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Tracking Variation in Systemic Risk at US Banks During 1974-2013

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Abstract

This paper proposes a theoretically based and easy-to-implement way to measure the systemic risk of financial institutions using publicly available accounting and stock market data. The measure models the credit enhancement taxpayers provide to individual banks in the Merton tradition (1974) as a combination put option for the deep tail of bank losses and a knock-in stop-loss call on bank assets. This model expresses the value of taxpayer loss exposure from a string of defaults as the value of this combination option written on the portfolio of industry assets. The exercise price of the call is the face value of the debt of the entire sector. We conceive of an individual bank's systemic risk as its contribution to the value of this sector-wide option on the financial safety net. To the extent that authorities are slow to see bank losses or reluctant to exercise the call, the government itself becomes a secondary source of systemic risk. We apply our model to quarterly data over the period 1974-2013. The model indicates that systemic risk reached unprecedented highs during the financial crisis years 2008-2009, and that bank size, leverage, and asset risk are key drivers of systemic risk.

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Each new financial crisis intensifies efforts by policymakers and academics to improve strategies and protocols for monitoring and resolving losses at large, complex, and politically influential financial institutions. Key problems include the need to develop timely measures such as CoVar (Adrian and Brunnermier, 2008) and SRISK (Brownlee and Engel, 2015) that link the risk exposures undertaken by individual institutions to the risk of a breakdown in the financial system as a whole. This risk of breakdown is known as systemic risk.

We follow Engle, Jondeau, and Rockinger (2012) in defining an individual bank's systemic risk as its propensity to be undercapitalized when the financial system as a whole is undercapitalized. This definition allows us to include in the risk-generation process the channels through which regulation and supervision might mitigate or amplify this risk. It is well known that the existence of a safety net incentivizes banks to increase their exposure to ruinous losses, to under-reserve for these loss exposures, and to conceal such losses when they occur (Kane, 1989; Demirguc-Kunt and Huizinga, 2004; and Skinner, 2008). Profit-driven safety net abuse is deeply implicated in modern financial crises (Rochet, 2008). Even though policymakers recognize the depth of this incentive problem and seek to monitor the regulatory arbitrage it produces, profit-maximizing managers are driven to extract value from financial safety net support in hard-to-observe ways.

When tail risks drive a large, complex, or politically influential bank into insolvency, the difficulty of exercising the government's call can transform safety-net management into a nasty game of chicken whose outcome generates bailout expense for taxpayers.[1] When deep or widespread insolvencies emerge, fiscal and monetary authorities typically shift losses to

[1] This is essentially what is known popularly as the "too big to fail" problem.

taxpayers because it is the path of administrative and political least resistance (Honohan and Klingebiel, 2003; Veronesi and Zingales, 2010; Laeven and Valencia, 2013).

Regulators such as Timothy Geithner argue that it is in society's best interest to minimize the possibility of contagious defaults. As long as sovereign and cross-country credit support remains credible, authorities can prevent widespread substantial spillovers of actual defaults from taking place. This has led officials around the world to block actual defaults by "systemically important" firms. They have done this by guaranteeing such a firm's access to credit even when difficulties it encountered in rolling over its liabilities strongly suggested that it had become economically insolvent.

The goal of this paper is to propose a measure of systemic risk that is based in theory 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 stockholder equity 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, but reinterpret the losses to which banking-sector activity exposes taxpayers through the safety net as an implicit contra-liability that transfers responsibility for covering the losses of insolvent banks to taxpayers.

To fashion a role for forbearance, we interpret this contra-liability as the value of the combination of a put option written on the losses that can be generated by a portfolio of aggregate bank assets with a call on these same bank assets whose exercise price equals the face value of aggregate bank debt.[2] This interpretation treats the taxpayer put and call as helping to complete markets and lets us calculate each individual bank's systemic risk as its contribution to the value of the banking sector's aggregate portfolio of put-call positions.

From a contracting perspective, the option is a credit enhancement and the disruptive effects on the real economy from bank distress are separable from this. The value of the put and creditor predictions about the role of forbearance in exercising the associated call are impounded into the stock price, borrowing rates, and margin requirements for derivative contracts of every firm whose economic insolvency seems unlikely to be resolved promptly. The net value of the portfolio of twinned options provides a gross estimate of the cost to taxpayers of supporting the banking system. Given that benefits tend to dwarf deposit insurance premiums in crisis circumstances, during panics, it may be a good approximation of the net costs as well.

We estimate our model over the period 1974-2013, using quarterly data on U.S. bank holding companies. This 30-year observation window lets us compare the behavior of systemic risk during the financial crisis period 2008-2009 with its behavior in earlier crises and recessions.

The results track the effects of bank risk taking and regulatory forbearance on taxpayer risk exposure during and in advance of the last four business-cycle expansions and contractions, reaching an all-time high at the peak of the 2008-2009 crisis. We estimate the annualized per-quarter value of sample banks' stand-alone and 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 measure of risk tracks the broad ways in which banking risk has waxed and waned over recent business cycles.

[2] The simplicity of this approach is that the model need not limit the debt of banking organizations to deposits nor explicitly model differences in maturity and credit quality.

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 assumptions 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 for 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 summarizes 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 banking organizations ("banks"), 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 lessen their exposure to loss by lobbying and other forms of political or hedging activity.

There is no reason to expect that the balance of costs and benefits the safety net generates 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. In principle, the discounted value of current and future costs and benefits could be entered on institution balance sheets as intangible contra-assets and contra-liabilities, respectively. Both costs and benefits may be treated as put options whose control rights lie in the hands of regulators who are understood in difficult circumstances to favor forbearance over strict and prompt exercise of taxpayers' stop-loss rights. Protected institutions are *long* an option to put losses in excess of stockholder capital to other banks and nonbank taxpayers in various ways and *short* two other options. The first is an obligation to surrender the assets to the FDIC if regulators exercise their right to take over an insolvent bank. Their second position is an option to cover their share of safety-net expenses, including the future costs of replenishing the insurance fund for losses incurred at other banks. The costs in a bank's short positions include explicit insurance premiums and various costs of complying with (and sometimes circumventing) burdensome restrictions that safety-net managers might 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. Moreover, they maintain that compliance burdens generated by the Dodd-Frank Act are aggravating this situation. Our analysis provides an easy way to investigate and confirm this claim quantitatively.

We focus especially on the period 2008-2009, 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 Acharya, Schnabl, and Suarez, 2013, Gorton (2009), Laeven and Valencia (2012), Brunnermeier (2009), Adrian and Shin (2010), and Lo (2012).

It is not necessary to sort out the causal origins of the crisis to see that 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 troubled banks and began to lower interest rates. Because bailout programs seemed to rob low- and middle-income Peter to pay rich Paul, the crisis surfaced popular concern about the unfairness of too-big-to-fail policies (Veronesi and Zingales, 2010).

Other researchers propose alternative measures of systemic risk with which our results can be compared. Billio, Getmansky, Lo, and Pelizzon (2012) compare several of these alternative systemic risk measures. 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 (2008), marginal expected shortfall (MES) proposed by Acharya, Pedersen, Philippon, and Richardson (2010) and extended by Brownlees and Engle (2015), and network-based measures of systemic risk based on interbank contagion as, e.g., proposed by Cont (2010). Kim and Giesecke (2010) study the term structure of systemic risk.

Our measure differs from other measures of systemic risk in two important dimensions. First, our measure uses readily available stock market data on banking firms, and not data that are either not readily available (such as data on financial networks and interconnectedness) or market-value data for debt and derivatives that are available in thin markets or only for a small subset of firms. Jarrow (2012) shows that implied default probabilities from CDS spreads cannot provide reliable estimates. Second, our methods finesse the need to address the interconnectedness of banking firms directly. Instead, our measure of a banking firm's contribution to systemic risk gauges interconnectedness implicitly. It encompasses not only contagion risks arising from direct contractual linkages between banks, such as those that occur through interbank loans, but also from indirect linkages from balance sheet exposures to common external shocks. We regard the more timely and comprehensive availability of the input data our model needs to be a major advantage of our measure of systemic risk. In these respects, our measure resembles that of Brownlees and Engle (2015). But whereas these authors focus on estimating losses banking stocks might suffer during severe stock market declines, our model tracks safety-net subsidies across a longer history and treats all phases of stock-market behavior equally.

II. Measuring Stand-Alone and Systemic Bank Risk

A. Structural Model of Bank Default

Our measures of stand-alone and systemic bank risk extend 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 guaranteeing bank creditors against losses due to default during the period it covers.

Our model portrays stockholder 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.[3,4]

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:

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

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:

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

[4] We do not mean to imply that distributions with jumps or heavier tails could not be used or that such distributions might not give more accurate estimates (see, e.g., Bollerslev and Todorov, 2011).

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

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 total liabilities (quarterly Compustat item LTQ) and preferred equity (PTSQ).[5] The present value of the next four quarterly dividends, *DIV*, is calculated

[5] The results are similar when the face value of debt 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

assuming that, for the next four quarters, the bank will pay the same dollar amount as the last quarterly cash dividends per share (DVPSXQ) times the number of shares outstanding (CSHOQ) and using the yield on one-year Treasuries.[6] 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 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

equity (PTSQ). However, this alternative calculation cannot be performed for non-bank financial institutions that were part of Supervisory Capital Assessment Program and are presented later in Table 8.

[6] 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.

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 guaranteeing 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 financial data to measure systemic risk (e.g., Acharya *et al.* 2010)] cannot capture knock-on effects on employment and economic growth. For this reason, they all underestimate the full impact of systemic risk.

Our concept 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 individual-bank systemic risks estimates indirectly the linkages that tie the risks taken by any one sample bank to the systemic risks incurred by other banks. These linkages transfer extreme risks from one or a few banks across the system and, as the Allen and Gale model (2001) explains, can threaten its integrity.

III. Sample Selection, Data, and Summary Statistics

Our primary sample consists of commercial banking organizations (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 Compustat (both Bank and Fundamentals). Macroeconomic data, such as the consumer price index (CPI), one-year Treasury yields, and real GDP growth rates are downloaded from the website maintained by the Federal Reserve Bank of St. Louis.[7] Annualized standard deviations for stock returns are calculated using daily returns for the latest quarter and a screen requiring a minimum of 58 non-missing returns within the quarter. These screening criteria leave us with 40,522 bank-quarter observations.

