The End of Market Discipline? Investor Expectations of Implicit State Guarantees[*]

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Abstract

We find that bondholders of major financial institutions have an expectation that the government will shield them from losses and, as a result, they do not accurately price risk. While bond credit spreads are sensitive to risk for most financial institutions, credit spreads lack risk sensitivity for the largest institutions. This expectation of public support constitutes a subsidy to large financial institutions, allowing them to borrow at government-subsidized rates. We find that passage of Dodd-Frank did not eliminate expectations of government support. The issue of too-big-to-fail remains unresolved.

JEL Classifications: G21, G24, G28.

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I. Introduction

"If the crisis has taught a single lesson, it is that the too-big-to-fail problem must be resolved," declared U.S. Federal Reserve Chairman Ben Bernanke in 2010 when testifying before the U.S. Financial Crisis Inquiry Commission. We find that, despite efforts to end too-big-to-fail, the financial markets believe that the government will bail out major financial institutions in an emergency. The result is an implicit subsidy that allows these institutions to borrow at favorable rates.

The too-big-to-fail (TBTF) doctrine postulates that the government will not allow large financial institutions to fail if their failure would cause significant disruption to the financial system and economic activity. It is commonly claimed that, because of the TBTF doctrine, large financial institutions and their investors expect the government to back the debts of these institutions should they encounter financial difficulty. This expectation that the government will provide a bailout is referred to as an implicit guarantee; implicit because the authorities do not have any explicit, ex ante commitment to intervene.

Although it is often assumed that investors expect government bailouts for large financial institutions, few studies have attempted to provide evidence of that expectation, or to measure the funding subsidy that implicit government protection is alleged to offer. In this paper, we show that the implicit guarantee is priced by investors, and we quantify the value they place on it.

In the absence of an implicit government guarantee, market participants would evaluate a bank's financial condition and incorporate those assessments promptly into securities prices, demanding higher yields on uninsured debt in response to greater risk taking by the bank. However, for the market to discipline banks in this manner, debtholders must believe that they will bear the cost of a bank becoming insolvent or financially distressed. An implicit government guarantee dulls market discipline by reducing investors' incentive to monitor and price the risk taking of potential TBTF candidates. Anticipation of state support for major financial institutions could enable them to borrow at costs that do not reflect the risks otherwise inherent in their operations.

Nevertheless, some claim that Dodd-Frank ended TBTF expectations. Others argue that investors do not expect the government to implement TBTF policies, as there is no formal obligation to do so. The possibility of a bailout may exist in theory but not reliably in practice, and as a result, market participants do not price implicit guarantees. The government's long-standing policy of "constructive ambiguity" (Freixas 1999; Mishkin 1999) is designed to encourage that uncertainty. To prevent investors from pricing implicit support, authorities do not announce their willingness to support institutions they consider too big to fail. Rather, they prefer to be ambiguous about which institutions, if any, would receive support if they got into trouble. Ever since the Comptroller of the Currency named eleven banks "too big to fail" in 1984, authorities have walked a thin line between supporting large institutions and declaring that support was neither guaranteed nor to be expected, permitting institutions to fail when possible to emphasize the point. This has led authorities to take a seemingly random approach to intervention, for instance by saving AIG but not Lehman Brothers, in order to make it hard for investors to rely on a bailout.[1] Hence, it is an empirical question whether the implicit guarantee is considered credible by market participants and is therefore priced.

We find that expectations of state support are embedded in credit spreads on bonds issued by major U.S. financial institutions. We examine the relationship between the risk profiles of financial institutions and the credit spreads on their bonds. While a positive relationship exists between risk and spreads for medium and small institutions, the risk-to-spread relationship is not present for the largest institutions. In other words, bondholders of large financial institutions expect the government to shield them from the consequences of failure and, consequently, bond premiums do not fully reflect the institutions' risk taking. These results are robust to various bond-, firm- and macro-level controls. Expectations of state support reduce the cost of debt for these financial institutions. Because they pay a lower price for risk than other financial institutions, the perceived guarantee provides TBTF institutions with a funding advantage or subsidy.

