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Armen Hovakimian
Edward J. Kane
Luc Laeven

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ABSTRACT

This paper proposes a theoretically sound and easy-to-implement way to measure the systemic risk of financial institutions using publicly available accounting and stock market data. The measure models credit risk of banks as a put option on bank assets, a tradition that originated with Merton (1974). We extend his contribution by expressing the value of banking-sector losses from systemic default risk as the value of a put option written on a portfolio of aggregate bank assets whose exercise price equals the face value of aggregate bank debt. We conceive of an individual bank's systemic risk as its contribution to the value of this potential sector-wide put on the financial safety net. To track the interaction of private and governmental sources of systemic risk during and in advance of successive business-cycle contractions, we apply our model to quarterly data over the period 1974-2010. Results indicate that systemic risk reached unprecedented highs during the years 2008-2010, and that bank size, leverage, and asset risk are key drivers of systemic risk.

Armen Hovakimian
Department of Economics and Finance
Baruch College Zicklin School of Business
1 Bernard Baruch Way
New York, NY 10010
Armen_Hovakimian@baruch.cuny.edu

Edward J. Kane
Boston College
2325 E Calle Los Altos
Tucson, AZ 85718
and NBER
edward.kane@bc.edu

Luc Laeven
Deputy Division Chief
International Monetary Fund
700 19th Avenue, NW
Washington, DC 20431
and CEPR
Llaeven@imf.org

The ongoing global financial crisis is intensifying efforts by policymakers and academics to devise better strategies and frameworks for monitoring and resolving losses at large, complex financial institutions. Key problems include the need to develop timely measures for the risk that individual institutions impose on the financial system as a whole – known as systemic risk – and to determine whether and how authorities might enlist the institutions that a nation's or region's safety net protects to help them to monitor and police individual firms' contribution to this risk.

Definitions of systemic risk articulated by the Basel Committee and US policymakers lack the transparency needed to establish political accountability. Assessments based on these definitions turn on ad hoc judgments and confidential data that third parties cannot reliably replicate. The judgments in question combine subjective perceptions of individual-institution distress with projections of the ex ante potential for spillovers of individual defaults across a particular country's financial sector and from this sector to the national and global real economy.

This way of looking at systemic risk is not only unreproducible, it is logically incomplete, and can be bureaucratically self-serving. It excludes from the risk-generation process the channels through which financial safety-net management can mitigate or amplify financial stability. The existence of a safety net incentivizes banks to raise their risk profiles, under-reserve for loss exposures, and to conceal actual losses (Kane, 1989; Demirguc-Kunt and Huizinga, 2004; Skinner, 2008; Huizinga and Laeven, 2011). Unless policymakers vigilantly and conscientiously address this incentive problem and the regulatory arbitrage it produces, aggressive firms will be tempted to abuse the financial safety net in clever ways.

Regulatory arbitrage is exemplified today by the growing use of unconventional monetary policies by central banks, including the provision of liquidity support against weak collateral. When hidden risk-taking goes sour, it can transform a firm's riskiest exposures into political games of chicken whose outcome generates bailout expense for taxpayers. Because it is the path of least resistance, fiscal and monetary authorities tend to shift losses to taxpayers when deep or widespread insolvencies emerge (Honohan and Klingebiel, 2003; Veronesi and Zingales, 2010; Laeven and Valencia, 2011).

Authorities take refuge in the untested claim that it is in society's best interest to minimize the possibility of contagious defaults. This hypothesis leads them to short-circuit the default process by characterizing firms that are politically, economically, or administratively difficult to fail and unwind (DFU)[5] as "systemically important" and supporting a DFU firm's access to credit whenever difficulties in rolling over the firm's liabilities suggests it may have to become economically insolvent. Until and unless sovereign credit support loses its credibility, authorities can prevent widespread substantial spillovers of actual defaults across the private financial sector from actually taking place.

The goal of this paper is to propose a measure of systemic risk that is theoretically sound and easy to implement using publicly available financial and stock market data. Our methods are rooted in academic literature for modeling credit risk pioneered by Merton (1974). Merton models credit risk as a put option that stockholders write on firm assets. Merton (1977, 1978), Marcus and Shaked (1984), Ronn and Verma (1986), Duan, Moreau and Sealey (1992) and others have adapted this approach to express the value of US deposit insurance as if it were a one-year put option written by the Federal Deposit Insurance Corporation (FDIC). In this paper, we build on this tradition by modeling the losses to which banking-sector activity exposes taxpayers through the safety net as the value of the put option written on a portfolio of aggregate

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[5] Also referred to as the "too big to fail" problem.

bank assets with an exercise price equal to the face value of aggregate bank debt. This interpretation treats the taxpayer put as a market-completing contract and lets us calculate each individual bank's systemic risk as its contribution to the value of the banking sector's aggregate portfolio put. From a contracting perspective, the put is not an externality. The value of the put and predictions about forbearance are impounded into the stock price, borrowing rates, and margin requirements for derivative contracts of every firm whose economic insolvency is unlikely to be resolved promptly. It provides a gross estimate of the cost to taxpayers of insuring banks. Given that deposit insurance premiums tend to be close to zero in crisis circumstances it is a good approximation of the net costs as well.

We estimate our model over the period 1974-2010, using quarterly data on U.S. bank holding companies, allowing us to contrast the behavior of systemic risk during the financial crisis period 2008-2010 with its behavior in earlier recessions and crisis episodes.

The results portray our estimate of how private and governmental sources of systemic risk evolved during and in advance of a succession of business-cycle expansions and contractions, reaching an all time high at the peak of the 2008-2010 crisis period. We estimate the per-quarter value of systemic risk using financial statements from the Compustat database for U.S. banks and daily stock returns from CRSP. The cyclical and long-period patterns that our model generates conform to conventional wisdom about how sectoral risks actually varied over time. This supports our contention that our measures of stand-alone and systemic risk track the ways in which systemic risk has waxed and waned over the last four business cycles.

Our paper proceeds as follows. Section I interprets the safety net as a contracting structure that generates a contingent mix of benefits and obligations for taxpayers, regulators, and protected institutions. Section II explains the methods we use to model banking-sector exposure to default and individual banks' contribution to systemic risk. Section III describes the data sources and sampling procedures we use, and presents summary statistics on our estimates of sectoral and individual systemic risk. Section IV examines the evolution of sectoral and individual systemic risk over time. Section V analyzes the cross-sectional variation in sectoral and individual systemic risk. Section VI concludes by summarizing our findings.

I. Bank and Taxpayer Positions in the Safety Net

It is instructive to think of a country's safety net as an incomplete contracting structure. Contracts imbedded in this structure assign explicit and implicit responsibility for preventing, detecting, and paying for crippling losses at protected institutions. The parties to the contracts are regulators, nonbank taxpayers, and institutional stakeholders. Regulators may be conceived as parties to all safety-net contracts and to enjoy a great deal of *ex post* flexibility in setting and enforcing contract terms. Although counterparties cannot trade their positions in these contracts, they can alter their value by lobbying and other forms of political or hedging activity.

There is no reason to expect that the balance of costs and benefits from the safety net is the same either for all banks or for all nonbank taxpayers. For a sample of banks, this paper tracks the value of banks' individual and aggregate claims on the safety net over time. At each date, the value of an individual institution's claim on the safety net is the expected difference between the benefits of the particular protections it enjoys and the costs that safety-net administrators might impose upon it. Both costs and benefits may be treated as put options whose control rights lie in the hands of regulators who are understood to favor forbearance over prompt exercise. Protected institutions are *long* an option to put losses to other banks and nonbank taxpayers in various ways and *short* an option to cover its share of safety-net expenses, including the costs of replenishing the insurance fund for losses incurred at other banks. The costs in a bank's short position include explicit insurance premiums and various costs of complying with (and sometimes circumventing) burdensome restrictions that safety-net managers seek to impose on their operations.

Community banks have long complained that, on average, giant money-center and regional banks enjoy a more favorable mix of safety-net costs and benefits than they do. Our analysis provides a way to investigate and confirm this claim quantitatively.

We focus especially on the period 2008-2010, which coincides with the maturing of the mortgage securitization crisis that began in August, 2007. During that period, unprecedented losses were incurred by large and systemically important U.S. financial institutions in particular. A comprehensive review of salient events contributing to the crisis can be found in Gorton (2008), Laeven and Valencia (2008), Brunnermeier (2009), Adrian and Shin (2010), and Lo (2012).

Precisely what factors sustained the boom in mortgage credit in the United States during the decade prior to the crisis is a source of debate, though there is broad agreement that innovations in asset securitization, government policies to increase homeownership, cross-country imbalances in trade and savings flows, expansionary monetary policy, and weak regulatory oversight all played substantial roles (Keys et al. 2010). The boom was exacerbated by financial institutions' ability to exploit loopholes in capital regulation by moving assets off balance sheet and by funding themselves increasingly with wholesale and short-term instruments (Gorton 2008, Brunnermeier 2009, and Acharya, Schnabl, and Suarez, 2010). Higher asset prices supported a boom in leverage as increases in home values encouraged increases in debt (Adrian and Shin 2008, Mian and Sufi 2009). The asset price boom was further fueled by lax lending practices that caused an explosion of subprime and other nontraditional forms of mortgage credit (Dell'Ariccia et al. 2010). As losses in securitized loans deepened, their ultimate ownership became hard to verify and the reliability of banks' accounting reports fell increasingly into question. Banks no longer trusted each other, leading to a crisis in confidence that threatened the liquidity of strong and weak institutions alike.

However one ranks the relative influence of factors driving the crisis, the systemic risk of U.S. financial institutions increased dramatically during this period, and was aggravated by ad hoc and inconsistent policy responses (Kane, 2010). Authorities initially offered massive liquidity support to banks and lowered interest rates. The panic intensified after the collapse of Lehman Brothers (a major investment bank) and the first installment of the $180 billion program for rescuing the American International Group (which had developed an unparalleled amount of losses in derivatives positions). Both AIG and Lehman had global financial linkages, whose need for unwinding increased individual and systemic bank risk. The scale of interventions to recapitalize and support the banking system was unprecedented, and large banks were the major beneficiaries of these government programs. The anti-egalitarian pattern of the resulting wealth redistribution deepened popular concerns about the too-big-to-fail problem (Veronesi and Zingales, 2010).