Table 1 reports the number of quarterly observations and the mean values of assets and Tier 1 capital by year. The number of sample banks starts at 497 in the first quarter of 1974, expands steadily during the 1970s, remains stable in 1980s, almost triples in the fourth quarter of 1993, remains relatively stable during the rest of the precrisis period, and declines thereafter. 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% prior to the crisis and have risen into the 14% range since. The remaining sections of the paper explore the time-series and cross-sectional behavior of our measurements.

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[7] http://research.stlouisfed.org/fred2/.

IV. 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 160 calendar quarters from 1974 to 2010 and for each sample bank, we calculate values for an appropriate individual guarantee fee (expressed as an Insurance Premium for Debt, *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 and fell back afterwards. But our evidence shows that the mean value of the stand-alone put grew larger in the 1990s and fell back more slowly in later business cycles. Because a large number of small banks is added in the fourth quarter of 1993, data before and after that date must be compared cautiously. Nevertheless, from a large-bank perspective, the 40 years of data show the dangers of trying – as envisioned in the Basel system of capital control – to contain the taxpayer loss exposure *mainly* by regulating the book value of bank leverage. The data show that implied capital (Figure 2) and implied asset volatility (Figure 3) fluctuated substantially over each cycle. But during 1993-2013 the value of regulators' control variable --on-balance-sheet Tier 3 capital (Figure 4)-- changed hardly at all.

Although *IPD*, implied capital, and asset volatility are not publicly reported or explicitly monitored by banking regulators today, these measures have the advantage that they can be calculated promptly from available data. Unlike methods that rely on the prices of credit default swaps or on data measuring interbank exposures to one another, stock prices are available in deep markets in real time and regulators collect intraquarter balance-sheet data for large banks and could collect these data more frequently if they wished.

Swings in our synthetic measurements prove much more extensive than the swings in on-balance-sheet capital depicted in Figure 4. It is clear that although accounting leverage declined during the 1990s, hidden leverage 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 are bound to 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. Figures 5A and 5B plot the time-series behavior of sectoral *IPD* (labeled *IPDBS*). These charts underscore the extraordinary depth of the 2008-2009 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 (IPDBS) remained low because significant parts of the financial system remained sound. Even in the absence of policies designed to limit dividend payouts in banks receiving so-called "live-bank" assistance, the insurance premium for the sectoral portfolio never exceeded a few basis points. In contrast, at the peak of the crisis, Figure 5A that, if we assume dividend forbearance, the mean annualized *IPD* reached 450 basis points. Figure 5B shows that this value could have been reduced by about 100 basis points if authorities had promptly stopped dividend payouts at assisted banks, something the Dodd-Frank Act allows them to do going forward. In addition to the effect of sharp increases in mean stand-alone risk, the surge in taxpayer loss exposure 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 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 2008-2009 the mean value surges dramatically, reaching -2000 basis points in 2009. Although we maintain that the negative sign attached to these values supports the claims made by community banks, this sign may seem counterintuitive and surprising at first. Our interpretation 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, portfolio risk, and tax 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 supports community-bank claims that the future premiums and regulatory burdens regulators are likely to place on the assets of smaller banks exceed 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 and the sector as a whole became positive and very large during this period. Figures 8, 9, and 10 show that for very large banks systemic risk surged and sectoral leverage and volatility expanded.

The results presented in Figures 1-7 are summarized in Table 2. The table reports mean values separately for the precrisis period (1974-2007), crisis (2008-2009) and postcrisis (2010-2013) years. Both statistically and economically, stand-alone risk (*IPD*) and sectoral risk (*IPDBS*) run markedly 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 guaranteeing 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 became 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 initiatives seeking to impose a capital surcharge or incremental dollar premium for banks of 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 banking risks varied over time. We interpret 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 (*IPDBS*) to forecast future sectoral risk at one-to-twelve month forecasting horizons. At the one-month horizon, predictive power is strong: the slope coefficient is 0.868, the *t*-statistic is 38.3, and the R^2 is 0.754. The magnitude and significance of the slope (and therefore model fit) decline monotonically as the forecast horizon grows. At the nine-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 systemic pressures in advance. 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 (whose time-series behavior is shown in Figure 11). 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 over 2- to 8-month horizons. At longer horizons, the magnitude of the growth-rate coefficient declines and becomes insignificant beyond the nine-month horizon. R^2 lies in the 10% to 14% range for horizons of nine-months or less. For longer horizons, the influence of the growth rate declines monotonically, and the R^2 drops off to 4.7% at the 12-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 average about six percentage points above corresponding regressions that omit the Herfindahl variable. These results suggest that the dramatically more concentrated structure Figure 11 shows for the US banking system in recent years may have increased its susceptibility to systemic crisis. While there is considerable industry resistance to the idea of breaking up large banks or capping their asset growth, our work provides another drop in a rapidly filling bucket of evidence that mega-banking organizations pose hard-to-manage problems for our nation's financial stability.

V. 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), crisis (2008-2009) and postcrisis (2010-2013) years. Results are qualitatively unaltered if we partition the sample by medians rather than means.

In the first two periods, the stand-alone risk premium tends to decrease across the first three size quartiles, backs up a bit in quartile 4, but remains below the levels shown for quartiles

2 and (especially) quartile 1. The stand-alone premium for the fourth quartile drops off in the postcrisis years.

While the smallest banks consistently pose the largest stand-alone risks, the pattern is different for systemic risk. Systemic risk increases in the large-bank quartile. This finding holds in all periods. This supports the hypothesis that a country's largest banks are the main source of systemic risk, which helps to validate our use of 1974-1992 data. However, before and after the crisis, the difference we observe between the smallest and the largest quartiles is a mere 0.2 to 0.3 basis points. During the height of the crisis, the difference surges to over 600 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 volatility tend to be highest and market 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 a straightforward aggregation of individual-bank stand-alone risk.

Table 6 shows how different the top fifteen sample banks for stand-alone risk (Panel A) are from the fifteen banks that posed the most systemic risk (Panel B). There is not a single instance of overlap between these lists. As in Table 5, high stand-alone risk is found in small banks, but high systemic risk depends on a bank's business plan and can be posed by banks of all sizes.

Table 7 identifies the 30 largest financial institutions in our sample by total assets in their 2007 fiscal year. It also states the maximum stand-alone and systemic risk premiums they experienced during the 2008-2009 financial crisis. The high levels of these maxima underscore how much value federal credit support contributed to these banks and to their counterparties due to 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 more elegant 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 with the indices of capital shortfall prepared by the Federal Reserve, Acharya et al. (2010), and Brownless and Engle (2015) for these firms.[8]

The correlation between our dollar measures of stand-alone and systemic risk and the SCAP measure of capital shortfall are respectively 0.723 and 0.791, indicating that our more timely and simpler-to-compute measures of risk are good approximations for complicated regulatory efforts to measure capital shortfall at major financial institutions. This supports the usefulness of our measure of systemic risk. Still, our data suggest that some banks generated far more systemic risk than was suggested by SCAP or acknowledged by regulators. The

[8] The values of our measures of stand-alone and systemic risk presented in the table are for the fiscal quarters starting in July 2008 and ending in June 2009. The values of SRISK are from Brownlees and Engle (2015) as reported for first quarter of 2009.

correlations with the MES measure of capital shortfall developed by Acharya et al. (2010) are lower at 0.461 for stand-alone risk and only 0.202 for systemic risk. The correlations of the stand-alone and systemic risk premiums with the SRISK measure of Brownlees and Engle (2010) are 0.072 for stand-alone risk and only 0.462 for systemic risk. The relatively low values of the last two correlations suggest that they may span different components of systemic risk, so that regulators might find all three approaches useful supplements to data now being generated with considerably more effort by stress tests.

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 *IPD* 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 institution, 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 time series of regression estimates. Because the distributions of the coefficient estimates are highly skewed with particularly large values observed during the financial crisis, we use non-parametric methods to assess their statistical significance. Our inference focuses on the number of coefficient estimates that show the same sign as the time-series mean. Significance tests are conducted for the 160 quarters in the full sample period 1974-2013 and for the four crisis quarters separately using a sign test.

The tests reinforce the hypothesis 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 average size effect is positive, though not significantly so, both in the full sample and during the four crisis quarters. The positive influence of size on *systemic risk* is significant even with these controls and is positive during all four crisis quarters. This reinforces the hypothesis that bank size and leverage are key drivers of systemic risk.

The effect of deposits on *stand-alone risk* is significantly negative in the full sample but is significantly positive in the crisis quarters. The deposit effect proves significantly negative for *systemic risk* in both the full sample and crisis subperiod. This pattern of results is consistent with the hypothesis that authorities' rescue propensities provide banks that have more complex liability structures with forms of implicit credit support that tempt such firms to make themselves systemically riskier.

To test whether stand-alone and systemic risks are especially large for giant institutions, Table 10 re-estimates these regressions adding indicators of great size to the right-hand side. "Large" is an indicator set to one for top 10 percent (by book value of assets) of banks in each calendar quarter. "Very large" is an indicator set to one for the top 5 percent of banks (by book value of assets) in each calendar quarter. Neither indicator is significant in stand-alone risk regressions. This is consistent with our earlier findings that asset size is not a major determinant of stand-alone risk.

On the other hand, in the systemic risk regressions, the large-bank indicator is significantly positive both in the full sample and during the four crisis quarters. The very large bank indicator is significantly positive during the financial crisis but not in the full sample. The magnitudes of these coefficient estimates imply that, during the financial crisis, systemic risk premia for large banks ran almost 400 basis points higher than the risk premia of smaller banks. The risk premia for the top 5 percent increased by an *additional* 400 basis points. Taken together, these results indicate that taxpayer loss exposure reached unprecedented highs during the financial crisis, and that not only leverage and asset risk but also bank size were key drivers of systemic risk.