The funding subsidy does not arise because large institutions are safer than smaller ones. We address potential endogeneity in the relationship between size and spreads by showing that large institutions are not less risky than smaller institutions. Our findings contradict the "charter value" hypothesis put forth by Bliss (2001 and 2004) and others. We find, instead, that large financial institutions are as risky or even riskier than their smaller counterparts. Nevertheless, the large financial institutions enjoy lower spreads.

[1] In a press briefing the day Lehman filed for bankruptcy, Treasury Secretary Paulson said: "Moral hazard is something I don't take lightly."

We alleviate endogeneity concerns further by examining rating agencies' expectations of state support. Certain rating agencies (such as Fitch) estimate a financial institution's stand-alone financial condition separate from its likelihood of receiving external support. Using these third-party estimates of risk and state support, we find that investors price the institution's likelihood of state support but not its stand-alone financial condition.

In addition, we address endogeneity concerns by conducting an event study in order to examine shocks to investor expectations of support. We find that, following the government's rescue of Bear Stearns, the passage of Troubled Asset Relief Program (TARP) and other liquidity and equity support programs, larger financial institutions experienced greater reductions in spreads than smaller institutions experienced. Following the collapse of Lehman Brothers, larger financial institutions experienced greater increases in their spreads than smaller institutions experienced. We also find that passage of Dodd-Frank did not eliminate expectations of future government support.

As additional robustness, we also examine investor expectations of implicit guarantee for non-financial companies. We repeat our analyses of investor expectations of implicit support using non-financial firms as controls. Our results continue to hold when we use a triple-differencing method comparing large financial institutions to large corporates when assessing the size subsidy.

In addition to showing that investors in large financial institutions expect government support, we also estimate the value of that expectation. That is, we provide an estimate of the reduction in funding costs for TBTF financial institutions as a result of implied government support. While the direct cost of government bailouts is relatively straightforward to identify and quantify, the indirect cost arising from implicit government guarantees is more challenging to compute and has received less attention. We find that the implicit subsidy has provided large institutions an average funding cost advantage of approximately 24 basis points per year over the 1990-2011 period, peaking at more than 100 basis points in 2009. The total value of the subsidy amounted to about $30 billion per year on average over the 1990-2011 period, topping $170 billion in 2009. Internalizing this cost would better align risk with return for implicitly guaranteed institutions, producing a more stable and efficient financial system.

In the next section, we discuss the related literature. Section III describes the data and methodology we use in this study. Our main results appear in Section IV. Section V contains robustness tests. Section VI discusses policy implications and recommendations, and Section VII concludes.

II. Related Literature

A line of literature examines whether the market can provide discipline against bank risk taking (DeYoung et al. 2001; Jagtiani, Kaufman and Lemieux 2002; Jagtiani and Lemieux 2001; Allen, Jagtiani and Moser 2001; Morgan and Stiroh 2000 and 2001; Calomiris 1999; Levonian 2000; Federal Reserve Board 1999; and Flannery 1998). This literature examines whether there is a relationship between a bank's funding cost and its risk. Studies present some evidence that subordinated debt spreads reflect the issuing bank's financial condition and consequently propose that banks be mandated to issue subordinated debt. While these studies find that a bank's risk profile has some effect on spreads, the existence of risk-sensitive pricing does not necessarily mean that investors are not also pricing an implicit guarantee. These studies do not consider potential price distortions arising from conjectural government support. For large institutions, the spread-to-risk relationship might diminish or break down if implicit guarantees are factored into market prices. In other words, these studies do not address TBTF.

In contrast to the extensive literature studying the spread-to-risk relationship in banking, a much smaller literature focuses on the role of implicit government guarantees in that relationship. These studies examine how the spread-to-risk relationship changes as investor perceptions of implicit government support changes. Their premise is that investors will price bank-specific risk to a lesser extent during times of perceived liberal application of TBTF policies, and will price bank-specific risk to a greater extent during times of perceived restricted application of TBTF policies. The empirical results, however, have been mixed.

