank. The model allows for correlated bank exit types. Each column represents a single regression and the coefficients for both types of exits in a column are jointly estimated. For each variable, we report the marginal effect evaluated at the sample mean. A positive effect (in percentage points) denotes an increasing hazard of bank exit through that type of exit event. *Top 3 Assets* is a dummy variable that takes one if the bank is ranked in the top three in the country based on total assets. *Top 3 Loans* is a dummy variable that takes one if the bank is ranked in the top three in the country based on total loans. *Top 3 Deposits* is a dummy variable that takes one if the bank is ranked in the top three in the country based on total deposits. *Top 3 Employee Expenses* is a dummy variable that takes one if the bank is ranked in the top three in the country based on employee expenses. *Capital Ratio* is total equity divided by total assets. *Income* is operating income divided by total assets. *Capital Ratio_Other Banks* is the weighted average (by total assets) of capital ratio of other banks in that country. All are book values and as of year t - 1. *Before Election* is a dummy variable that takes one if the bank fails in the latter half of the electoral cycle or, in the case of no exit, the end of bank's accounting year falls within the latter half of the electoral cycle. Macro and crisis control variables include *GDP per Capita*, *GDP Growth*, *Banking Crisis*, *Currency Depreciation*, *Inflation Rate*, *Real Interest Rate* and *IMF Loans/GDP*. All variables are as of t- 1. p-values of a Wald test that all coefficients are jointly zero are reported for each type of bank exit and then for both types of bank exit. Heteroscedasticity-robust standards errors, corrected for clustering at the country level, are in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Government Takeover/Closure	Acquisition	Government Takeover/Closure	Acquisition	Government Takeover/Closure	Acquisition	Government Takeover/Closure	Acquisition
Top 3 Assets	-2.122**	-0.357						
	(0.878)	(0.633)						
Top 3 Loans			-2.269***	-0.455				
			(0.839)	(0.640)				
Top 3 Deposits					-2.137**	-0.386		
					(0.885)	(0.608)		
Top 3 Employee Expenses							-1.666*	-0.145
							(1.004)	(0.750)
Capital Ratio	-0.394***	0.046	-0.389***	0.048	-0.399***	0.044	-0.471***	0.034
	(0.069)	(0.159)	(0.066)	(0.160)	(0.068)	(0.160)	(0.137)	(0.180)
Income	-0.099	-0.221**	-0.094	-0.219**	-0.095	-0.218**	-0.085	-0.298**
	(0.104)	(0.095)	(0.102)	(0.094)	(0.102)	(0.096)	(0.183)	(0.120)
Before Election	-1.963*	-0.896	-1.990*	-0.902	-1.964*	-0.884	-2.129*	-1.330
	(1.180)	(0.825)	(1.596)	(0.827)	(1.141)	(0.826)	(1.293)	(0.966)
Capital Ratio_Other Banks	1.697***	0.662	1.668***	0.646	1.695***	0.660	1.666***	0.836
	(0.220)	(0.592)	(0.218)	(0.582)	(0.215)	(0.579)	(0.245)	(1.097)
Macro & Crisis Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Observations	521		521		520		461	
p-value (all)	0.000		0.000		0.000		0.000	