VI. SUMMARY AND CONCLUSIONS

The great financial crisis underscored the need to devise a timely and comprehensive measure of the risk that particular institutions impose on the financial system as a whole. This paper introduces a theoretically based 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 the credit enhancement that the put conveys 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 bank managers to gamble for resurrection rather than to focus on loans and investments that could more reliably expand job opportunities and customer profits.

Time trends and patterns in our aggregate and individual measures of systemic risk are consistent with the outcomes of formal stress tests and with popular and academic understanding of how systemic and individual risks varied over time and across institutions. In particular, we find that during crises bank size is a key driver of systemic risk. We conclude that, although our estimates of systemic and stand-alone risk might be biased in some way, they capture the *qualitative* behavior of these risks. Our findings support the strategy of imposing a graduated capital surcharge on banks of large size and suggest how such premia might be made commensurate with measures of each bank's quarter-by-quarter contribution to systemic risk.

Our ultimate goal is to help to enhance financial stability. We believe our methods provide a useful starting point for tracking systemic banking pressures in a more timely fashion and for promptly identifying institutions whose activities might generate dangerous amounts of systemic risk. Because our measure is so uncomplicated, we hope further research will refine our methods and deepen everyone's understanding of systemic risk.

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Figure 1. Mean value of IPD using the dividend-forbearance model, 1974-2013

This figure reports the average value of our estimate of stand-alone risk (IPD) in equation (4), assuming continuing dividend forbearance. Averages are computed across a sample of U.S. bank holding companies over the 1974-2013 period and reported quarter by quarter in basis points. Financial statement data are from the Compustat database for U.S. banks and daily stock returns are from CRSP.

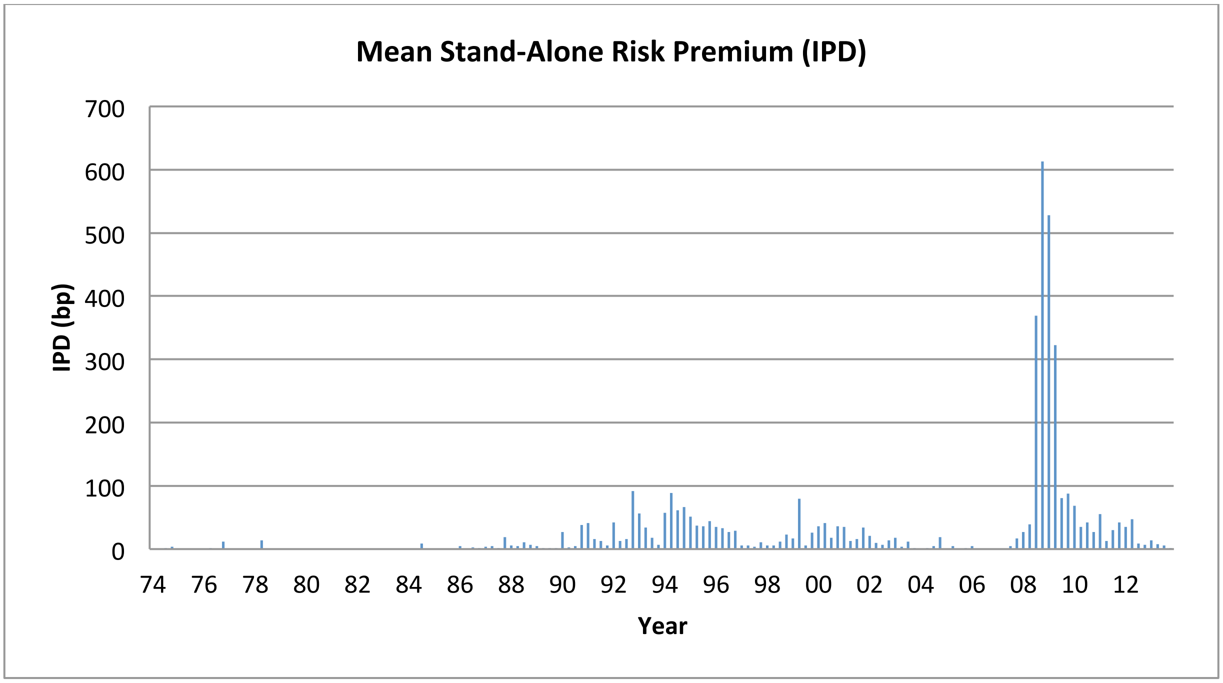


Figure 2. Mean ratio of model-implied equity capital to assets, 1974-2013

This figure reports the average value of the model-implied ratio of equity to assets (E/V), with E computed as in equation (1), assuming continuing dividend forbearance. Averages are computed across a sample of U.S. bank holding companies over the 1974-2013 period and reported quarter by quarter in percentage points. Financial statement data are from the Compustat database for U.S. banks and daily stock returns are from CRSP.

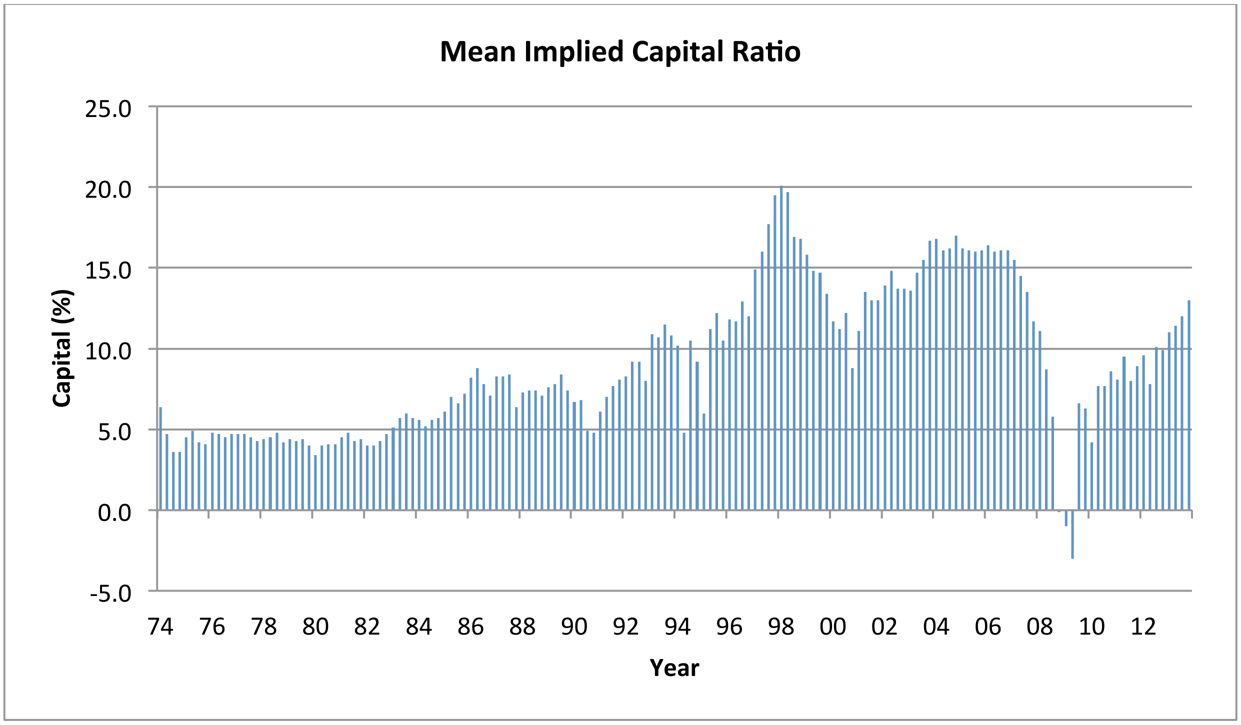


Figure 3. Mean value of implied asset volatility, 1974-2013

This figure reports the average value of the model-implied asset volatility (σ_V), with σ_V computed as in equation (5) under the assumption of continuing dividend forbearance. Averages are computed across a sample of U.S. bank holding companies over the 1974-2013 period, reported quarter by quarter, and expressed as a decimal fraction. Financial statement data are from the Compustat database for U.S. banks and daily stock returns are from CRSP.

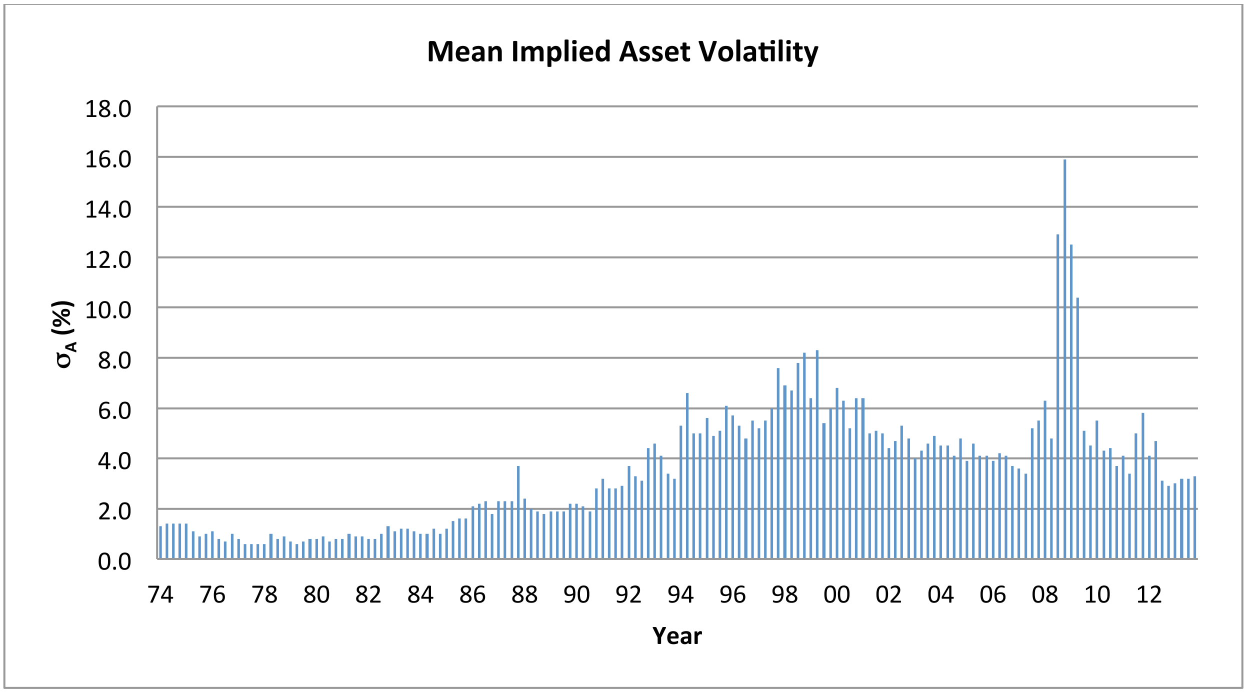


Figure 4. Mean ratio of Tier-3 capital to assets, 1993-2013

This figure reports the average value of the Tier-3 capital ratio. Averages are computed across a sample of U.S. bank holding companies over the 1993-2013 period, reported quarter by quarter, and expressed in percentage points. Financial statement data are from the Compustat database for U.S. banks.