Flannery and Sorescu (1996) examine yield spreads on subordinated debt of U.S. banks over the 1983-1991 period. Flannery and Sorescu believe that the perceived likelihood of a government guarantee declined over that period, which began with the public rescue of Continental Illinois in 1984 and ended with the passage of the FDIC Improvement Act (FDICIA) in 1991. They find that yield spreads were not risk sensitive at the start of the period, but came to reflect the specific risks of individual issuing banks at the end of the period, as conjectural government guarantees weakened. Sironi (2003) reaches a similar conclusion in his study of

European banks during the 1991-2001 period. During this period, Sironi argues, implicit public guarantees diminished due to loss of monetary policy by national central banks and public budget constraints imposed by the European Union. Sironi uses yield spreads on subordinated debt at issuance to measure cost of debt and finds that spreads became relatively more sensitive to bank risk in the second part of the 1990s, as the perception of public guarantees diminished. In other words, these studies argue that as the implicit guarantee was diminished through policy and legislative changes, debt holders came to realize that they were no longer protected from losses and responded by more accurately pricing risk.

Other studies, however, reach different conclusions about the spread-risk relationship. These studies focus on the banks declared "too big to fail" by the Comptroller of the Currency in 1984, in order to differentiate TBTF banks from non-TBTF banks. Morgan and Stiroh (2005) determine that the spread-risk relationship was flatter for the named TBTF banks than it was for other banks. They find that this flat spread-risk relationship for the TBTF banks existed during the 1984 bailout of Continental Illinois and persisted into the 1990s, even after the passage of FDICIA, contrary to the findings of Flannery and Sorescu (1996). Similarly, Balasubramnian and Cyree (2011) suggest that the spread-risk relationship flattened for TBTF banks following the rescue of Long-Term Capital Management in 1998. In these studies, however, the TBTF definition (one of the eleven banks named "too big to fail" by the Comptroller) is one originating in 1984. Not only do these studies focus on a short list of banks from 1984, they also examine a limited period of time. In contrast, we identify TBTF institutions by employing multiple measures of bank size and systemic risk contribution. Our TBTF definition captures time variation and is a more relevant definition in today's environment. While their definition of TBTF may suit the time period they analyze (the 1980s and 1990s), we analyze a longer period of time (1990-2011), including the recent financial crisis. We also undertake a more detailed analysis of the role TBTF status plays in the spread-risk relationship. In addition, we address endogeneity issues by performing multiple robustness tests. And we do more than ask whether implicit guarantees impact borrowing costs for TBTF institutions; we also provide a quantitative measure of the subsidy.

Although most research on implicit government guarantees has examined debt prices, some studies have looked at equity prices. These papers provide indirect evidence of a funding subsidy arising from implicit government support. While the immediate and most-valued beneficiaries of TBTF policies will be the debtholders, equity studies conjecture that implicit support will impact a bank's stock price by reducing the bank's cost of funds, thereby increasing profitability. Studies find a positive relationship between bank size and equity prices. O'Hara and Shaw (1990) find that positive wealth effects accrued to shareholders of the eleven banks named TBTF by the Comptroller in 1984. Other studies suggest that shareholders benefit from mergers and acquisitions that result in a bank achieving TBTF status. Studies report that mergers undertaken by the largest banks increase market value for shareholders, while this is not the case for smaller banks, suggesting market prices reflect safety net subsidies for TBTF banks (e.g., Kane 2000). Hence, studies have focused on premiums paid in bank M&A activity, finding that greater premiums are paid in larger transactions, reflecting the benefits of safety net subsidies (Brewer and Jagtiani 2007; Molyneux, Schaeck and Zhou 2010).

Our paper is also related to a large literature that examines implicit guarantees and risk taking by banks. Although we focus on investors, implicit guarantees can also affect bank managers. The empirical literature on moral hazard generally concludes that banks increase their risk taking in the presence of government guarantees, as the guarantee provides protection against losses (Duchin and Sosyura 2012; Gropp, Hakenes and Schnabel 2010; Gropp, Gruendl and Guettler 2010; De Nicoló 2000; Hovakimian and Kane 2000; Boyd and Runkle 1993; Boyd and Gertler 1994; Demirguc-Kunt and Detragiache 2002, 2006). However, the evidence is far from unambiguous and some studies find that guarantees reduce risk taking (Kacperczyk and Schnabl 2011; Gropp and Vesala 2004; Cordella and Yeyati 2003), possibly resulting from increased charter values (Bliss 2001 and 2004; Keeley 1990) or greater regulatory oversight.