Many studies propose other measures of systemic risk with which our results can be compared and contrasted. Lehar (2005) and Avesani, Pascual, and Li (2006) propose the probability of default as a measure of systemic risk, and they estimate this using CDS, option, and equity market data. Additional measures include: conditional value at risk (CoVaR) proposed by Adrian and Brunnermeier (2009), marginal expected shortfall (MES) proposed by Acharya, Pedersen, Philippon, and Richardson (2010) and extended by Brownlees and Engle

(2011), and a network-based systemic risk measure proposed by Cont (2010). Kim and Giesecke (2010) study the term structure of systemic risk and Billio, Getmansky, Lo, and Pelizzon (2010) compare several alternative systemic risk measures.

Our measure differs from these other measures of systemic risk in two important dimensions. First, our measure uses readily available stock market data on banking firms, unlike many of these other approaches to measuring systemic risk that rely on data that are either not readily available (such as data on financial networks and interconnectedness) or data that are available only for a small subset of firms (such as CDS spreads). Second, we do not explicitly measure the interconnectedness of banking firms, for which data is generally not readily available, although our measure of a banking firm's contribution to systemic risk gauges interconnectedness indirectly. We regard the ready availability of data a major advantage of our proposed measure of systemic risk. In both respects, our measure resembles that of Brownlee and Engle (2011) who focus on and extrapolate equity losses suffered during intervals that they designate as crisis periods.

I. Measuring Stand-Alone and Systemic Bank Risk

A. Structural Model of Bank Default

Our measures of stand-alone and systemic bank risk derive from the structural model of deposit-insurance benefits developed by Merton (1977). Merton assumes that the value of bank assets is governed by geometric Brownian motion and that bank liabilities have a zero coupon and mature in one year. One year is assumed to be the frequency of audit by bank regulators as well. At the time the debt is due, the bank is assumed to default if the asset value falls below the face value of debt. In earlier work, Merton (1974) showed that stockholders' stake in such a firm can be viewed as a call option on firm assets whose exercise price equals the face value of debt and whose tenor (i.e., option maturity) equals the maturity of the debt. These assumptions let us view the value of risky debt as the value of risk-free debt less the value of creditors' side of a put option on firm assets. Because it expresses the value of creditor loss exposure, this limited-liability put represents the fair cost of insuring bank creditors against losses due to default during the period it covers.

Our model portrays bank equity as a single-period European call option on the bank's assets and treats bank equity as the sum of a dividend-unprotected European call option and the present value of dividends distributed before the option's expiration date. The model expresses the value of a bank's equity, *E*, as:

$$E = DIV + (V - DIV)N(x_1) - DN(x_2)\ . \tag{1}$$

In (1), E is the value of bank equity, V is the value of bank assets, DIV is the present value of interim dividends distributed in the year before the debt becomes due, D is the face value of outstanding deposits and other debt, and $N(x_i)$ states the probability that the variate value x is ≤ x_i, given that x is distributed with zero mean and unit variance.[6]

The value of the limited-liability put can be extracted from the conservation-of-value condition that the value of bank assets equals the value of all claims on those assets:

$$LLP = E + D - V\ . \tag{2}$$

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[6] $x_1 \equiv \dfrac{\ln[(V - DIV)/D] + \sigma_V^2 T/2}{\sigma_V \sqrt{T}}$, $x_2 = x_1 - \sigma_V \sqrt{T}$, where σ_V is the instantaneous standard deviation of asset returns and T = 1 is the assumed maturity of debt.

Substituting equation (1) for E, the value of the limited-liability put becomes:

$$LLP = D(1 - N(x_2)) - (V - DIV)(1 - N(x_1)) . \tag{3}$$

The fair value of the annual premium for insuring a dollar of debt against creditor losses due to default can then be found by dividing the LLP value obtained in (3) by the face value of debt, *D*:

$$IPD = [1 - N(x_2)] - (V - DIV)[1 - N(x_1)] / D . \tag{4}$$

Because the explicit deposit insurance premiums that U.S. banks pay to the FDIC are minimal (prior to the recent crisis, 97 percent of FDIC-insured institutions paid zero premia to the FDIC), the fair value premium estimate can in most cases be interpreted as the subsidy a bank manages to extract from the safety net.

B. Measuring Stand-Alone and Systemic Bank Risk

There is a long tradition in the literature on deposit insurance to use the fair annual premium for insuring a dollar of deposits against depositor losses to measure fluctuations in the size of the FDIC's exposure to individual-bank default. Following this tradition, we make IPD as defined in equation (4) our measure of stand-alone bank risk. Using equation (4) requires knowledge of the value of bank assets, V, and asset risk, σ_V, which are not directly observable. Earlier literature [e.g., Marcus and Shaked (1984) and Ronn and Verma (1986)] solved this problem by estimating V and σ_V by numerical methods using two option-pricing equations. The first equation is the call-option formulation (1) for equity, E. The second equation links σ_V to E, V and σ_E as follows:

$$\sigma_V = \sigma_E(E/V) / N(x_1). \quad (5)$$

Our calculations use the following definitions. The value of equity, E, is calculated as the number of outstanding shares times the share price. The face value of debt, D, is calculated as the sum of the balance-sheet values of deposits (quarterly Compustat item DPTCQ), long-term debt (DLTTQ), debt in current liabilities (DLCQ), and preferred equity (PTSQ). The present value of the next four quarterly dividends, DIV, is calculated assuming that, for the next four quarters, the bank will pay the same dollar amount as the last quarterly cash dividends (DVCQ) and using the yield on one-year Treasuries.[7] The equity risk, σ_E, is measured as the annualized standard deviation of one year of daily stock returns. This approach to modeling and estimating individual bank risk has been applied in a large number of papers (see, for example, Pennacchi, 1987; Hovakimian and Kane, 2000).

Our goal is to use this framework to measure both: (1) the fragility of the entire banking sector (i.e. a portfolio of banks) as the value of the put option on the portfolio of aggregate sample-bank assets with an exercise price equal to the aggregate sample-bank debt, and (2) the contribution that each individual bank makes to this notion of systemic risk. The details of this calculation are as follows. At the end of each calendar month, we form a value-weighted portfolio of all sample banks. We then calculate daily portfolio returns for the 12-month period preceding the date of portfolio formation. In addition, we calculate this portfolio's market value as the sum of market values of component banks on the date of portfolio formation and portfolio

[7] In Figure 5, we contrast results for this "dividend forbearance model" with estimates in which bailout packages include an immediate "dividend stopper." As suggested by the intensity of troubled banks' efforts to use the outcomes of Federal Reserve stress tests to win permission to increase or resume dividends, estimates of IPD that ignore the possibility of dividend disbursements (such as Carbo, Kane, and Rodriguez, 2011) develop much smaller values.

debt as the sum of debt values of component banks as of the last fiscal quarter ending on or before the date of portfolio formation. For example, for the portfolio formed on June 30, 2000, we use stock returns from July 1, 1999 to June 30, 2000, market values of equity as of June 30, 2000, and book values of debt as of June 30, May 31, or April 30, depending on the end of the last fiscal quarter of each bank. In forming these portfolios, we limit the sample to banks with non-missing values of market value of equity, book value of debt, and at least 246 reported daily returns.

We use these portfolio values to solve equations (1) and (5) numerically for the synthetic values of banking-sector assets, V_{BS}, and banking-sector asset risk, σ_{VBS}. We plug these values into equation (4) to obtain a fair value of the premium appropriate for insuring a dollar of debt against losses that would be generated by a hypothetical default of the whole banking sector, IPDBS. Because the values of the assets held by various banks are imperfectly correlated, the value of the put option on the portfolio of bank assets is less than the value of the portfolio of put options on assets of individual banks. To the extent that this correlation varies over time, the time profile of our sectoral risk measure will diverge from the time-series profile of the average of individual-bank IPD's.

We estimate an individual bank's *systemic risk* as its contribution to the sectoral IPD. Specifically, for each bank *i* and month *t*, we modify our overall bank portfolio by removing this particular bank from the portfolio and using the procedure we have just described to estimate the hypothetical insurance premium for a sectoral portfolio that excludes bank *i*: $IPDBS_{i,t}$. At each date, t, an individual bank's systemic risk emerges as the difference between the insurance premium for the portfolio that includes the bank and the insurance premium for the portfolio that excludes it:

$$IPDS_{i,t} = IPDBS_t - IPDBS_{-i,t} . \tag{6}$$

Our procedures for calculating the insurance premia from option-pricing equations (1)-(6) incorporate a number of simplifying assumptions. These include assumptions about the structure and the characteristics of debt and the assumption that regulators resist pressure for forbearance and shut down economically insolvent banks promptly. Such assumptions introduce measurement errors into our estimates and limit the economic significance of the numerical values of individual estimates. Nevertheless, the risk measures we develop rise and fall appropriately over recognized business cycles and crisis periods, which establishes a presumptive case for their qualitative usefulness and reliability. On the hypothesis that the measurement errors do not vary systematically across banks and across time, our estimates can serve both as a timely guide to the ebb and flow of the systemic risk posed by the banking sector as a whole and as a way to identify specific institutions whose activities impose substantial risk on the safety net. The advantage of our method is that it is easy to implement using readily available data, unlike other methods that require data that are not readily available, such as information on counterparty risk and interbank exposures, or data that are available only for a subset of firms, such as CDS spreads.

Our measure of an individual bank's contribution to systemic risk reflects the spillovers imposed on other banks when the bank fails (for example, through interbank exposures). However, our measure of systemic risk [as is the case for other methods relying on stock price data to measure systemic risk (e.g., Acharya et al. 2010)] cannot capture knock-on effects on employment and economic growth. As such, it is likely to underestimate the true value of systemic risk.

Our measure of systemic risk is related to, but different from systematic risk. Systematic risk is typically measured by the beta coefficient that a firm's equity return receives in market-model regressions. Our measure of systemic risk captures the expansion of systematic risk in extreme circumstances (as evidenced by the high realizations of our measure during the recent crisis). But our measure of systemic risks captures linkages between the systematic risks of sample banks. These linkages transfer extreme risks from one or a few banks across the system and threaten its integrity.