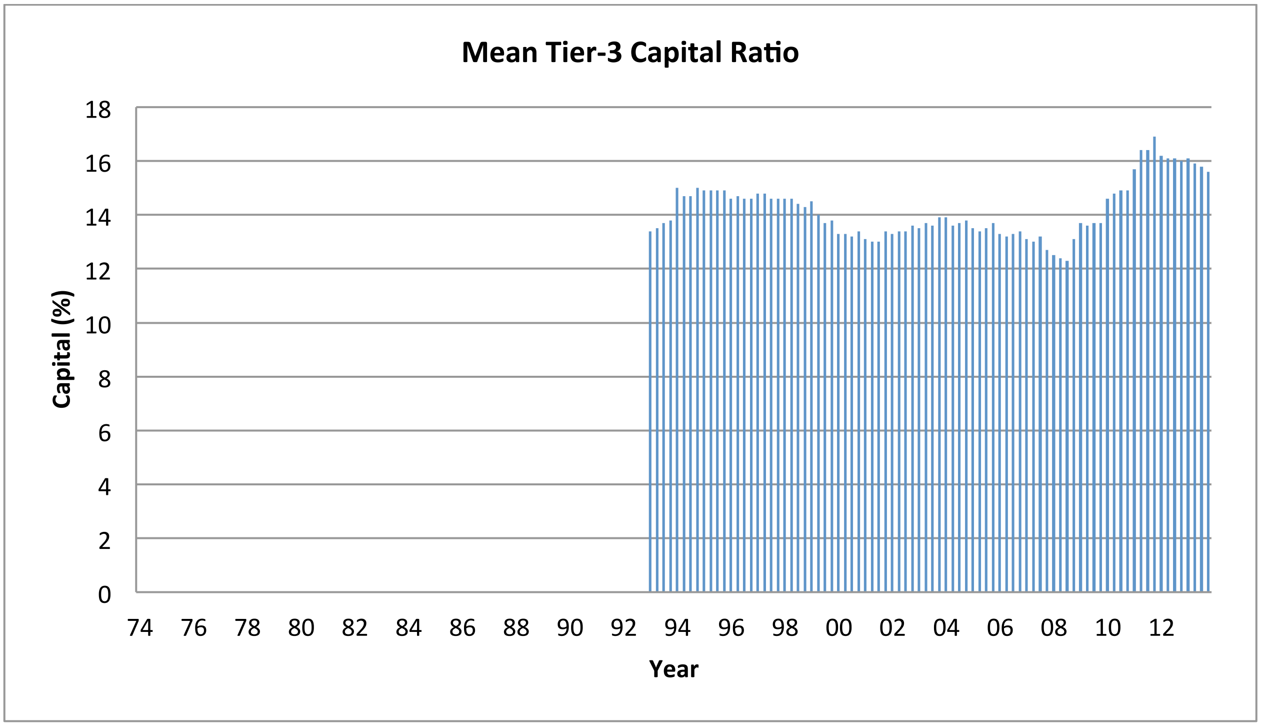
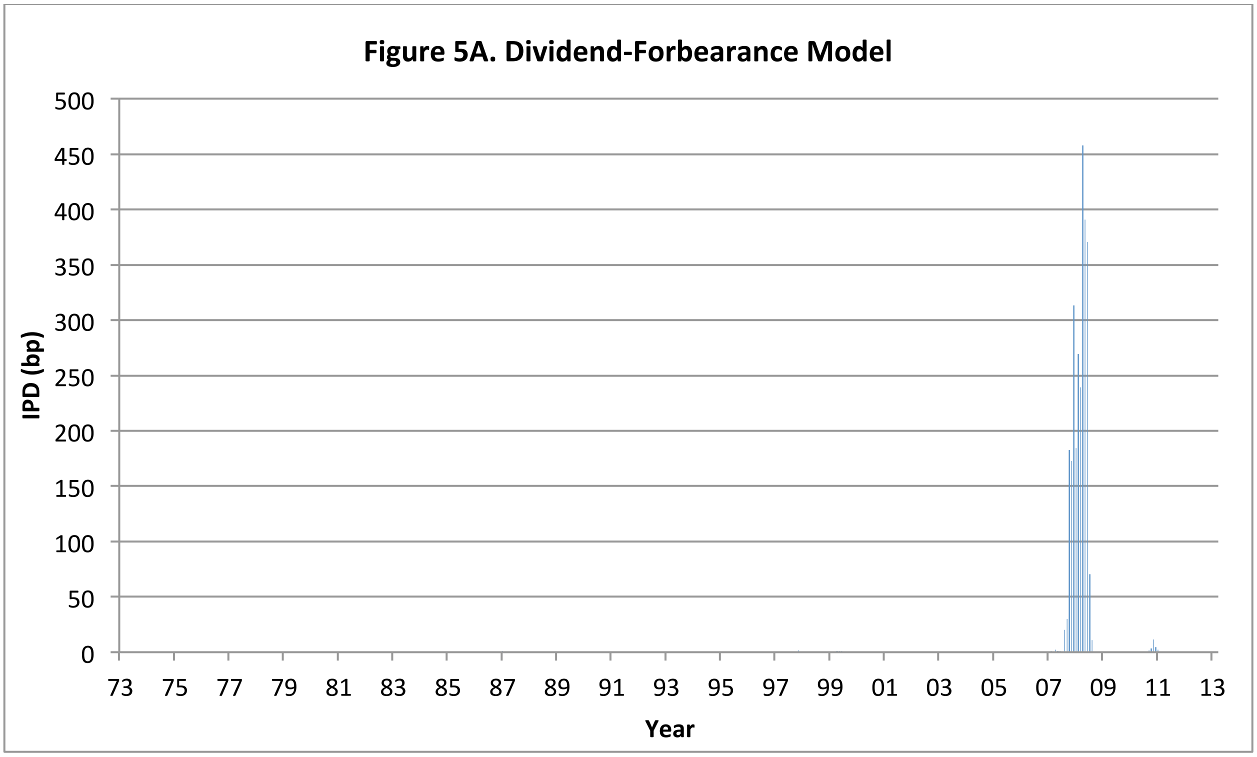


Figure 5. Sectoral risk premium (IPDBS), 1974-2013

This figure reports average estimates of the sectoral risk premium (IPDBS) based on the dividend-forbearance model (Figure 5A) or the dividend stopper model (Figure 5B). Averages are computed across a sample of U.S. bank holding companies over the 1974-2013 period, reported quarter by quarter, and expressed in basis points. Financial statement data are from the Compustat database for U.S. banks and daily stock returns are from CRSP.



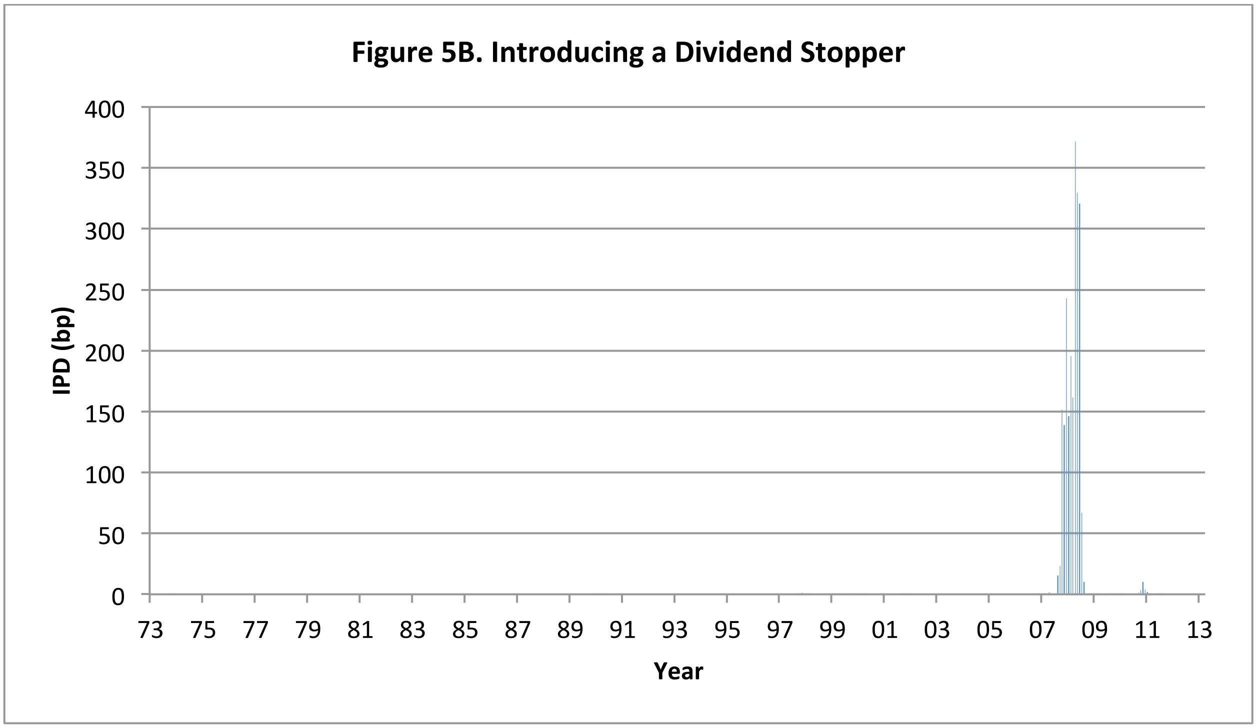


Figure 5B. Introducing a Dividend Stopper
IPD (bp)
400
350
300
250
200
150
100
50
0
73
75
77
79
81
83
85
87
89
91
93
95
97
99
01
03
05
07
09
11
13
Year

Figure 6. Correlations between individual bank and sectoral portfolio returns, 1974-2013

This figure reports average correlations between daily returns on an individual bank stock and bank sectoral portfolio. Averages are computed over the 1974-2013 period, month by month, and reported as a decimal fraction. Daily stock return data are from CRSP.