III. Data and Methodology

We collect data for corporates and financial firms. Financial firms are classified using a two-digit Standard Industrial Classification (SIC) code of 60 to 64 (banks, broker-dealers, exchanges, and insurance companies), and 67 (other financial firms). We exclude debt issued by government agencies and government-sponsored enterprises. Firm-level accounting and stock price information are obtained from COMPUSTAT and CRSP for the 1980–2011 time period.[2] Bond data come from three separate databases: the Lehman Brothers Fixed Income Database (Lehman) for the period 1980 to 1998, the National Association of Insurance Commissioners

[2] We obtained similar results using BANKSCOPE data.

Database (NAIC) for the period 1998 to 2006, and the Trade Reporting and Compliance Engine (TRACE) system dataset from 2006 to 2011. We also use the Fixed Income Securities Database (FISD) for bond descriptions. Although the bond dataset starts in 1980, it has significantly greater coverage starting in 1990. In this paper, we focus on the 1990-2011 period.

Our sample includes all U.S.-issued bonds of financial institutions listed in the above datasets that satisfy a set of selection criteria commonly used in the corporate bond literature (see, for instance, Anginer and Yildizhan 2010 and Anginer and Warburton 2013). We exclude all bonds that are matrix-priced (rather than market-priced). We remove all bonds with equity or derivative features (i.e., callable, puttable, and convertible bonds), bonds with warrants, and bonds with floating interest rates. Finally, we eliminate all bonds that have less than one year to maturity. There are a number of extreme observations for the variables constructed from the bond datasets. To ensure that statistical results are not heavily influenced by outliers, we set all observations higher than the 99th percentile value of a given variable to the 99th percentile value. There is no potential survivorship bias in our sample, as we do not exclude bonds issued by firms that have gone bankrupt or bonds that have matured. In total, we have 567 unique financial institutions and 84,057 observations that have corresponding spread and financial information (Panel A of Table 1).

For each financial institution, we compute the beginning-of-month credit spread on its bonds (*spread*), defined as the difference between the yield on its bonds and that on the corresponding maturity-matched treasury bond. We are interested in systemically important financial institutions, as these firms will be the beneficiaries of potential TBTF interventions. Dodd-Frank emphasizes size in defining systemically important financial institutions. Although size is not the only characteristic that can make a financial institution systemically important, recent literature suggests that it is the most significant driver.[3] Adrian and Brunnermeier (2011), for instance, show that the systemic risk contribution of a given financial institution is driven significantly by the relative size of its assets. We employ multiple measures of firm size. One is the size (log of assets) of a financial institution (*size*) in a given year. A second is whether a financial institution is in the top 90th percentile of financial institutions ranked by assets in a given year (*size90*), and a third is whether a financial institution is one of the ten largest

[3] Other characteristics include interconnectedness, number of different lines of business, and complexity of operations. But these characteristics tend to be highly correlated with the size of a financial institution's balance sheet.

institutions in terms of size in a given year (*size_top_10*). These two measures are meant to capture very large institutions, which are likely to benefit most from TBTF policies. We also define TBTF firms in terms of systemic risk (*covar* and *srisk*).

A number of different measures of risk have been used in the literature. In this study, we use distance to default (*mertondd*) as our primary risk measure. Distance to default is a measure of credit risk based on the structural credit risk model of Merton (1974). This approach treats the equity value of a firm as a call option on the firm's assets. Distance to default is the difference between the asset value of the firm and the face value of its debt, scaled by the standard deviation of the firm's asset value. The Merton distance-to-default measure has been shown to be a good predictor of defaults, outperforming accounting-based models (Campbell, Hilscher and Szilagyi 2008; Hillegeist et al. 2004). Although the Merton distance-to-default measure is more commonly used in bankruptcy prediction in the corporate sector, Merton (1977) points out the applicability of the contingent claims approach to pricing deposit insurance in the banking context. Anginer and Demirguc-Kunt (2011), Bongini, Laeven, and Majnoni (2002), Bartram, Brown and Hundt (2008) and others have used the Merton model to measure default probabilities of commercial banks.[4] We follow Campbell, Hilscher and Szilagyi (2008) and Hillegeist et al. (2004) in calculating Merton's distance to default. The details of the calculation are set forth in Appendix A. A higher distance-to-default number signals a lower probability of insolvency.[5]