II. Sample Selection, Data, and Summary Statistics

Our sample consists of commercial banks (with a 3-digit SIC code value of 602) with at least one million dollars in total assets. Bank-level data from 1974 through 2010 are constructed from two sources. Daily stock prices and returns are obtained from CRSP. Quarterly balance-sheet accounting data come from Bank Compustat. Macroeconomic data, such as the consumer price index (CPI) and one-year Treasury yields, are downloaded from the website maintained by the Federal Reserve Bank of St. Louis.[8] To guard against reporting errors in data collection, observations generating extremely high values (above the ninety-ninth percentile) for our variables are trimmed away. Annualized standard deviations for stock returns are calculated using daily returns and a screen requiring a minimum of 246 non-missing returns within the year. These screening criteria leave us with 36,217 bank-quarter observations.

Table 1 reports the number of sample observations and the mean values of assets and Tier 1 capital. The number of sample banks starts at 340 in 1974, increases steadily during the 1970s,

[8] http://research.stlouisfed.org/fred2/. Unfortunately, employing this mix of sources resulted in excluding Citigroup, Fannie Mae, and Freddie Mac from our sample. But including these zombie firms is bound to strengthen our finding that smaller banks have been disadvantaged by the bailout policies federal regulators have pursued.

remains stable in 1980s, then almost doubles in 1994 and remains relatively stable during the rest of the sample period. Average asset size for sample banks tends to grow over time, except it drops substantially in 1994 when the Compustat database for banks expanded its coverage to include a large number of relatively small banks. Tier 1 capital ratios, which are available from 1993 on, hover around 11-12% with no discernible trend. The remaining sections of the paper explore the time-series and cross-sectional behavior of our measurements.

III. Aggregate Time-Series Results

A. *Variation in stand-alone and systemic risks over time*

In this section, we examine the time-series behavior of differently aggregated measures of bank risk. For each of the 148 calendar quarters from 1974 to 2010 and for each sample bank, we calculate mean values for the individual insurance premium, IPD, implied volatility of assets, σ_V, implied capital ratio, E/V, and Tier 1 capital ratio. The quarterly time series of mean IPD values (i.e., stand-alone risk) is plotted in Figure 1. The chart shows that the mean value of IPD at sample banks surged during cyclical contractions. Moreover, as bankers came to understand the benefits they could extract by expanding their exposure to tail risk, the mean value of the stand-alone put grew larger in each successive business cycle. Because the number of banks in the sample more than doubles in the fourth quarter of 1993, data before and after that date must be compared cautiously. Nevertheless, from a strategic point of view, these data show the dangers of trying – as envisioned in the Basel system of capital control – to contain the taxpayer put *only* by regulating the book value of bank leverage. The data show that, while implied capital

(Figure 2) and implied asset volatility (Figure 3) fluctuated substantially over each cycle, during the sample period the value of on-balance-sheet Tier 1 capital (Figure 4) changed hardly at all.

Although IPD and implied capital and asset volatility are not publicly reported or explicitly monitored by banking regulators today, our methods have the advantage that they can be estimated from publicly available data. Unlike methods that rely on the prices of credit default swaps or on data measuring interbank exposures to one another, stock-price and balance-sheet data are readily accessible.

Swings in our synthetic measurements prove much more extensive than the directly observable swings in on-balance-sheet capital depicted in Figure 4. It is clear that although accounting leverage declined during the 1990s, hidden leverage greatly expanded in advance of the crisis. The difference between reported and opportunity-cost values of leverage underscores the dangers of trying to control a bank's risk-taking by controlling its reported risk-weighted capital position. To control systemic risk, it is necessary also to allow for the effects of the innovative ways in which bank managers arbitrage patterns of fixed risk weights and unchanging statistical definitions of regulatory capital.

Increases in individual-bank risk are especially worrisome when they propagate through the banking sector. Figure 5 plots the time-series behavior of sectoral IPD (IPDBS). The chart underscores the extraordinary depth of the current financial crisis. A comparison of Figures 1 and 5 shows that, although pre-2008 financial crises led to substantial increases in mean IPD's, the aggregate risk of the banking sector remained low because significant parts of the financial system remained sound. As a result, prior to 2008 even without a dividend stopper, the insurance premium for the sectoral portfolio never exceeded a few basis points. In contrast, in 2009, our dividend-forbearance model shows an IPD of 600 basis points, but this value could be cut almost in half by a dividend stopper. In addition to the effect of sharp increases in average bank IPDs, this surge was driven by an increased correlation in credit risk within the banking sector. Figure 6 reports average correlations of individual-bank returns with an equal-weighted portfolio of sample banks. This chart shows that correlation between individual-bank returns grew in advance of systemic distress, and grew especially sharply during the years leading up to the current crisis.

Figure 7 plots the time-series behavior of the cross-sectional mean of our measure of individual-bank systemic risk. The mean value of systemic risk is small and moves only slightly during most of the sample period, but in 2008-2010 the mean value surges dramatically, reaching -470 basis points in 2009. Attaching a negative sign to these values may seem counterintuitive and surprising at first. Our interpretation of this result is as follows. During a very deep financial crisis, bank asset and equity values become more positively correlated, especially at very large and interconnected banks. This means that the benchmark sectoral portfolios become much less diversified and that adding a large bank to the sectoral portfolio offers little or no diversification or financing benefit. On the other hand, assuming that small banks have very different business plans and risk exposures than large banks, their asset values and survival would not be greatly threatened by the collapse of the securitization and mortgage-lending bubbles. During crisis periods, these banks give more support to the safety net than the safety net gives them in return.

An average bank in our sample is a relatively small bank. A negative mean value for individual-bank systemic risk during the crisis years implies that the future premiums and regulatory burdens regulators are likely to place on the assets of smaller banks exceeded the current costs of supporting these banks' liabilities. As explained in the next section, even though the contribution to mean systemic risk becomes negative during the crisis period, the systemic risk of *particular* sample banks became positive and very large during this period.

The results presented in Figures 1-7 are summarized in Table 2. The table reports mean values separately for the precrisis period (1974-2007) and crisis years (2008-2010). Both statistically and economically, stand-alone risk (IPD) and sectoral risk (IPDBS) run significantly higher during the crisis period. The table reports values in two ways: per dollar of debt (in basis points) and in dollar value. While mean per-dollar values are negative, mean dollar values of IPDBS are positive. This implies that larger banks tend to increase the aggregate cost of insuring the debt of the sectoral portfolio and that, on average, smaller banks help taxpayers to finance this cost. In keeping with the literature on regulatory arbitrage, asset and equity risks became significantly higher and implied bank capital significantly lower during the crisis period. In contrast, the differences in these periods between Tier 1, Tier 2, and Tier 3 capital ratios are insignificant. These findings support Dodd-Frank and Basel proposals to impose a capital surcharge or incremental dollar premium based on very large size.

As noted earlier in this section, the time trends and patterns presented in Figures 1-7 and our first two tables are consistent with small-bank complaints and with academic understanding of how the true risks varied over time. We offer this as evidence that our measures of stand-alone and systemic risk capture the broad outlines the behavior of these risks.

B. Time-series forecasts of commercial banking sector risk

An important academic and practical question is whether increases in sectoral risk can be predicted and, if so, what explanatory factors might be identified. .Table 3 reports on regression models that use current values of bank sectoral risk to forecast future sectoral risk at one-to-twelve month forecating horizons. At the 1-month horizon, predictive power is strong: the slope coefficient is 0.901, the t-statistic is 43.6, and R^2 is 0.812. The magnitude and significance of the slope and therefore model fit) decline monotonically as the forecast horizon grows. At the 9-month horizon, the slope is no longer significant and the R^2 of the regression becomes trivial. These results suggest that rising levels of sectoral risk can serve as early-warning indicators of further increases over the next few months and could be used to frame a forward-looking policy response to evidence of impending crisis.

We next expand the forecasting model to examine whether business-cycle and banking-industry characteristics might also help predict future systemic crises. We introduce two business-cycle variables: the US growth rate in real GDP and a recession indicator based on NBER business-cycle expansion and contraction data. To measure banking concentration, we use a Herfindahl index constructed based on the book values of sample-bank assets. Panel A of Table 4 reports the results of regressions using current values of the NBER business-cycle variable to predict systemic sectoral risk contemporaneously and at horizons extending from one to twelve months. The recession indicator significantly predicts sectoral risk at every horizon. The GDP growth rate has a significantly negative effect on bank sectoral risk up to a four-month horizon, with no discernible trend. At longer horizons, the magnitudes and the significance of the growth-rate estimate declines and becomes insignificant beyond the 6-month horizon. R^2 lies in the 16% to 18% range at horizons of 4-months or less. For longer horizons, the influence of the growth rate declines monotonically, falling to about 5% at the12-month horizon.

Panel B of Table 4 adds the sectoral Herfindahl index to the set of predictors. The results show that when the banking sector becomes more concentrated, (i.e., as the Herfindahl index rises) sectoral risk rises, too. The effect of the Herfindahl index is statistically significant at all horizons and the R^2 of individual regression models stands about ten percentage points above corresponding regressions that omit the Herfindahl variable. These results suggest that the increasingly concentrated structure of the US banking system in recent years may have increased its susceptibility to systemic crisis. While we would not recommend an interventionist turn in industrial-organization policy based on a single study and a mere 27 years of data from a limited panel of banks, we regard our work as providing another drop in a rapidly filling bucket of evidence that megabanking firms could be dangerous to our nation's financial health.

IV. Bank-level Results

A. *Univariate results*

This section focuses on variations in stand-alone risk (IPD) and systemic risk (IPDS) across individual banks. We start by examining the impact of bank size on stand-alone and systemic risks. For each year and quarter, we sort banks into size quartiles, based on the book value of their assets. For each quartile, Table 5 contrasts the mean values of key variables during the precrisis period (1974-2007) and crisis years (2007-2010). Results are qualitatively unaltered if we partition the sample by medians rather than means.