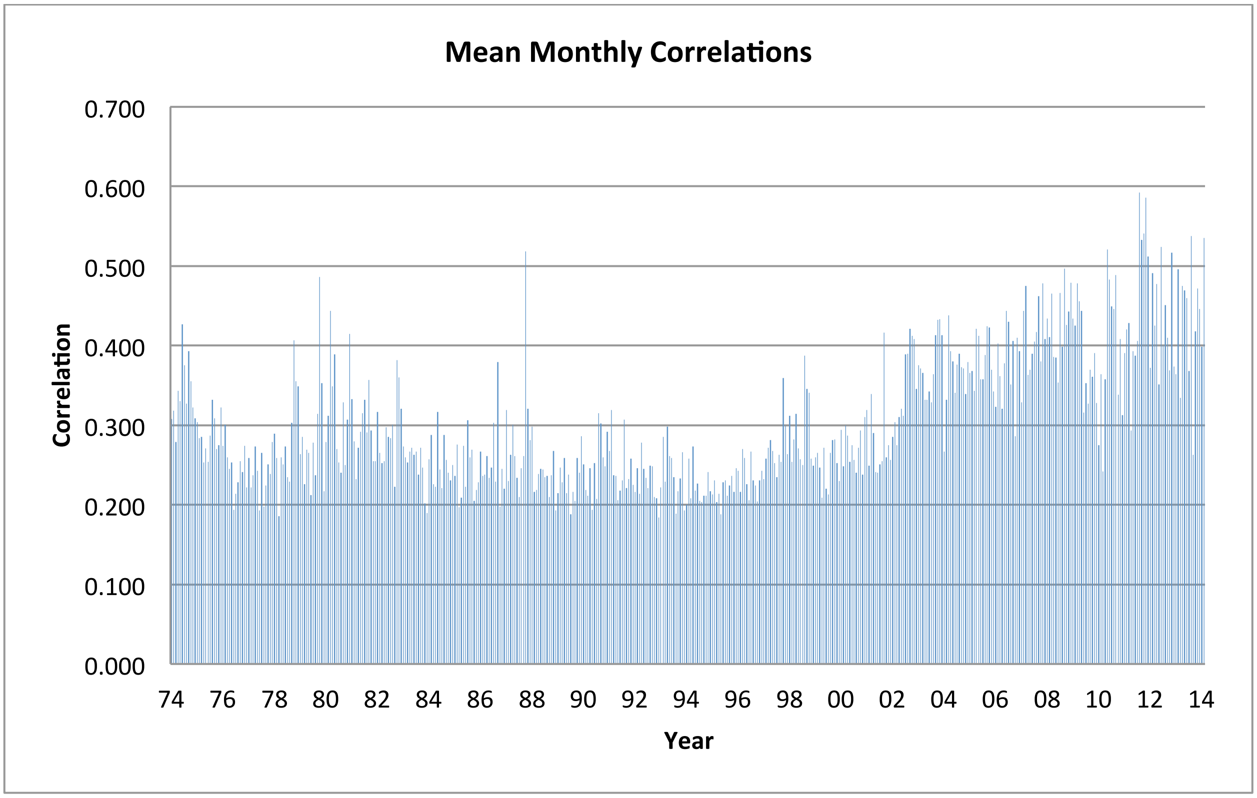


Figure 7. Mean individual-bank systemic risk premium (IPDS), 1974-2013

Figure reports mean values of the individual-bank systemic risk premium (IPDS) estimates using the dividend-forbearance model. Averages are computed across a sample of U.S. bank holding companies over the 1974-2013 period. Averages are computed quarter by quarter and reported in basis points. Financial statement data are from the Compustat database for U.S. banks and daily stock returns are from CRSP.

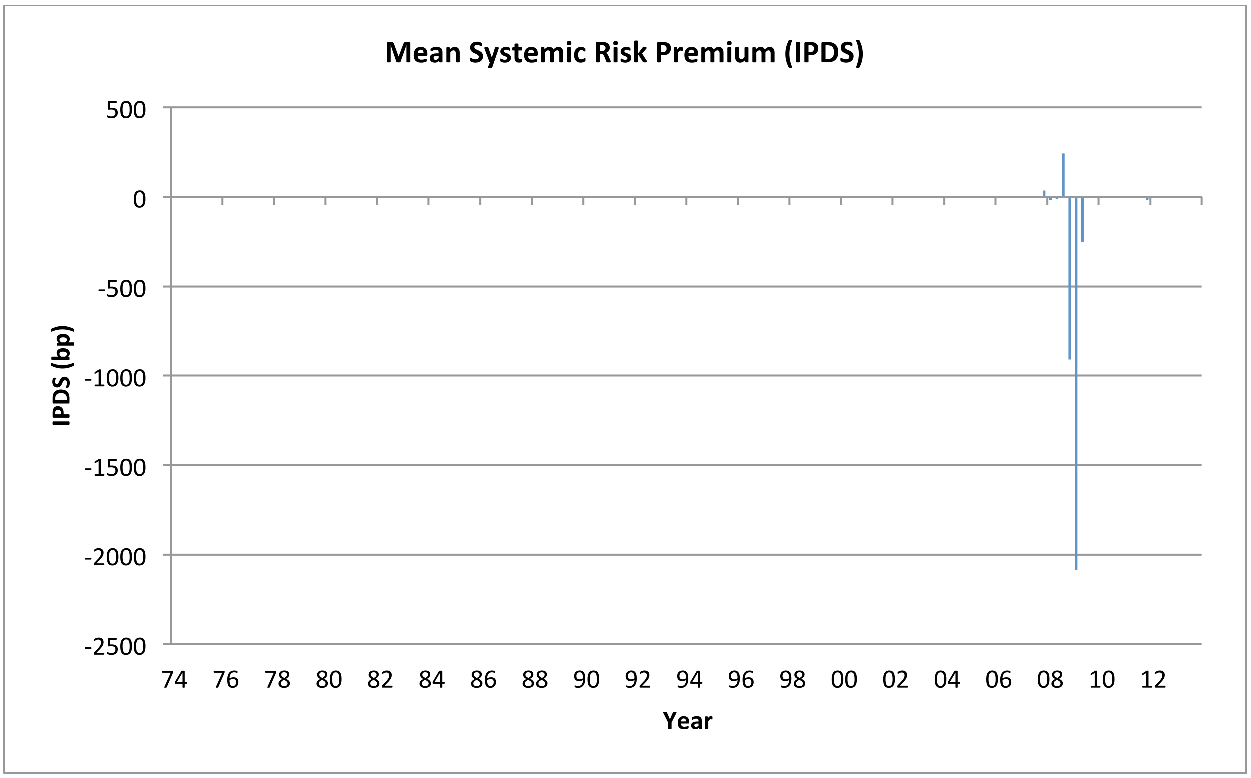


Figure 8. Mean systemic risk premium (IPDS) for large banks only, 1974-2013

Figure reports mean values of the individual-bank systemic risk premium (IPDS) estimates using the dividend-forbearance model for large banks only. Averages are computed across the top decile of sampled U.S. bank holding companies over the 1974-2013 period. Averages are computed quarter by quarter and reported in basis points. Financial statement data are from the Compustat database for U.S. banks and daily stock returns are from CRSP.

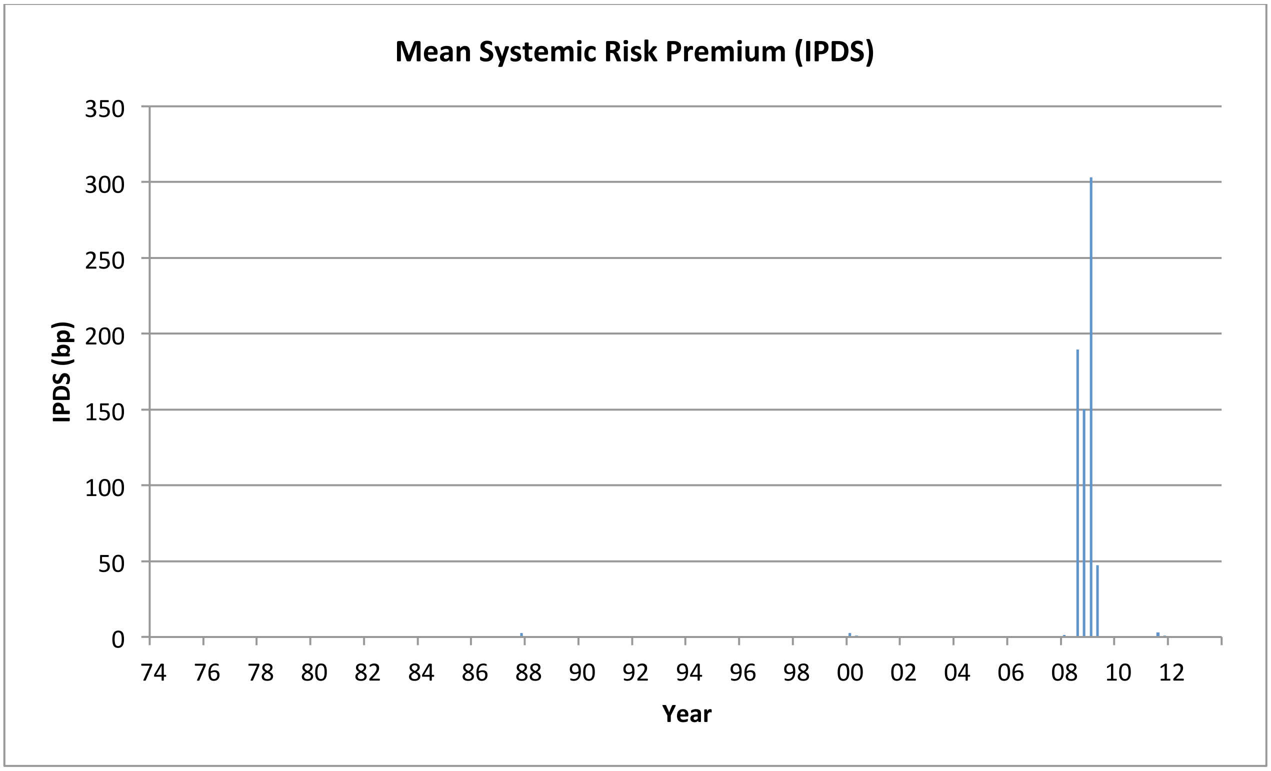


Figure 9. Implied capital-to-asset ratio for the banking sector, 1974-2013

This figure shows the average synthetic capital-to-asset ratio implied by our model for the banking sector over the period 1974-2013. Averages are computed across a sample of U.S. bank holding companies over the 1974-2013 period after aggregating individual bank data at the banking sector level. Averages are computed quarter by quarter and reported in percentage points. Financial statement data are from the Compustat database for U.S. banks and daily stock returns are from CRSP.