Following Flannery and Sorescu (1996) and Sironi (2003), our controls include leverage, return on assets, time to maturity, seniority, market-to-book ratio, and issue rating. Leverage (*leverage*) is the ratio of total liabilities to total assets. Return on assets (*roa*) is the ratio of annual net income to year-end total assets. Time to maturity (*ttm*) is time to maturity (in years) of the issue. Seniority (*seniority*) is the senior versus subordinated status of the bond. Market-to-book ratio (*mb*) is the ratio of the market value of total equity to the book value. Issue rating (*rating*) is the issue rating assigned by Standard & Poor's. We follow convention and use a numeric rating scale to convert ratings: 1 for AAA, …, 21 for CC. In addition, we include maturity mismatch (*mismatch*), defined as the ratio of short-term debt (minus cash) to total debt,

[4] We verify our results using z-score in place of distance to default. Although z-score is more commonly used in the banking literature than Merton's distance-to-default measure, it does not exploit market prices like the Merton measure. In our analyses, we get substantially similar results using z-score in place of distance to default.
[5] Default probability for a firm is given by *N(-distance-to-default)*, where *N()* is the cumulative normal distribution.

as an additional control. We also include monthly macro factors (*mkt, term* and *def*). The construction of the variables is described in more detail in Appendix A.

Summary statistics appear in Table 1 (Panel B). Although it is larger financial institutions that issue public debt, we see significant dispersion in asset size.

IV. Results

In this section, we show first that bondholders of major financial institutions have expectations of receiving state support, providing a funding subsidy to these institutions. We then quantify the value of that subsidy on a yearly basis over the 1990-2011 time period.

1. Expectations of State Support

We begin by examining how the size of a financial institution affects the credit spread on its bonds. Following the empirical model in Campbell and Taksler (2003), we estimate the following regression using a panel with one observation for each bond-month pair:

$$\begin{aligned} Spread_{i,b,t} = \propto &+ \beta^1 TBTF_{i,t-1} + \beta^2 Risk_{i,t-1} + \beta^3 Bond\ Controls_{i,b,t} \\ &+ \beta^4 Firm\ Controls_{i,t-1} + \beta^5 Macro\ Controls_t + \ Firm\ FE + Year\ FE \\ &+ \varepsilon_{i,b,t} \end{aligned} \tag{1}$$

In equation (1), the subscripts *i*, *b*, *t* indicate the financial firm, the bond, and the time (month), respectively, and the term *FE* denotes fixed effects. The dependent variable is the spread. To measure systemic importance of an institution (*TBTF*), we use multiple measures of an institution's size and systemic risk contribution, as discussed in Section III. We use Merton's distance to default (*mertondd*) as our measure of risk ($Risk_{i,t}$). We also control for the following firm characteristics: leverage (*leverage*), return on assets (*roa*), market-to-book ratio (*mb*), and maturity mismatch (*mismatch*). In addition, we control for the following bond characteristics: the time to maturity of the bond (*ttm*) measured in years, and the S&P issue rating (*rating*), and the senior versus subordinated status of the bond (*seniority*). We also control for the following monthly macro factors: the market risk premium (*mkt*), the yield spread between long-term (10-year) treasury bonds and the short-term (three-month) treasuries (*term*) as a proxy for unexpected changes in the term structure, and the BAA-AAA corporate bond spread (*def*) as a proxy for default risk. The construction of the variables is described in Appendix A.