In both periods, stand-alone risk tends to decrease across the first three size quartiles but backs up a bit in quartile 4, while remaining below the levels shown for quartiles 2 and (especially) quartile 1. This arrangement holds both before and during crisis years. The pattern characterizes the smallest banks as posing the largest stand-alone risks. But the pattern is different for systemic risk, which increases monotonically across size quartiles. This further supports the hypothesis that a country's largest banks are the main source of systemic risk. This finding holds in both periods. However, before the crisis, the difference we observe between the smallest and the largest quartiles is a mere 0.027 basis points. During the extreme or "tail" events of the crisis, the difference surges to 148 basis points, a number that is significant economically and statistically.

Interquartile patterns of variation in equity, asset volatility, and implied capital resemble those shown for stand-alone risk. Equity and asset risk tend to be highest and implied capital ratios tend to be lowest for the smallest banks. Tier 1 capital ratios vary only slightly and are highest for small banks.

Table 5 indicates that banks that pose high stand-alone risk differ from those with high systemic risk: stand-alone risk falls with asset size, while a bank's contribution to systemic risk increases with size. This shows that systemic risk does not arise as aggregation of individual-bank stand-alone risk.

Table 6 shows how different the top ten sample banks for stand-alone risk (Panel A) are from the ten banks that posed the most systemic risk (Panel B). These lists do not overlap in even a single instance. As in Table 5, high stand-alone risk is found in small banks, but high systemic risk is posed by very large banks. Table 6 also suggests that stand-alone risks are better disciplined than systemic risks. Focusing on the ten sample banks with the highest stand-alone risk, by the end of our sample period, six had been shut down by regulators, three were subject to consent orders, and one had been acquired. At this writing, none of the leaders in systemic risk has been subjected to any of these definitive treatment protocols.

Table 7 identifies the largest financial institutions in our sample by assets. It also states the maximum stand-alone and systemic risk premiums they experienced. The high levels of these maxima underscore how much value federal credit support contributed to these banks and their counterparties given the subsidized terms on which it was supplied.

Next, we assess the validity of our measure of systemic risk by comparing our estimates with those obtained from stress tests conducted by regulators and with existing measures of systemic risk proposed in the literature. Specifically, we compare our measure of systemic risk with the capital shortfall calculated in the supervisory Capital Assessment Program conducted in February 2009 (referred to as SCAP) and with the Marginal Expected Shortfall (MES) calculated by Acharya et al. (2010) from data in periods during which stock market returns lie below their fifth percentile (taken to represent extremely bad outcomes). For 18 of the institutions that the Fed stress-tested in March 2009, Table 8 compares our risk measures for the second quarter of 2009 with the indices of capital shortfall prepared by the Federal Reserve and Acharya et al. (2010) for these firms.

The correlation between our measure and the SCAP measure of capital shortfall is 0.8, indicating that our more timely and simpler-to-compute measure of systemic risk is a good approximation for complicated regulatory efforts to measure capital shortfall at major financial institutions. This supports the usefulness and validity of our measure of systemic risk. Still, our data suggest that a number of banks, including Wells Fargo, Fifth Third Bancorp, American Express, Suntrust Banks, and US Bancorp, may have generated far more systemic risk than suggested by SCAP and suspected by regulators. The correlation with the MES measure of capital shortfall developed by Acharya et al. (2010) is lower at 0.2. Although this correlation is statistically significant, the low value suggests that regulators might find both approaches useful in gauging systemic risk.

B. Regression Evidence of Other Influences on Stand-Alone and Systemic Risk

The univariate analysis presented thus far suggests that bank size is a key driver of systemic risk. However, relating risk only to size is apt to exaggerate its effect on risk appetites. We think it is useful to consider the effects of at least a few other variables on stand-alone and systemic risks.

This section introduces controls for two determinants of credit risk: leverage and asset volatility. Our method of calculating IPP makes stand-alone risk an explicit function of leverage and asset volatility, and these variables' contribution to systemic risk is obviously substantial. In addition, one might expect stand-alone risk to increase with the weight of insured deposits in an organization's funding structure since non-deposit debtholders have a stronger incentive to worry about risk-shifting than depositors do. A similar effect might be observed even for systemic risk. However, on the dual hypothesis that systemically important banks tend to have more complex balance sheets and that complexity raises the odds that an institution will be allowed to operate for long periods as a government-supported zombie, then banks with high deposit-to-asset ratios may prove less risky systemically.

Table 9 reports multiple regression equations for our measures of stand-alone risk (Panel A) and systemic risk (Panel B), using size, deposits, leverage, and asset volatility as regressors. Because substantial variation occurs in sectoral credit risk over time, we adopt a Fama-MacBeth framework. This means that we estimate regressions separately for each quarter and analyze the distribution of coefficients that emerges. In particular, we study the means of various time-series of regression estimates and t-statistics calculated using the standard deviations of each time-series of quarterly coefficient estimates. Inference focuses on the number of coefficient estimates that show the same sign as the time-series mean. Significance tests are conducted for the full sample period 1974-2010 and for the 1974-2007 and 2008-2010 periods separately. We choose the breakpoint to isolate the recent crisis episode.

The tests indicate that systemic risk does not arise as the simple aggregation of individual-bank risk and that systemic risk is related to asset risk and leverage in a substantial way. Once we control for leverage and asset risk, the negative effect of size on *stand-alone* credit risk actually disappears. The size effect proves insignificant in the full sample and in both subperiods. But the positive influence of size on *systemic risk* remains significant even with these controls and is especially strong during the 2008-2010 crisis period. This reinforces our earlier finding that bank size is a key driver of systemic risk.

The significantly positive effect of deposits on stand-alone risk is consistent with the hypothesis that deposit insurance intensifies moral-hazard incentives at insured financial institutions and leads to higher individual-bank risk exposures. Nevertheless, the deposit effect proves negative for systemic risk, albeit insignificantly so during the crisis period. This pattern of results is consistent with the hypothesis that authorities' rescue option provides banks with more complex balance sheets forms of implicit credit support that tempt such firms to make themselves systemically riskier.

V. Summary and Conclusions

The ongoing global financial crisis has underscored the need to devise a timely and comprehensive measure of the risk that individual institutions impose on the financial system as a whole. This paper introduces a theoretically sound measure for systemic risk that is easy to implement using publicly available financial and stock market data.

The value of a firm's taxpayer put represents the government's implicit equity stake in its future operations. Unless this stake is monitored and serviced at a market rate of return, beneficiary firms are incentivized to increase the value of their put by undertaking excessively risky and hard-to-monitor balance-sheet positions. Bubbles in the prices of hard-to-regulate assets caused by these risk-shifting activities harm the real economy by diverting resources from more appropriate activities. Crisis-management policies that unconditionally support the credit of large zombie firms prolong macroeconomic downturns. They do this by encouraging their managers to engage in gambles for resurrection (as exemplified by the disastrous endgame gambles undertaken by the American Insurance Group (AIG) and MF Global) rather than looking patiently for loans and investments that reliably create new jobs and sustainable profits.

The paper shows that the time trends and patterns in our aggregate and individual measures of systemic risk are consistent with the outcome of formal stress tests and with popular and academic understanding of how the true risks varied over time and across institutions. In particular, we find that bank size is a key driver of systemic risk. We conclude that our measures of systemic and stand-alone risk capture the qualitative behavior of these risks. We believe our methods provide a useful starting point for improving procedures for monitoring the buildup of systemic banking pressure and for identifying institutions whose activities generate dangerously large amounts of systemic risk. Obviously, further research can refine our methods and further contribute to understanding the drivers of systemic risk. For academics and regulators alike, the ultimate goal is to improve the effectiveness of policy interventions meant to establish macroeconomic and financial stability.

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Figure 1. Mean Value of IPD Using the Dividend-Forbearance Model for sample U.S. bank holding companies, 1974-2010 (quarter by quarter in basis points)

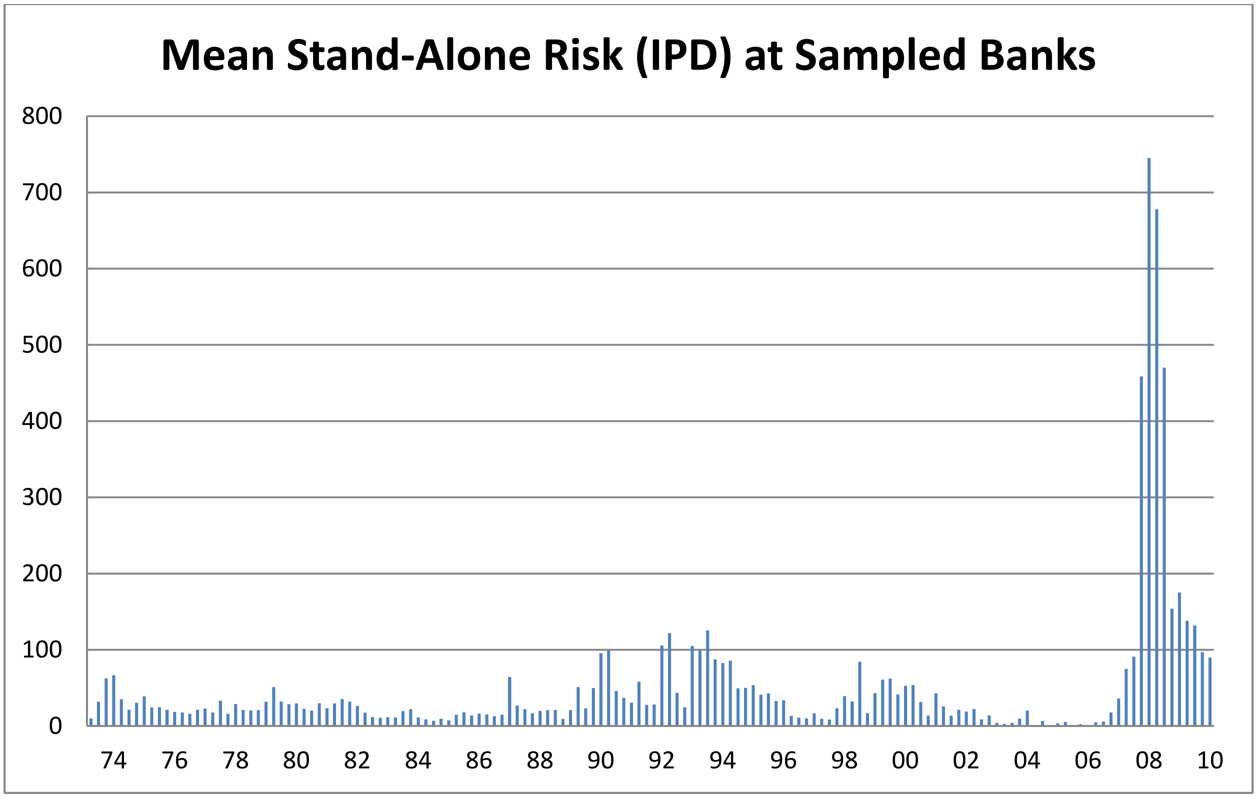


Figure 2. Mean Ratio of Model-Implied Equity Capital to Assets at Sampled U.S. bank holding companies, 1974-2010 (quarter by quarter in percent)