Table 6. Understanding the Reasons behind Too Many To Fail

The table presents the results of a competing risk proportional hazard model for bank failure, where there are two types of bank failure: government takeovers and sales. The model allows for correlated bank exit types. Each column represents a single regression and the coefficients for both types of exits in a column are jointly estimated. For each variable, we report the marginal effect evaluated at the sample mean. A positive effect (in percentage points) denotes an increasing hazard of bank exit through that type of exit event. *Total Assets/GDP* is the bank's total assets normalized by the country's GDP. *Capital Ratio* is total equity divided by total assets. *Income* is operating income divided by total assets. *Before Election* is a dummy variable that takes one if the bank fails in the latter half of the electoral cycle or, in the case of no failure, the end of bank's accounting year falls within the latter half of the electoral cycle. *High Budget Balance* is a dummy variable that takes one if the budget balance (the government's fiscal budget balance normalized by the country's GDP) is greater than the median budget balance for the sample. *Capital Ratio_Other Banks* is the weighted average (by total assets) of capital ratio of other banks in that country. Macro and crisis control variables include *GDP per Capita*, *GDP Growth*, *Banking Crisis*, *Currency Depreciation*, *Inflation Rate*, *Real Interest Rate* and *IMF Loans/GDP*. *Interbank Deposits/GDP* are the deposits of other banks in the bank, normalized by the bank's total assets and the country's GDP, respectively. *Rated Bank* is a dummy variable that takes one if the bank has any debt rated by Moody's Investor Service. All are book values and as of year *t* - 1. *p*-values of a Wald test that all coefficients are jointly zero are reported for each type of bank exit and then for both types of bank exit. Heteroscedasticity-robust standards errors, corrected for clustering at the country level, are in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Government Takeover/Closure	Acquisition	Government Takeover/Closure	Acquisition	Government Takeover/Closure	Acquisition
Total Assets/GDP	-2.815***	-1.330**	-5.215***	-1.581	-1.885***	-0.876
	(0.550)	(0.527)	(1.554)	(1.477)	(0.455)	(0.602)
Capital Ratio	-0.453***	-0.010	-0.950***	-0.091	-0.369***	0.004
	(0.086)	(0.151)	(0.354)	(0.332)	(0.084)	(0.157)
Income	-0.221**	-0.187*	-0.185	-0.383*	-0.188	-0.140*
	(0.103)	(0.104)	(0.431)	(0.205)	(0.118)	(0.084)
Before Election	-3.771**	-1.337	-6.654**	-1.376	-3.336**	-0.955
	(1.620)	(0.912)	(2.938)	(0.545)	(1.319)	(0.746)
High Budget Balance	4.421	1.380				
	(4.324)	(2.613)				
Capital Ratio_Other Banks	2.269***	0.837	4.392***	1.775**	1.835***	0.417
	(0.452)	(1.006)	(0.739)	(0.812)	(0.318)	(0.435)
Capital Ratio_Other Banks* High Budget Balance	-9.073***	-4.006*				
	(3.133)	(2.113)				
Interbank Deposits/GDP			-0.746	-2.110		
			(1.671)	(1.770)		
Rated Bank					-0.914	-0.861
					(0.886)	(1.006)
Macro & Crisis Controls	Yes	Yes	Yes	Yes	Yes	Yes
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Observations	490		441		523	
p-value (all)	0.000		0.000		0.000	

Table 7. Too Many To Fail: Bank-Level Interaction Effects

The table presents the results of a competing risk proportional hazard model for bank failure, where there are two types of bank exit: takeovers or closures of banks by the government and the acquisition of the bank by another bank. The model allows for correlated bank exit types. Each column represents a single regression and the coefficients for both types of exits in a column are jointly estimated. For each variable, we report the marginal effect evaluated at the sample mean. A positive effect (in percentage points) denotes an increasing hazard of bank exit through that type of exit event. *Total Assets/GDP* is the bank's total assets normalized by the country's GDP. *Large Banks* is a dummy variable that takes one if the size (total assets normalized by GDP) for the bank is greater than the median size for the sample. *Income* is operating income divided by total assets. *High Income* is a dummy variable that takes one if the operating income for the bank is greater than the median operating income for the sample. *Capital Ratio* is total equity divided by total assets. *High Capital Ratio* is a dummy variable that takes one if the capital ratio for the bank is greater than the median capital ratio for the sample. *Capital Ratio_Other Banks* is the weighted average (by total assets) of capital ratio of other banks in that country. Macro and crisis control variables include *GDP per Capita, GDP Growth*, *Banking Crisis, Currency Depreciation, Inflation Rate, Real Interest Rate* and *IMF Loans/GDP*. All variables are as of *t*- 1. *Before Election* is a dummy variable that takes one if the bank fails in the latter half of the electoral cycle or, in the case of no exit, the end of bank's accounting year falls within the latter half of the electoral cycle. *p*-values of a Wald test that all coefficients are jointly zero are reported for each type of bank exit and then for both types of bank exit. Heteroscedasticity-robust standards errors, corrected for clustering at the country level, are in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Government Takeover/Closure	Acquisition	Government Takeover/Closure	Acquisition	Government Takeover/Closure	Acquisition
Total Assets/GDP			-1.964***	-1.087*	-2.003***	-1.175
			(0.520)	(0.606)	(0.464)	(1.451)
Large Banks	-2.246***	-1.122				
	(0.846)	(1.710)				
Capital Ratio	-0.356***	0.033			-0.520***	-0.001
	(0.103)	(0.154)			(0.124)	(0.163)
High Capital Ratio			0.429	0.914		
			(0.679)	(1.812)		
Income	-0.126	-0.206**	-0.402***	-0.179**		
	(0.143)	(0.105)	(0.096)	(0.087)		
High Income					3.032*	0.327
					(1.643)	(3.759)
Before Election	-3.340**	-0.823	-3.348**	-1.276	-3.287**	-0.745
	(1.623)	(0.810)	(1.372)	(0.911)	(1.337)	(2.323)
Capital Ratio_Other Banks	1.854***	0.502	1.543***	0.518	1.773*	0.309
	(0.368)	(0.446)	(0.395)	(0.331)	(1.051)	(0.655)
Capital Ratio_Other Banks* Large Banks	1.749***	1.701				
	(0.370)	(2.323)				
Capital Ratio_Other Banks* High Capital Ratio			-2.655**	-0.582		
			(1.247)	(1.512)		
Capital Ratio_Other Banks* High Income					-10.363***	-1.284
					(3.983)	(4.321)
Macro & Crisis Controls	Yes	Yes	Yes	Yes	Yes	Yes
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Observations	523		523		523	
p-value (all)	0.000		0.000		0.000	