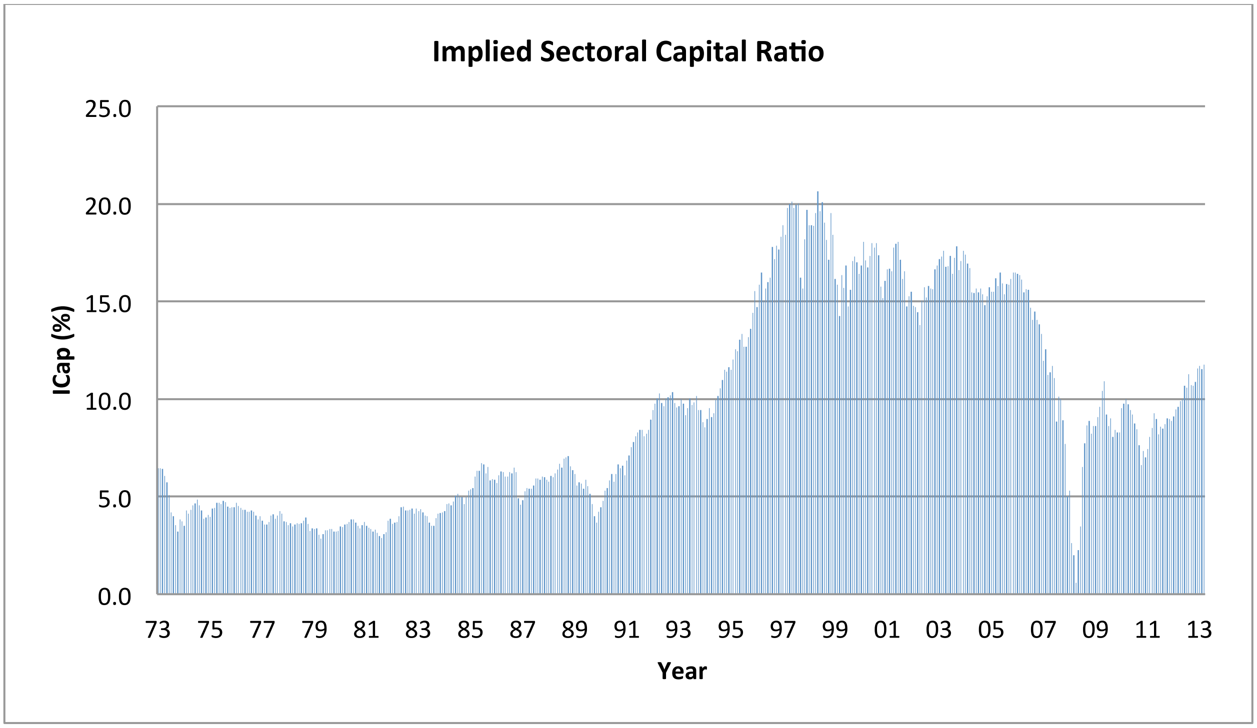


Figure 10. Implied asset volatility for the banking sector, 1974-2013

This figure shows the average asset volatility implied by our model for the banking sector over the period 1974-2013. Averages are computed across a sample of U.S. bank holding companies over the 1974-2013 period after aggregating individual bank data at the banking sector level. Averages are computed quarter by quarter. Financial statement data are from the Compustat database for U.S. banks and daily stock returns are from CRSP.

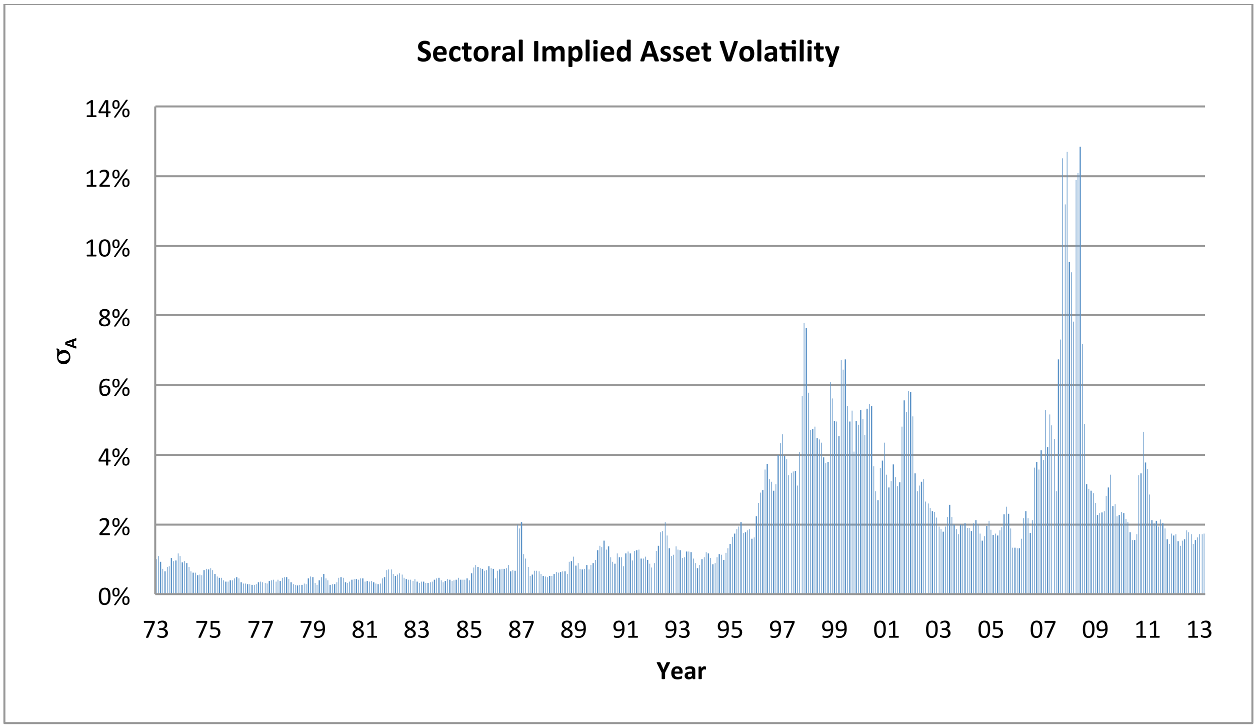


Figure 11. Herfindahl index for the banking sector, 1974-2013

This figure shows the Herfindahl index of banking assets for the banking sector over the period 1974-2013. The Herfindahl index is computed quarter by quarter across a sample of U.S. bank holding companies over the 1974-2013. Data on total bank assets for individual bank holding companies are from the Compustat database for U.S. banks.

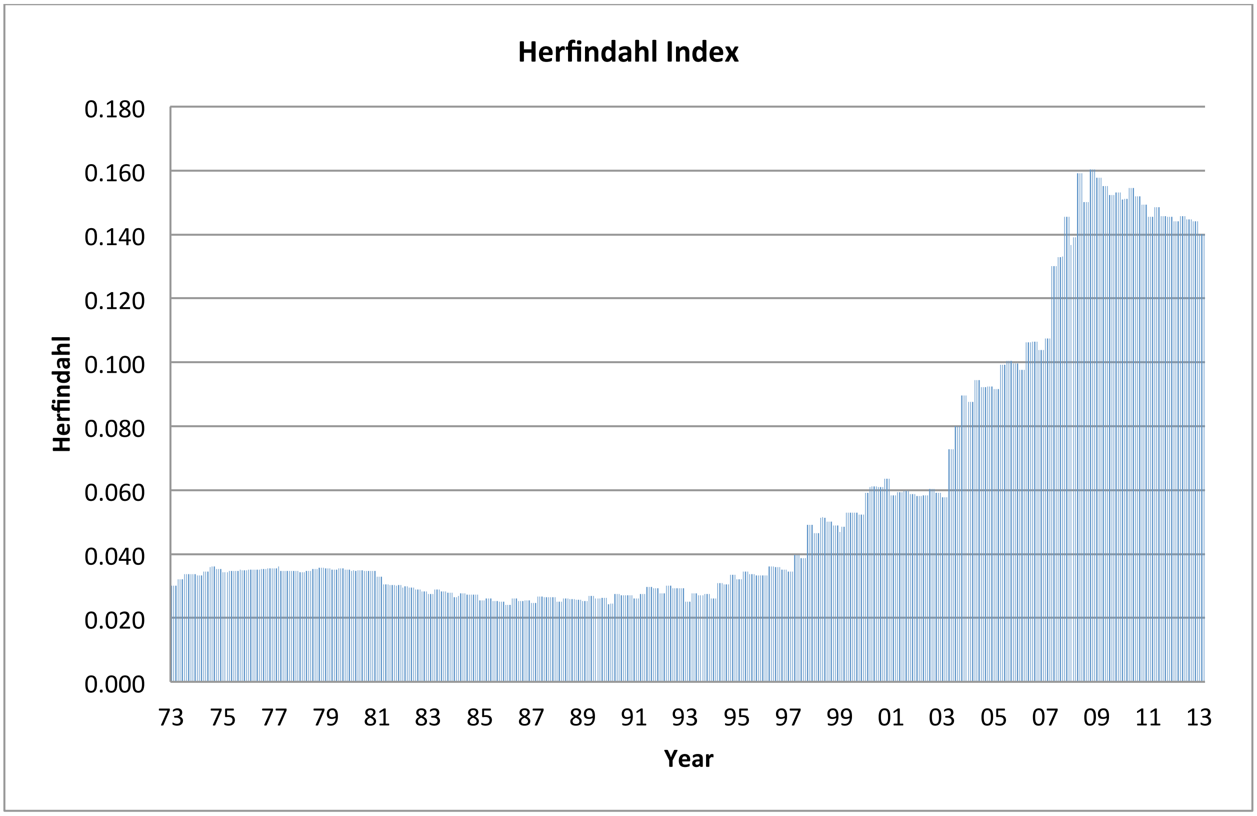


Table 1. Sample size, book value of assets, and Tier-1 capital ratios, 1974-2013

This table shows the variation in sample size, average book value of assets, and mean Tier-1 capital ratios for our sample of U.S. bank holding companies, with averages computed annually, over the period 1974-2013. Asset values are stated in billions of dollars and Tier 1 capital is reported as a percentage. Financial statement data are from the Compustat database for U.S. banks.