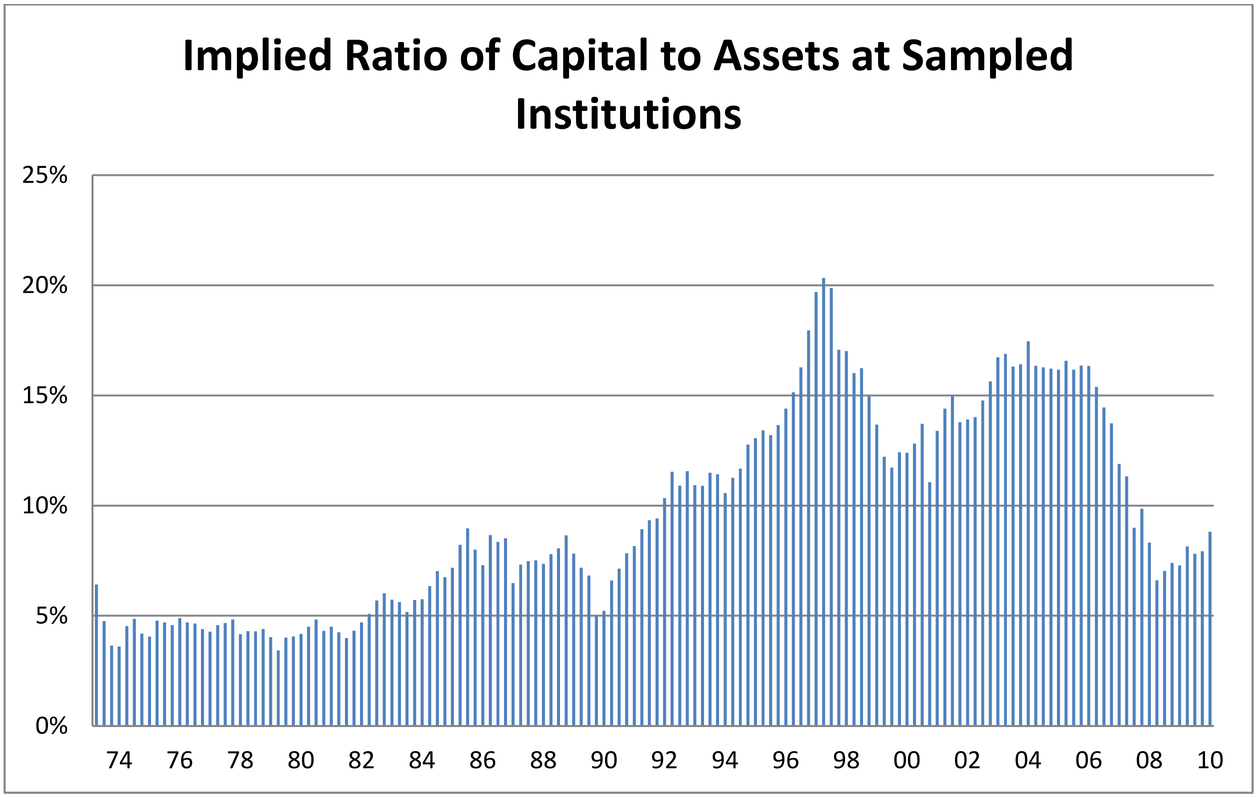


Figure 3. Mean Value of Implied Asset Volatility at Sampled U.S. bank holding companies for Model assuming continuing dividend forbearance, 1974-2010 (quarter by quarter expressed as a decimal fraction)

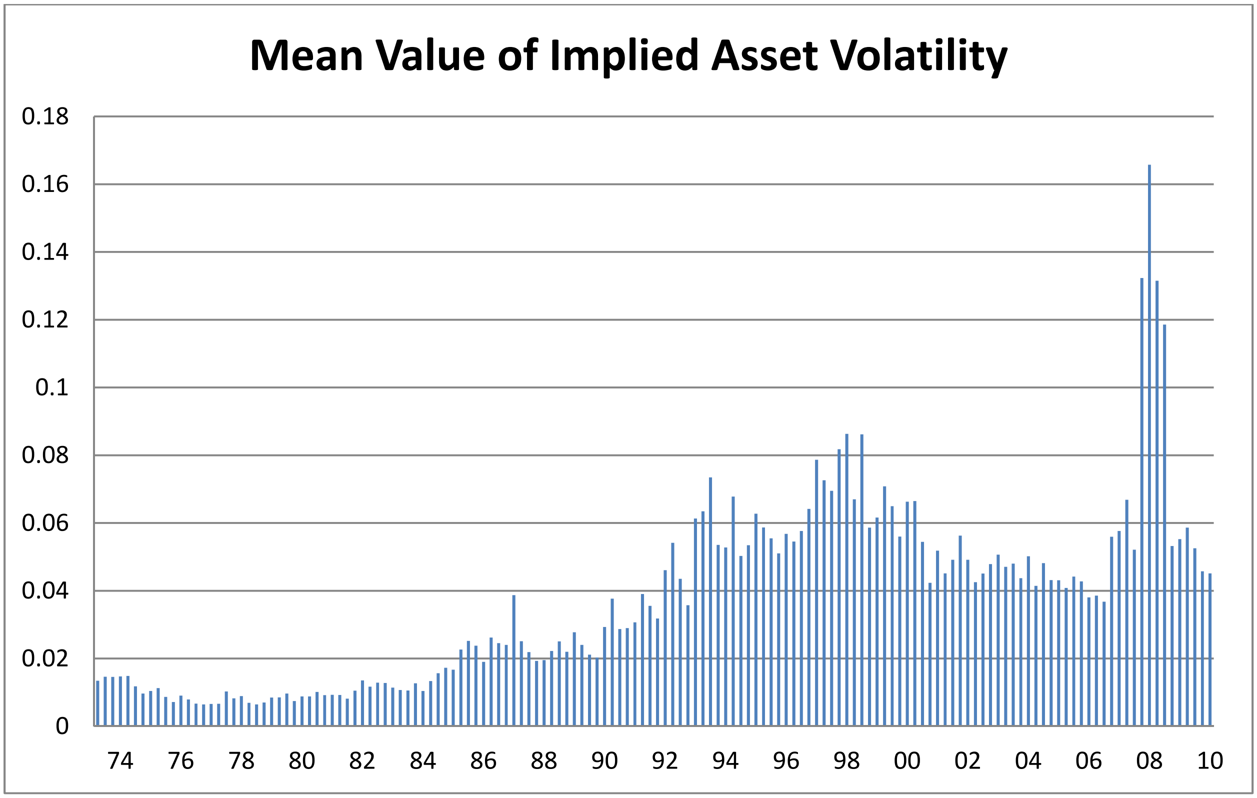
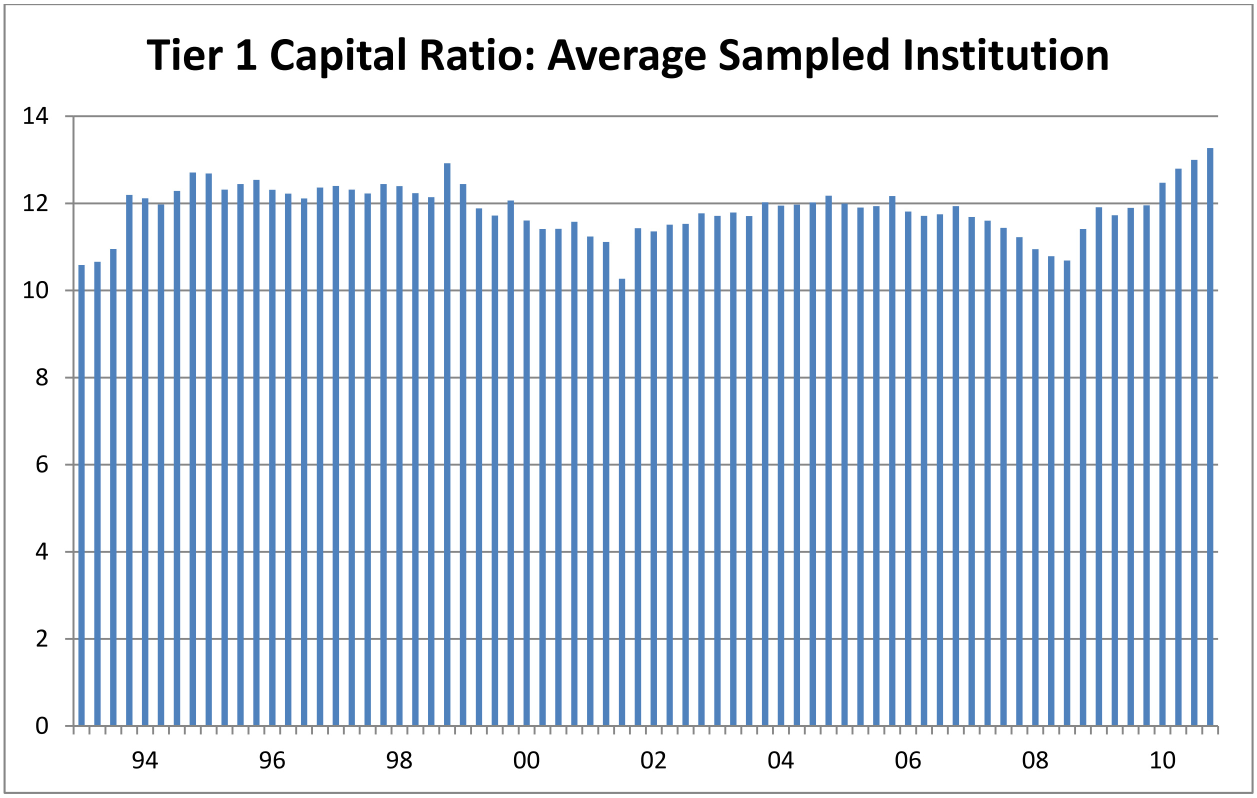
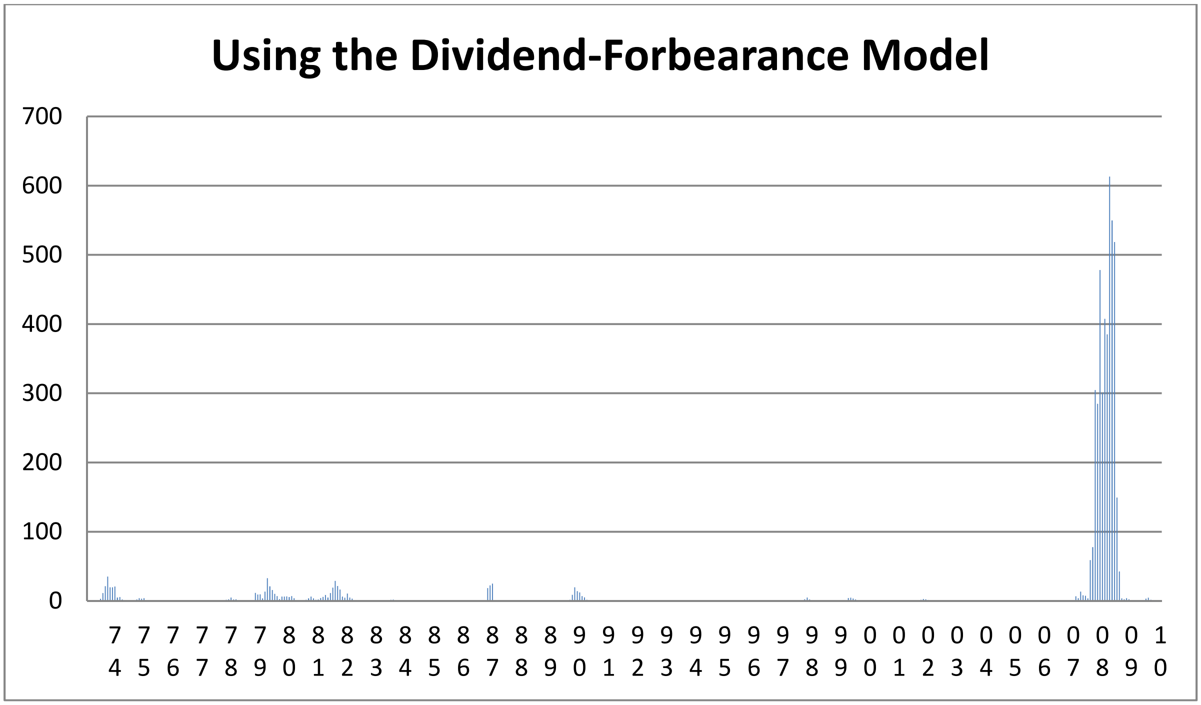