Table 8. Too Many To Fail: Alternative Measures of Banking System Weakness

The table presents the results of a competing risk proportional hazard model for bank failure, where there are two types of bank exit: takeovers or closures of banks by the government and the acquisition of the bank by another bank. The model allows for correlated bank exit types. Each column represents a single regression and the coefficients for both types of exits in a column are jointly estimated. For each variable, we report the marginal effect evaluated at the sample mean. A positive effect (in percentage points) denotes an increasing hazard of bank exit through that type of exit event. *Total Assets/GDP* is the bank's total assets normalized by the country's GDP. *Capital Ratio* is total equity divided by total assets. *Income* is operating income divided by total assets. *Before Election* is a dummy variable that takes one if the bank fails in the latter half of the electoral cycle or, in the case of no exit, the end of bank's accounting year falls within the latter half of the electoral cycle. Macro and crisis control variables include *GDP per Capita, GDP Growth, Banking Crisis, Currency Depreciation, Inflation Rate, Real Interest Rate* and *IMF Loans/GDP*. *Liquid Reserves_Other Banks* is the weighted average (by total assets) of the equity reserves of other banks in that country. *Income_Other Banks* is the weighted average (by total assets) of income of other banks in that country. *Capital Ratio_No Fail Banks* is the weighted average (by total assets) of capital ratio of banks in that country that did not fail by government takeover or closure. All values are as of year *t* - 1. *p*-values of a Wald test that all coefficients are jointly zero are reported for each type of bank exit and then for both types of bank exit. Heteroscedasticity-robust standards errors, corrected for clustering at the country level, are in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Government Takeover/ Closure	Acquisition	Government Takeover/ Closure	Acquisition	Government Takeover/ Closure	Acquisition
Total Assets/GDP	-2.213***	-1.088**	-2.320***	-1.099**	-1.989***	-1.032*
	(0.472)	(0.551)	(0.484)	(0.556)	(0.490)	(0.558)
Capital Ratio	-0.391***	0.005	-0.378***	0.009	-0.421***	-0.034
	(0.087)	(0.149)	(0.094)	(0.154)	(0.077)	(0.172)
Income	-0.170*	-0.131	-0.190*	-0.152	-0.093	-0.123
	(0.100)	(0.102)	(0.114)	(0.094)	(0.083)	(0.102)
Before Election	-3.237**	-0.793	-3.140**	-0.774	-3.245**	-0.799
	(1.442)	(0.787)	(1.381)	(0.776)	(1.316)	(0.811)
Liquid Reserves_Other	1.943***	0.236				
	(0.384)	(0.426)				
Income_Other Banks			2.018***	0.399		
			(0.355)	(0.298)		
Capital Ratio_No Fail					3.541***	0.805
					(0.924)	(1.086)
Macro & Crisis Controls	Yes	Yes	Yes	Yes	Yes	Yes
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Observations	523		523		523	
p-value (all)	0.000		0.000		0.000	