Year	Book Value of Assets	Tier-1 Capital Ratio	Number of Observations (N)
1974	4,927		497
1975	4,908		515
1976	5,108		525
1977	5,737		529
1978	6,212		567
1979	7,009		580
1980	7,864		577
1981	8,809		569
1982	8,532		652
1983	8,917		669
1984	9,852		658
1985	10,889		642
1986	12,442		639
1987	13,122		636
1988	13,790		609
1989	15,105		610
1990	15,091		617
1991	15,049		644
1992	15,992		629
1993	18,594	10.9	576
1994	7,939	12.3	1,598
1995	7,935	12.4	1,598
1996	9,122	12.2	1,575
1997	10,076	12.3	1,562
1998	9,968	12.2	1,516
1999	10,770	11.9	1,545
2000	9,993	11.4	1,719
2001	11,026	11.2	1,684
2002	11,416	11.5	1,710
2003	12,294	11.8	1,749
2004	13,006	12.0	1,697
2005	14,679	12.0	1,705
2006	16,405	11.8	1,661
2007	18,644	11.4	1,585
2008	20,424	10.9	1,501
2009	21,657	11.9	1,393
2010	24,853	13.1	1,323
2011	28,733	14.7	1,247
2012	31,237	14.4	1,185
2013	32,912	14.4	1,163
	Sample mean = 14,048	Sample mean = 12.2	Total N = 42,656

Table 2. Averages of focal variables under dividend forbearance

This table reports mean values of our focal variables for the model assuming dividend forbearance, with averages computed separately over the 1974-2007, 2008-2009, and 2010-2013 periods. Averages are computed across our sample of U.S. bank holding companies. Financial statement data are from the Compustat database for U.S. banks and daily stock returns are from CRSP.

Variable	1974-2007	2008-2009	2010-2013
Stand-alone risk, IPD (bp)	15.7	256.9	28.0
Stand-alone risk ($MM)	2.1	900.3	6.6
Systemic risk, IPDS (bp)	0.3	-365.4	-1.7
Systemic risk ($MM)	0.0	215.9	0.9
Equity volatility (%)	31.8	79.8	41.9
Asset volatility (%/)	4.0	9.1	4.0
Market capital (%)	11.3	4.4	9.2
Tier 1 capital (%)	11.8	11.4	14.1
Tier 2 capital (%)	2.0	1.7	1.7
Assets ($BB)	11,319	21,017	29,281
Average number of banks	256	362	307

Table 3. Time-series regressions predicting banking sector risk

This table reports the results of time-series regressions predicting banking sector risk (*IPDBS*) at various horizons using its current values. Banking sector risk is estimated using the dividend forbearance model. Financial statement data are from the Compustat database for U.S. banks and daily stock returns are from CRSP.

Forecast horizon	Coef.	t	R^2	Observations
1 month	0.868**	38.3	0.754	481
2 months	0.771**	26.5	0.594	480
3 months	0.573**	15.3	0.328	479
4 months	0.520**	13.3	0.271	478
5 months	0.407**	9.7	0.166	477
6 months	0.345**	8.0	0.119	476
7 months	0.201**	4.5	0.040	475
8 months	0.111*	2.4	0.012	474
9 months	0.024	0.5	0.001	473
10 months	-0.003	-0.1	0.000	472
11 months	-0.015	-0.3	0.000	471
12 months	-0.016	-0.4	0.000	470

Table 4. Time-series regressions predicting banking sector risk using business cycle and banking structure variables

This table reports time-series regressions predicting banking sector risk (*IPDBS*) at various horizons using its current values as well as business cycle and banking structure variables. Regressions in panel A include recession indicators and GDP growth and regressions in panel B also include the Herfindahl index of banking assets. Banking sector risk is estimated using the dividend forbearance model. 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. Financial statement data are from the Compustat database for U.S. banks and daily stock returns are from CRSP.

Panel A. Recession indicators and GDP growth

Forecast horizon	Recession indicator	t-stat	GDP growth	t-stat	R^2	Obs.
0 months	33.287**	5.7	-1.892	-0.7	0.100	480
1 month	30.280**	5.2	-4.577	-1.7	0.106	480
2 months	26.804**	4.7	-7.500**	-2.9	0.115	480
3 months	24.284**	4.2	-9.597**	-3.7	0.125	479
4 months	21.909**	3.8	-11.536**	-4.4	0.135	478
5 months	21.156**	3.7	-12.119**	-4.6	0.138	477
6 months	21.469**	3.7	-11.844**	-4.5	0.136	476
7 months	23.097**	4.0	-10.477**	-4.0	0.128	475
8 months	24.833**	4.3	-8.756**	-3.3	0.118	474
9 months	27.817**	4.7	-5.866*	-2.2	0.104	473
10 months	27.612**	4.6	-3.638	-1.3	0.083	472
11 months	26.518**	4.4	-2.288	-0.8	0.068	471
12 months	22.492**	3.7	-1.540	-0.6	0.047	470

Panel B. Recession indicators, GDP growth, and Herfindahl index

Forecast horizon	Recession indicator	t-stat	GDP growth	t-stat	Herfindahl index	t-stat	R^2	Obs.
0 months	37.316**	6.7	2.601	1.0	289.676**	7.0	0.184	480
1 month	33.982**	6.1	-0.449	-0.2	266.152**	6.4	0.176	480
2 months	30.196**	5.4	-3.718	-1.4	243.790**	5.9	0.174	480
3 months	27.269**	4.9	-6.202*	-2.4	224.549**	5.4	0.175	479
4 months	24.662**	4.4	-8.331**	-3.2	218.161**	5.2	0.182	478
5 months	23.740**	4.2	-9.032**	-3.4	216.510**	5.2	0.184	477
6 months	24.020**	4.3	-8.740**	-3.3	217.842**	5.2	0.183	476
7 months	25.542**	4.5	-7.444**	-2.8	212.852**	5.0	0.172	475
8 months	27.191**	4.8	-5.771*	-2.2	209.554**	4.8	0.160	474
9 months	30.125**	5.2	-2.895	-1.1	207.112**	4.7	0.144	473
10 months	29.937**	5.1	-0.593	-0.2	210.714**	4.7	0.125	472
11 months	28.808**	4.9	0.765	0.3	209.734**	4.6	0.109	471
12 months	24.675**	4.1	1.449	0.5	207.827**	4.5	0.086	470

Table 5. Averages of focal variables under dividend forbearance by asset size quartile

This table reports the mean values of the focal variables for our model assuming dividend forbearance. Statistics are reported across asset-size quartiles, and separately for the 1974-2007, 2008-2009, and 2010-2013 periods. Financial statement data are from the Compustat database for U.S. banks and daily stock returns are from CRSP.

Panel A. Pre-crisis years: 1974-2007	Quartile 1	Quartile 2	Quartile 3	Quartile 4
Stand-alone risk, IPD (bp)	53.5	6.2	2.3	2.9
Stand-alone risk ($MM)	0.8	0.5	0.4	6.4
Systemic risk, IPDS (bp)	1.5	-0.2	-0.2	0.0
Systemic risk ($MM)	0.0	0.0	0.0	0.2
Equity volatility (%)	38.4	31.9	29.9	27.4
Asset volatility (%/)	5.1	3.9	3.7	3.5
Market capital (%)	9.3	11.5	11.7	12.6
Tier 1 capital (%)	12.9	12.4	11.9	10.5
Tier 2 capital (%)	2.0	1.7	1.6	2.6
Assets ($BB)	667	1435	3095	38980
Panel B. Crisis years: 2008-2009				
Stand-alone risk, IPD (bp)	429.1	178.8	171.5	255.5
Stand-alone risk ($MM)	16.4	18.0	38.3	3487.7
Systemic risk, IPDS (bp)	-721.3	-429.1	-227.4	-99.6
Systemic risk ($MM)	-12.1	-41.3	-50.6	957.1
Equity volatility (%)	90.1	73.4	76.9	79.1
Asset volatility (%/)	11.5	7.2	7.7	9.9
Market capital (%)	-1.7	5.6	6.6	6.8
Tier 1 capital (%)	12.4	11.2	11.2	11.1
Tier 2 capital (%)	1.4	1.5	1.6	2.3
Assets ($BB)	468	1073	2424	79152
Panel C: Post-crisis years: 2010-2013				
Stand-alone risk, IPD (bp)	68.0	23.3	14.8	7.0
Stand-alone risk ($MM)	2.0	2.4	3.5	18.5
Systemic risk, IPDS (bp)	-6.0	-1.0	0.0	0.3
Systemic risk ($MM)	-0.2	-0.1	0.0	3.8
Equity volatility (%)	53.3	43.1	39.1	32.5
Asset volatility (%/)	5.2	3.5	3.7	3.6
Market capital (%)	6.1	8.3	10.5	11.6
Tier 1 capital (%)	14.8	13.9	14.2	13.6
Tier 2 capital (%)	1.5	1.5	1.6	2.1
Assets ($BB)	557	1263	3008	111247

Table 6. Identity of Top-15 Banks Ranked by Stand-Alone and Systemic Risk, 1974-2013

This table reports the difference in identity of the top-15 banks ranked by stand-alone and systemic risk over the period 1974-2013. Panel A reports the ranking of the stand-alone risk premium and panel B reports the ranking of systemic risk.