Figure 4. Mean Ratio of Tier-1 Capital to Assets at Sampled U.S. bank holding companies, 1993-2010 (quarter by quarter in percentage points)



Sources: Described in text

Figure 5. Sectoral Stand-Alone Risk Premium (IPD) for Sampled U.S. bank holding companies, 1974-2010 (quarter by quarter in basis points)



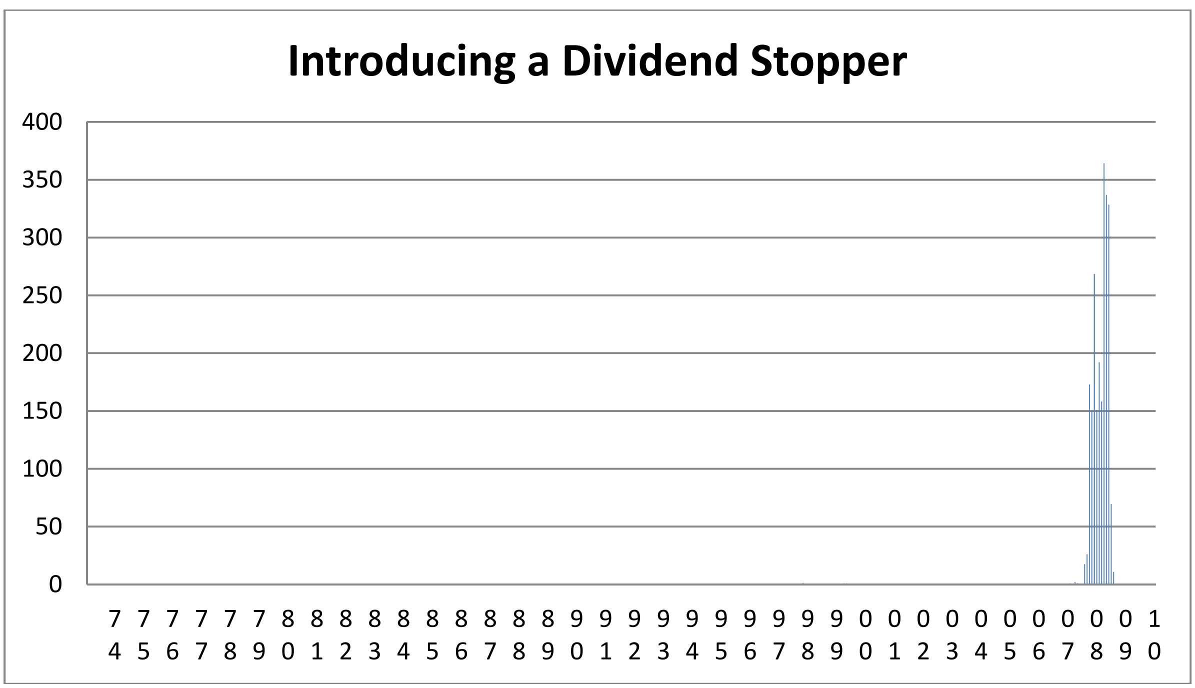


Figure 6. Average correlation between returns on an individual bank stock and bank sectoral portfolio, 1974-2000 (by quarter number as a decimal fraction).

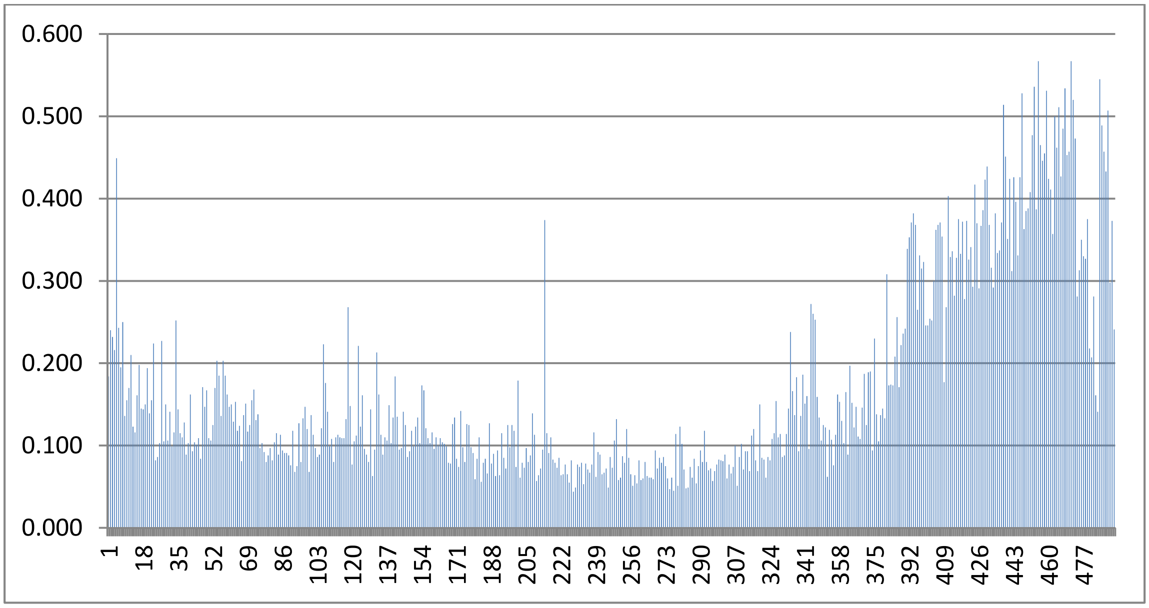


Figure 7. Mean individual-bank systemic risk premium (IPDS) at sampled U.S. bank holding companies using the Dividend-Forbearance Model, 1974-2010 (quarter by quarter in basis points)