Table 9. Too Many To Fail: Alternative Specifications

The table presents the results of a competing risk proportional hazard model for bank failure, where there are two types of bank exit: takeovers or closures of banks by the government and the acquisition of the bank by another bank. The model allows for correlated bank exit types. Each column represents a single regression and the coefficients for both types of exits in a column are jointly estimated. For each variable, we report the marginal effect evaluated at the sample mean. A positive effect (in percentage points) denotes an increasing hazard of bank exit through that type of exit event. The first column uses the first occurrence of negative operating income as the time of bank exit instead of the date of government takeover/closure. The second column uses only acquisitions by a foreign entity as the occurrence of bank exit instead of acquisitions by all types of entities. The third column uses the base specification in addition to feedback terms. *Total Assets/GDP* is the bank's total assets normalized by the country's GDP. *Capital Ratio* is total equity divided by total assets. *Income* is operating income divided by total assets. *Capital Ratio_Other Banks* is the weighted average (by total assets) of capital ratio of other banks in that country. Macro and crisis control variables include *GDP per Capita* , *GDP Growth*, *Banking Crisis*, *Currency Depreciation*, *Inflation Rate*, *Real Interest Rate* and *IMF Loans/GDP*. All values are as of year *t* - 1. *Before Election* is a dummy variable that takes one if the bank fails in the latter half of the electoral cycle or, in the case of no exit, the end of bank's accounting year falls within the latter half of the electoral cycle. *p*-values of a Wald test that all coefficients are jointly zero are reported for each type of bank exit and then for both types of bank exit. Heteroscedasticity-robust standards errors, corrected for clustering at the country level, are in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Government Takeover/Closure Initial Sign of Banking Problems	Acquisition Initial Sign of Banking Problems	Government Takeover/Closure Base Specification	Acquisition Base Specification with Acquisitions by Foreign Entities Only
Total Assets/GDP	-2.122***	-1.044*	-2.113***	-1.523*
	(0.456)	(0.560)	(0.498)	(0.910)
Capital Ratio	-0.321***	-0.012	-0.401***	-0.036
	(0.106)	(0.162)	(0.082)	(0.126)
Income	-0.163	-0.142	-0.136	-0.045
	(0.112)	(0.096)	(0.095)	(0.084)
Before Election	-2.455**	-0.791	-3.310**	-0.067
	(1.239)	(0.802)	(1.429)	(1.045)
Capital Ratio_Other Banks	1.843***	0.353	1.865***	0.372
	(0.389)	(0.430)	(0.384)	(0.406)
Macro & Crisis Controls	Yes	Yes	Yes	Yes
p-value	0.000	0.000	0.000	0.000
Observations	522		523	
p-value (all)	0.000		0.000	

Table 10. Too Many To Fail: Domestic Financial Development

The table presents the results of a competing risk proportional hazard model for bank failure, where there are two types of bank exit: takeovers or closures of banks by the government and the acquisition of the bank by another bank. The model allows for correlated bank exit types. Each column represents a single regression and the coefficients for both types of exits in a column are jointly estimated. For each variable, we report the marginal effect evaluated at the sample mean. A positive effect (in percentage points) denotes an increasing hazard of bank exit through that type of exit event. *Total Assets/GDP* is the bank's total assets normalized by the country's GDP. *Capital Ratio* is total equity divided by total assets. *Income* is operating income divided by total assets. *Capital Ratio_Other Banks* is the weighted average (by total assets) of capital ratio of other banks in that country. All are book values and as of year t - 1. *Before Election* is a dummy variable that takes one if the bank fails in the latter half of the electoral cycle or, in the case of no exit, the end of bank's accounting year falls within the latter half of the electoral cycle. *Creditor Rights* represents an index of the quality of creditor rights in that country. *Depositor Insurance* is a dummy variable equal to one if there is the presence of depositor insurance in that country. *Stock Market Turnover* is the ratio of the value of total shares traded to average real market capitalization. Macro and crisis control variables include *GDP per Capita, GDP Growth, Banking Crisis, Currency Depreciation, Inflation Rate, Real Interest Rate* and *IMF Loans/GDP*. All variables are as of t- 1. p-values of a Wald test that all coefficients are jointly zero are reported for each type of bank exit and then for both types of bank exit. Heteroscedasticity-robust standards errors, corrected for clustering at the country level, are in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Government Takeover/ Closure	Acquisition	Government Takeover/ Closure	Acquisition	Government Takeover/ Closure	Acquisition
Total Assets/GDP	-1.703***	-1.057*	-2.124***	-1.026*	-2.301***	-1.060**
	(0.480)	(0.580)	(0.453)	(0.601)	(0.414)	(0.465)
Capital Ratio	-0.408***	-0.009	-0.393***	-0.032	-0.409***	-0.060
	(0.109)	(0.151)	(0.096)	(0.176)	(0.076)	(0.150)
Income	-0.160	-0.139	-0.170	-0.116	-1.431	-0.133
	(0.125)	(0.089)	(0.124)	(0.114)	(0.100)	(0.089)
Before Election	-3.533**	-0.825	-3.351**	-0.726	-3.201**	-1.168
	(1.423)	(0.831)	(1.433)	(0.792)	(1.375)	(0.916)
Capital Ratio_Other	2.038***	0.427	1.908***	0.385	1.992***	0.009
	(0.499)	(0.432)	(0.327)	(0.427)	(0.410)	(0.490)
Creditor Rights	-1.018	0.061				
	(0.980)	(0.435)				
Deposit Insurance			-0.750	0.666		
			(1.775)	(1.507)		
Stock Market					0.793	-4.927**
					(0.989)	(1.944)
Macro & Crisis	Yes	Yes	Yes	Yes	Yes	Yes
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Observations	523		523		523	
p-value (all)	0.000		0.000		0.000	