Panel A. Top 15 Banks Ranked by Stand-Alone Risk Premium

#	Name	Assets ($MM)
1	CONNECTICUT BANK&TRUST CO/NE	267
2	FLORIDA BANKS INC	151
3	CBC BANCORP INC	104
4	FIRST COML BANCORP INC	170
5	UNIVERSITY BANCORP INC	48
6	AMERICAN PACIFIC BANK -CL B	46
7	OHIO LEGACY CORP	186
8	OPTIMUMBANK HOLDINGS INC	154
9	JACKSONVILLE BANCORP INC/FL	437
10	FIRST BANCSHARES INC/MS	483
11	CARROLLTON BANCORP/MD -OLD	415
12	VALLEY FINANCIAL CORP	799
13	BSD BANCORP INC	399
14	LIBERTY BELL BANK	157
15	FIRST REGIONAL BANCORP	122

Panel B. Top 15 Banks Ranked by Systemic Risk Premium

#	Name	Assets ($MM)
1	AUBURN NATIONAL BANCORP	729
2	FIRST COMMUNITY CORP/SC	634
3	CAROLINA TRUST BANK	137
4	STATE STREET CORP	142,144
5	GLEN BURNIE BANCORP	315
6	JACKSONVILLE BANCORP INC/FL	452
7	WELLS FARGO & CO	1,285,891
8	PNC FINANCIAL SVCS GROUP INC	286,422
9	OLD LINE BANCSHARES INC	245
10	CAPITAL BANK CORP/NC	250
11	NORTHERN STATES FINANCIAL CP	645
12	FIRST FINANCIAL CORP/IN	2303
13	TRICO BANCSHARES	1976
14	BANCTRUST FINANCIAL GRP INC	2088
15	PACWEST BANCORP	4496

Table 7. Stand-alone and systemic risk premiums: Thirty largest banks by the book value of assets

This table reports the 30 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 ($billions)	Stand-alone risk premium (bp)	Systemic risk premium (bp)
1	Bank of America Corp	1,716	2,859	583
2	JPMorgan Chase & Co	1,562	821	526
3	Wells Fargo & Co	575	2,836	1,173
4	US Bancorp	238	966	208
5	Bank of New York Mellon Corp	198	1,148	520
6	Suntrust Banks Inc	180	1,254	383
7	State Street Corp	143	4,102	1,607
8	Regions Financial Corp	141	3,405	541
9	PNC Financial Services Group Inc	139	2,734	1,067
10	BB&T Corp	133	605	343
11	Fifth Third Bancorp	111	1,306	368
12	Keycorp	100	2,986	432
13	Santander Holdings USA Inc	85	6,106	513
14	Northern Trust Corp	68	512	268
15	M&T Bank Corp	65	165	-12
16	Comerica Inc	62	431	207
17	Marshall & Ilsley Corp	60	2,210	570
18	Huntington Bancshares	55	2,576	415
19	Zions Bancorporation	53	1,427	401
20	Popular Inc	44	1,008	58
21	First Horizon National Corp	37	1,787	361
22	Synovus Financial Corp	33	1,245	290
23	Colonial Bancgroup	26	5,563	311
24	Associated Banc-Corp	22	379	75
25	Bok Financial Corp	21	80	-146
26	W Holding Co Inc	18	71	23
27	Webster Financial Corp	17	966	197
28	First Bancorp	17	377	144
29	First Citizens Bancshares	16	90	-86
30	Commerce Bankshares Inc	16	159	-239

Table 8. Comparison of our measures of stand-alone and systemic risk with two other measures of capital shortage

This table shows a comparison of our measures of stand-alone and systemic risk (average values for the period starting in July 2008 and ending in June 2009) with two other measures of capital shortage for 18 of the 19 institutions that the Federal Reserve subjected to stress tests in early 2009. SCAP denotes the capital shortfall calculated in the supervisory Capital Assessment Program conducted in February 2009, 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, and SRISK is from Brownlees and Engle (2015).

	Other measures				Our measures			
	SCAP ($billions)	SCAP/Tier1 Capital (%)	Acharya et al. MES ($billions)	Brownlees and Engle SRISK (%)	Value of Stand-alone Support ($billions)	Stand-alone risk premium IPD (bp)	Value of systemic risk support ($billions)	Systemic risk premium IDPS (bp)
Bank of America Corp	33.9	19.6	15.1	14.14	258	1,304	65	341
Wells Fargo & Co	13.7	15.9	10.6	8.51	119	1,049	53	482
Citigroup Inc	5.5	4.6	15.0	17.50	269	1,474	35	192
Regions Financial Corp	2.5	20.7	14.8		26	2,053	4	297
Suntrust Banks Inc	2.2	12.5	12.9		13	780	4	260
Keycorp	1.8	15.5	15.4		12	1,228	3	279
Morgan Stanley Dean Witter & Co	1.8	3.8	15.2	4.44	138	2,202	5	86
Fifth Third Bancorp	1.1	9.2	14.4		18	1,657	3	262
PNC Financial Services Group Inc	0.6	2.5	10.6		21	803	7	266
American Express Co	0	0.0	9.8		4	328	-4	-389
Bank New York Inc	0	0.0	11.1		12	582	1	37
JPMorgan Chase & Co	0	0.0	10.5	13.58	74	371	45	228
US Bancorp	0	0.0	8.5		9	376	0	12
State Street Corp	0	0.0	14.8		19	1,303	6	455
BB&T Corp	0	0.0	9.6		4	319	0	33
Capital One Financial Corp	0	0.0	10.5		11	777	3	186
Goldman Sachs Group Inc	0	0.0	10.0	4.27	13	151	-4	-43
Metlife Inc	0	0.0	10.3	3.63	42	878	6	130

Table 9. Cross-sectional quarter-by-quarter regressions for stand-alone and systemic risk

This table reports mean coefficients of cross-sectional quarter-by-quarter regressions of stand-alone and systemic risk at sampled US bank holding companies. Regression results are reported separately for the whole period and for the four quarters starting in quarter 3 of 2008 and ending in quarter 2 of 2009. Results in panel A are for regressions of stand-alone risk (IPD) and results in panel B are for regressions of systemic risk (IPDS). The 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 columns labeled "Same Sign" report the number of coefficient estimates whose sign is the same as the reported mean coefficient. The p-values come from a nonparametric sign test.

	Full sample			Q3/08 – Q2/09		
Coefficients	Average	Same sign	p-value	Average	Same sign	p-value
Panel A: Determinants of stand-alone risk (IPD)						
Size	0.018	67	0.98	0.262	2	0.69
Deposits	-0.114	93	0.02	2.024	4	0.06
Asset volatility	18.774	160	0.00	48.648	4	0.06
Implied capital	-6.526	157	0.00	-9.929	3	0.31
Average R^2	0.587			0.907		
Observations	266			356		
Time periods	160			4		
Panel B: Determinants of systemic risk (IPDS)						
Size	0.025	138	0.00	0.984	4	0.06
Deposits	-0.499	103	0.00	-18.386	4	0.06
Asset volatility	-0.394	66	0.98	-9.043	2	0.69
Implied capital	-0.069	106	0.00	--7.790	3	0.31
Ave. R^2	0.195			0.134		
Ave. Obs.	266			356		
Time periods	160			4		

Table 10. Cross-sectional quarter-by-quarter regressions for stand-alone and systemic risk: Additional controls for size

This table reports mean coefficients of cross-sectional quarter-by-quarter regressions of stand-alone and systemic risk at sampled US bank holding companies. Regression results are reported separately for the whole period and for the four quarters starting in quarter 3 of 2008 and ending in quarter 2 of 2009. Results in panel A are for regressions of stand-alone risk (IPD) and results in panel B are for regressions of systemic risk (IPDS). The risk measures are in basis points. Size represents the lagged CPI-adjusted book value of assets in billions of dollars. Large is an indicator set to one for the top-10 percent of banks (by book value of assets) in each calendar quarter. Very large is an indicator set to one for the top-5 percent of banks (by book value of assets) in each calendar quarter. Deposits represent the lagged ratio of deposits to total assets expressed as a percent. Asset volatility is the standard deviation of asset returns (in %) implied by the call option model of bank equity. Implied capital reports the market value of equity as a percentage of the value of assets implied by the option model of bank equity. The reported slope coefficients, R^2, and observation counts are averages from quarterly cross-sectional regressions. The columns labeled "Same Sign" report the number of coefficient estimates whose sign is the same as the reported mean coefficient. The p-values come from a nonparametric sign test.

	Full sample			Q3/08 – Q2/09		
Coefficients	Average	Same sign	Significant	Average	Same sign	Significant
Panel A: Determinants of stand-alone risk (IPD)						
Large	8.735	80	0.53	11.3	3	0.31
Very large	-1.609	59	1.00	70.5	3	0.31
Size	0.004	51	1.00	0.2	3	0.31
Deposits	-0.051	80	0.53	2.4	4	0.06
Asset volatility	18.827	160	0.00	48.3	4	0.06
Implied capital	-6.593	157	0.00	-10.0	3	0.31
Average R^2	0.591			0.907		
Observations	266			356		
Time periods	160			4		
Panel B: Determinants of systemic risk (IPDS)						
Large	9.805	131	0.00	375.9	4	0.06
Very large	9.915	63	0.99	405.9	4	0.06
Size	0.001	118	0.00	0.0	2	0.69
Deposits	-0.374	101	0.00	-13.4	4	0.06
Asset volatility	-0.470	70	0.91	-12.1	3	0.31
Implied capital	-0.092	107	0.00	-8.7	3	0.31
Ave. R^2	0.207			0.177		
Ave. Obs.	266			356		
Time periods	160			4		