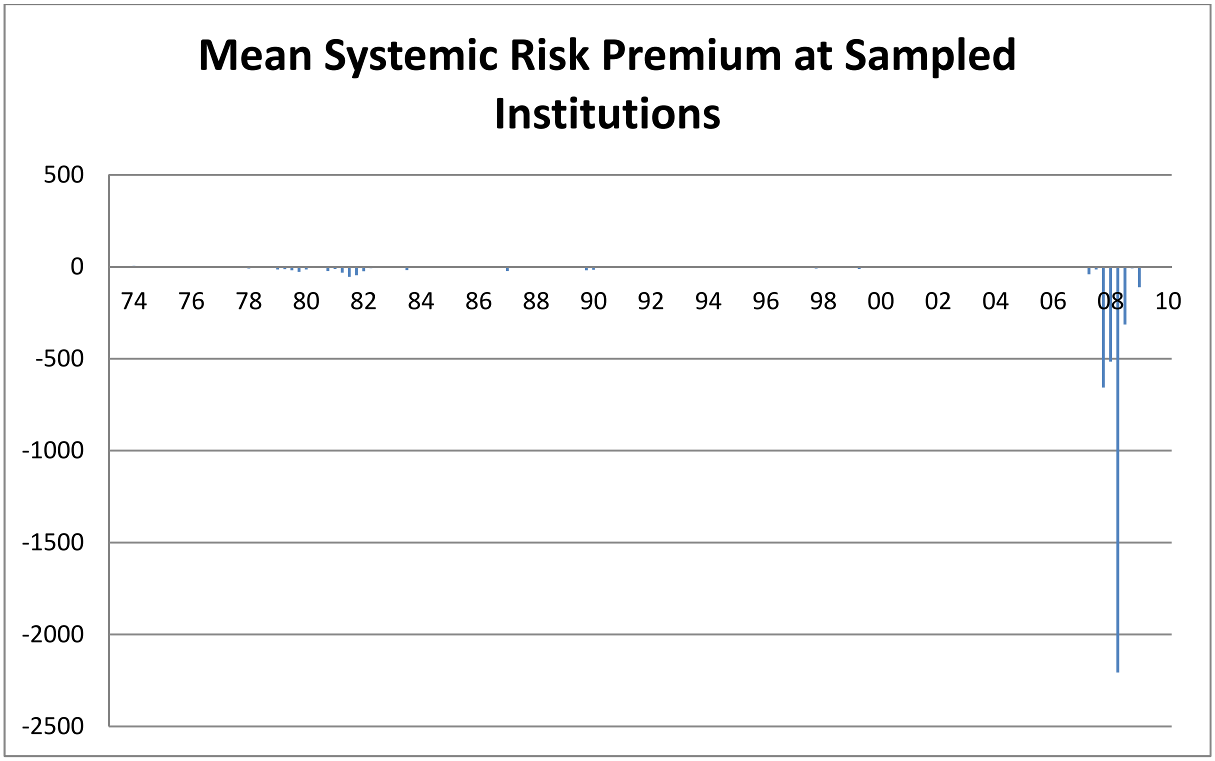


Figure 8. Mean systemic risk premium (IPDS) using the Dividend-Forbearance Model at large sampled U.S. bank holding companies, 1974-2010 (quarter by quarter in basis points)

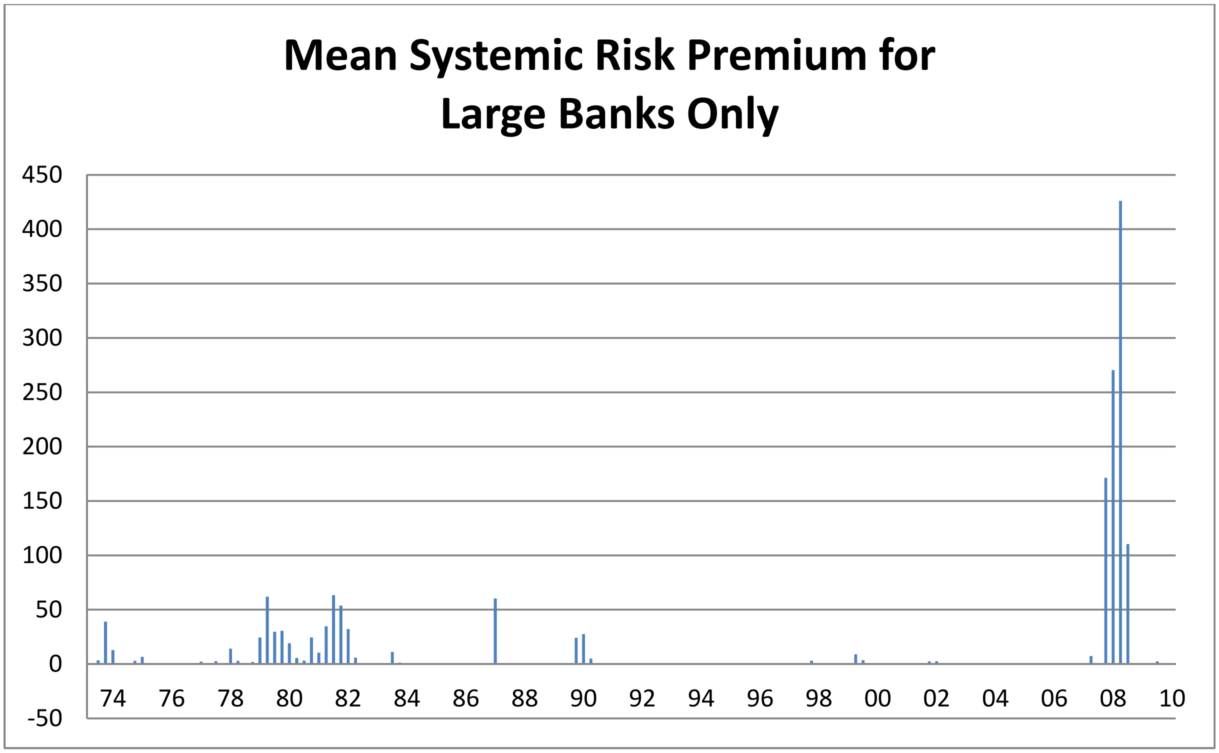


Table 1. Variation in Sample Size, Book Value of Assets, and Mean Tier-1 Capital Ratios, annually 1974-2010. (Asset values are stated in millions of dollars and Tier 1 capital is reported as a percentage).

Year	Book Value of Assets	Tier-1 Capital Ratio	Number of Observations (N)
1974	4,874		506
1975	4,915		514
1976	5,202		515
1977	5,851		515
1978	6,215		568
1979	7,088		572
1980	7,908		573
1981	8,762		574
1982	8,216		683
1983	8,787		684
1984	9,853		662
1985	10,500		685
1986	11,944		675
1987	12,776		674
1988	13,191		637
1989	14,244		639
1990	14,751		636
1991	14,567		685
1992	15,347		651
1993	12,832	11.49	864
1994	7,550	12.29	1,713
1995	8,177	12.50	1,728
1996	8,757	12.26	1,656
1997	9,779	12.35	1,637
1998	10,559	12.45	1,631
1999	10,018	12.03	1,703
2000	10,040	11.50	1,803
2001	10,345	11.26	1,342
2002	10,995	11.55	1,765
2003	11,856	11.82	1,804
2004	12,785	12.03	1,762
2005	14,249	12.01	1,769
2006	15,640	11.81	1,749
2007	17,766	11.48	1,663
2008	21,032	10.96	1,553
2009	23,820	11.87	1,450
2010	25,647	12.88	1,368
	Sample mean = 12,173	Sample mean = 11.93	Total N = 41,319

Table 2. Contrasting Behavior of Mean Values of Focal Variables for Model Assuming Dividend Forbearance: 1974-2007 and 2008-2010

Variable	1974-2007	2008-2010
Stand-alone risk, IPD (bp)	31.110	276.769
Stand-alone risk ($MM)	14.220	750.160
Systemic risk, IPDS (bp)	-2.480	-326.302
Systemic risk ($MM)	0.840	219.749
Equity volatility (%)	0.326	0.737
Asset volatility (%/100)	0.043	0.082
Market capital (%)	8.869	1.321
Tier 1 capital (%)	11.938	11.876
Tier 2 capital (%)	1.995	1.684
Assets ($MM)	10.957	23.401
Average number of banks	266	361

Table 3. Time-series regressions predicting commercial banking sector risk at various horizons using its current values.

Forecast horizon	Coef.	t	R^2	Observations
1 month	0.901**	43.6	0.812	443
2 months	0.814**	29.4	0.662	442
3 months	0.644**	17.7	0.415	441
4 months	0.571**	14.6	0.326	440
5 months	0.458**	10.8	0.210	439
6 months	0.386**	8.7	0.149	438
7 months	0.250**	5.4	0.062	437
8 months	0.154**	3.2	0.024	436
9 months	0.057	1.2	0.003	435
10 months	0.015	0.3	0.000	434
11 months	-0.009	-0.2	0.000	433
12 months	-0.014	-0.3	0.000	432

Table 4. Time-series regressions predicting commercial banking sector risk using business cycle and banking structure variables. Recession indicator is based on NBER US business cycle expansion and contraction data. GDP growth is the real GDP growth rate. Herfindahl index is calculated based on book asset values of sample banks.

Panel A.

Forecast horizon	Recession indicator	t-stat	GDP growth	t-stat	R^2	Obs.
0 months	35.710**	3.9	-17.590**	-4.3	0.166	444
1 month	32.827**	3.6	-20.214**	-5.0	0.180	443
2 months	30.864**	3.4	-21.483**	-5.3	0.185	442
3 months	31.208**	3.4	-20.768**	-5.1	0.179	441
4 months	33.224**	3.6	-18.789**	-4.6	0.167	440
5 months	37.675**	4.0	-15.241**	-3.7	0.151	439
6 months	43.905**	4.6	-10.507**	-2.5	0.136	438
7 months	51.202**	5.4	-5.031	-1.2	0.125	437
8 months	55.760**	5.8	-0.805	-0.2	0.117	436
9 months	59.762**	6.2	3.397	0.8	0.110	435
10 months	56.551**	5.8	4.870	1.1	0.092	434
11 months	54.169**	5.5	6.754	1.5	0.077	433
12 months	41.689**	4.2	3.695	0.8	0.049	432

Panel B.

Forecast horizon	Recession indicator	t-stat	GDP growth	t-stat	Herfindahl index	t-stat	R^2	Obs.
0 months	36.626**	4.2	-12.043**	-3.1	0.061**	7.9	0.268	444
1 month	33.414**	3.9	-15.011**	-3.8	0.058**	7.4	0.272	443
2 months	31.146**	3.6	-16.569**	-4.2	0.056**	7.0	0.268	442
3 months	31.205**	3.6	-16.109**	-4.1	0.054**	6.7	0.255	441
4 months	32.948**	3.7	-14.287**	-3.6	0.053**	6.4	0.239	440
5 months	37.131**	4.1	-10.846**	-2.7	0.053**	6.2	0.221	439
6 months	43.084**	4.7	-6.175	-1.5	0.053**	6.1	0.204	438
7 months	50.200**	5.5	-0.613	-0.1	0.054**	6.1	0.194	437
8 months	54.556**	5.9	3.734	0.9	0.056**	6.1	0.188	436
9 months	58.336**	6.3	8.095	1.9	0.058**	6.3	0.184	435
10 months	54.918**	5.9	9.806*	2.3	0.060**	6.4	0.170	434
11 months	52.310**	5.6	11.971**	2.8	0.063**	6.6	0.161	433
12 months	39.627**	4.1	9.095*	2.1	0.065**	6.5	0.136	432

Table 5. Comparison of Mean Value of Focal Variables for Model Assuming Dividend Forbearance Across Asset-Size Quartiles in 1974-2007 and 2008-2010

	1974-2007				2008-2010			
	Quartile 1	Quartile 2	Quartile 3	Quartile 4	Quartile 1	Quartile 2	Quartile 3	Quartile 4
Stand-alone risk, IPD (bp)	71.533	17.883	11.732	14.830	440.591	203.905	209.659	227.877
Stand-alone risk ($MM)	1.777	2.335	3.575	50.133	17.583	20.949	46.245	2,892.314
Systemic risk, IPDS (bp)	-4.918	-3.642	-1.857	0.376	-731.628	-326.920	-161.597	-65.732
Systemic risk ($MM)	-0.558	-0.749	-0.675	5.491	-19.836	-31.156	-35.567	968.260
Equity volatility (%)	0.391	0.323	0.301	0.276	0.852	0.686	0.711	0.680
Asset volatility (%)	0.054	0.041	0.039	0.036	0.109	0.064	0.068	0.083
Market capital (%)	11.225	11.634	11.893	12.639	7.682	7.519	8.077	10.022
Tier 1 capital (%)	12.939	12.402	11.988	10.479	12.614	11.597	11.608	11.724
Tier 2 capital (%)	1.969	1.723	1.621	2.590	1.331	1.539	1.557	2.253
Assets ($MM)	697	1486	3204	39506	485	1116	2476	90052
Average # of banks	63	64	64	64	90	90	90	90

Table 6. Difference in Identity of Top Ten Banks Ranked by Stand-Alone and Systemic Risk, 1974-2010

Panel A. Top 10 banks Ranked by Stand-Alone Risk

#	Bank	Regulatory or market response
1	1st Pacific Bancorp	Shut down
2	Bay National Corp	Shut down
3	Pacific State Bancorp/CA	Shut down
4	First Bankshares Inc/VA	Acquired
5	Community Shores Bank Corp	Consent order
6	Crescent Banking Co	Shut down
7	Ohio Legacy Corp	Consent order
8	Sun American Bancorp	Shut down
9	Bank of the Carolinas	Consent order
10	Sterling Banks Inc	Shut down

Panel B. Top 10 banks Ranked by Systemic Risk

#	Bank	Fiscal Quarter	Assets ($ million)
1	State Street Corp	2009 Q1	142,144
2	Wells Fargo & Co	2009 Q1	1,285,891
3	PNC Financial Services Group	2009 Q1	286,422
4	Trico Bancshares	2008 Q3	1,976
5	Regions Financial Corp	2008 Q3	144,292
6	Banctrust Financial Group	2008 Q4	2,088
7	Marshall & Ilsley Corp	2009 Q1	61,790
8	Bank of America Corp	2009 Q1	2,321,963
9	Pacwest Bancorp	2008 Q4	4,496
10	Frontier Financial Corp	2008 Q3	4,245

Table 7. Thirty largest banks by the book value of assets (in millions of dollars) in fiscal year 2007. The reported risk measures are for the dividend-forbearance model and state the maximum values reached during the 12 months from July 2008 to June 2009 when the commercial banks' sectoral risk was the highest. The risk measures are in basis points.

Rank	Name	Assets	Stand-alone risk premium	Systemic risk premium
1	BANK OF AMERICA CORP	1,715,746	3175	770
2	JPMORGAN CHASE & CO	1,562,147	1033	707
3	WELLS FARGO & CO	575,442	3114	1421
4	U S BANCORP	237,615	1149	319
5	BANK OF NEW YORK MELLON CORP	197,656	1322	658
6	SUNTRUST BANKS INC	186,385	1522	585
7	NATIONAL CITY CORP	154,166	1741	252
8	STATE STREET CORP	142,543	4329	1881
9	REGIONS FINANCIAL CORP	141,042	3722	826
10	PNC FINANCIAL SVCS GROUP INC	138,920	3011	1227
11	BB&T CORP	132,618	739	475
12	FIFTH THIRD BANCORP	110,962	1534	574
13	KEYCORP	99,983	3268	614
14	NORTHERN TRUST CORP	67,611	641	345
15	M & T BANK CORP	64,876	263	14
16	COMERICA INC	62,331	585	339
17	MARSHALL & ILSLEY CORP	60,768	2504	788
18	UNIONBANCAL CORP	55,728	67	-1118
19	HUNTINGTON BANCSHARES	55,304	2843	640
20	ZIONS BANCORPORATION	52,947	1641	601
21	POPULAR INC	47,280	1281	167
22	FIRST HORIZON NATIONAL CORP	38,829	2031	566
23	SYNOVUS FINANCIAL CORP	33,576	1504	475
24	COLONIAL BANCGROUP	25,976	2510	501
25	ASSOCIATED BANC-CORP	21,592	505	132
26	BOK FINANCIAL CORP	20,840	139	-204
27	W HOLDING CO INC	18,040	322	129
28	FIRST BANCORP P R	17,605	542	263
29	WEBSTER FINANCIAL CORP	17,202	1243	385
30	FIRST CITIZENS BANCSH	16,312	177	-83

Table 8. Comparison of Our Measures of Stand-Alone and Systemic risk with two other measures of capital shortage for 18 of the 19 institutions that the Federal Reserve Subjected to Stress Tests in early 2009

	Other Measures			Our Measures			
	SCAP ($Bil)	SCAP/Tier1 Capital	Acharya et al. MES ($Bil)	Value of Stand-alone Support ($MM)	Stand-alone Risk Premium IPD (bp)	Value of Systemic Risk Support ($MM)	Systemic Risk Premium IDPS (bp)
Bank of America Corp	33.9	19.57%	15.05	127300	619	40882	199
Wells Fargo & Co	13.7	15.86%	10.57	73645	617	40186	337
Citigroup Inc	5.5	4.63%	14.98	41073	232	37577	212
Regions Financial Corp	2.5	20.66%	14.80	11692	916	2265	177
Suntrust Banks Inc	2.2	12.50%	12.91	12690	800	3986	251
Keycorp	1.8	15.52%	15.44	4662	521	1912	214
Morgan Stanley Dean Witter & Co	1.8	3.81%	15.17	5100	80	8418	133
Fifth Third Bancorp	1.1	9.24%	14.39	34300	3240	3173	300
PNC Financial Services GRP INC	0.6	2.49%	10.55	8249	319	5881	228
American Express Co	0	0.00%	9.75	4489	433	2755	266
Bank New York Inc	0	0.00%	11.09	985	56	-8965	-510
JPMorgan Chase & Co	0	0.00%	10.45	23715	126	16893	90
US Bancorp	0	0.00%	8.54	8302	343	6021	249
State Street Corp	0	0.00%	14.79	4204	297	2109	149
BB&T Corp	0	0.00%	9.57	4491	326	3197	232
Capital One Financial Corp	0	0.00%	10.52	13137	896	2156	147
Goldman Sachs Group Inc	0	0.00%	9.97	2047	25	10407	125
Metlife Inc	0	0.00%	10.28	6960	144	6376	132

Notes: SCAP is the capital shortfall calculated in the supervisory Capital Assessment Program conducted in February 2009 and MES is the Marginal Expected Shortfall calculated by Acharya et al. (2010) from data in periods during which stock-market returns lie below their fifth percentile.

Table 9. Mean coefficients of cross-sectional Quarter-by-Quarter Models for Stand-Alone and Systemic Risk at Sampled US Bank Holding Companies for 1974-2010 and for 1974-2010 separately.

	Full sample			1974-2007			2008-2010		
	Coef.	t-stat.	Same sign	Coef.	t-stat.	Same sign	Coef.	t-stat.	Same sign
Panel A: Determinants of stand-alone credit risk (IPD)									
Size	-0.056	-0.6	45/147	-0.058	-0.6	38/135	-0.039	-1.0	7/12
Deposits	0.092**	3.6	83/147	0.058*	2.5	73/135	0.472**	3.6	10/12
Asset volatility	16.703**	21.6	145/147	15.406**	20.9	133/135	31.302**	25.1	12/12
Implied capital	-11.006**	-17.2	147/147	-9.984**	-16.7	135/135	-22.513**	-10.2	12/12
R^2	0.541			0.519			0.791		
Observations	258			252			327		
Panel B: Determinants of systemic credit risk (IPDS)									
Size	0.089**	2.9	139/147	0.032**	3.2	127/135	0.730*	2.4	12/12
Deposits	-0.107*	-2.3	115/147	-0.046**	-3.9	105/135	-0.794	-1.5	10/12
Asset volatility	1.424**	4.6	99/147	1.349**	4.5	95/135	2.258	1.2	4/12
Implied capital	-4.882**	-4.9	129/147	-4.637**	-4.4	117/135	-7.634*	-2.5	12/12
R^2	0.525			0.542			0.338		
Observations	253			251			277		

Notes: The credit risk measures are in basis points. Size is lagged CPI-adjusted book value of assets in billions of dollars. Deposits is lagged ratio of deposits to total assets in %. Asset volatility is standard deviation of asset returns (in %) implied by the call option model of bank equity. Implied capital is market value of equity as the percentage of the value of assets implied by the option model of bank equity. The reported slope coefficients, R^2, and the numbers of the observations are the averages from quarterly cross-sectional regressions. The t-statistics are based on standard deviations of the time-series of coefficient estimates. There are 147 regressions in the full sample, 135 regressions in the 1974-2007 period, and 12 regressions in the 2008-2010 period. The numbers reported in columns labeled "Same sign" report the number of coefficient estimates with the same sign as the reported mean coefficient estimate, followed by the total number of regression estimates.