The results appear in Table 2. The table indicates a significant inverse relationship between spreads and systemic importance. First, we use asset size (*size*) to identify systemic importance (columns 1 and 2). We see that *size* has a significant negative effect on *spread*. Larger institutions have lower spreads. Next, we identify systemic importance as a financial institution in the top 90th percentile in terms of size (*size90*) (column 3). The coefficient on the *size90* dummy variable is significant and negative, indicating that very large institutions have lower spreads. In column 4, we add dummy variables indicating an institution between the 60th and 90th percentiles (*size60*) and between the 30th and 60th percentiles (*size30*). The coefficients on *size60* and *size30* lack significance. These results suggest that the effect of size on spreads comes mostly from the very large financial institutions. In column 5, we define a systemically important institution as one of the ten largest institutions in terms of size in a given year (*size_top_10*). Results again show that TBTF status has a significant negative effect on spreads.

As a robustness check, we also define systemic importance in terms of systemic risk. Results appear in Table 8. Following Adrian and Brunnermeier (2011), we use an institution's contribution to systemic risk (*covar*) to identify systemic importance. Higher values of *covar* indicate greater systemic risk contribution. Results show a significant negative relationship between *covar* and *spread* (column 3). That is, the greater an institution's contribution to systemic risk, the lower its spread. We use a second systemic risk measure (*srisk*) based on the expected capital shortfall framework developed by Acharya, Engle and Richardson (2012). Results show a significant negative relationship between *srisk* and *spread* (column 4). The greater the institution's systemic risk, the lower its spread. Overall, our results suggest a negative relationship between systemic importance and the cost of debt.

We also look at whether this relationship varies by type of financial institution. We interact *size90* with a dummy variable indicating whether the financial institution is a bank, insurance company or broker-dealer (based on its SIC code). Results appear in Table 2 (column 6). The effect of size on spreads is significant for the banks. Size does not reduce spreads to a significant degree when the financial institution is an insurance company or a broker-dealer.

As an additional robustness test, we also include non-financial companies (column 7 of Table 2). A dummy variable (*financial*) is set equal to one for a financial firm and zero for a non-financial firm. We are interested in the term interacting *financial* with *size90* (*size90* indicates a firm in the top 90th percentile of its size distribution). This interaction term captures the differential effect size has on spreads for financials compared to corporates. The estimated coefficient is negative and statistically and economically significant, suggesting that the effect of large size on spreads is larger for financials than for corporates. In all, we find significant effects of large size on spreads event after controlling for effect of large size on spreads for corporates.

In addition to indicating a relationship between credit spreads and the systemic importance of a financial institution, Table 2 also indicates that there is a significant relationship between credit spreads and the risk of a financial institution. The coefficient on distance to default (*mertondd*) is significant and negative in Table 2. This result indicates that less-risky financial institutions (those with a greater distance to default) generally have lower spreads on their bonds.

Does a financial institution's size affect this relationship between spreads and risk? To answer that question, we interact the size and risk variables. Results appear in Table 3. There is a significant and positive coefficient on the term interacting *size90* and *mertondd* (column 1). It indicates that the spread-risk relationship diminishes with TBTF status. For institutions that achieve systemically-important status, spreads are less sensitive to risk. The result is consistent with investors pricing an implicit government guarantee for the largest financial institutions. Moreover, the result is robust to different measures of risk. In place of *mertondd*, we employ z-score (*zscore*)[6] in column 2 and volatility (*volatility*) in column 3. In each specification, the coefficient on the interaction term is significant and offsets the coefficient on the risk variable, indicating that the spread-risk relationship diminishes for the largest institutions.

These relationships can be seen in Figures 1 and 2. Figure 1 shows the relationship between the size of a financial institution and the credit spread on its bonds. It shows a negative relationship between size and spreads: larger institutions have lower spreads. Why do larger institutions have lower spreads? Are they less risky than smaller ones? Figure 2 plots the size of a financial institution against its risk (distance to default). There does not appear to be any observable relationship between size and risk. That is, Figure 2 suggests that larger institutions

[6] We compute z-score on a rolling basis as the sum of return on assets and equity ratio (ratio of book equity to total assets), averaged over four years, divided by the standard deviation of return on assets over four years (see Roy 1952). The z-score measures the number of standard deviations that a financial institution's rate of return on assets can fall in a single period before it becomes insolvent. A higher z-score signals a lower probability of insolvency. A z-score is calculated only if we have accounting information for at least four years.

do not offer lower risk of large loses than smaller institutions.[7] Hence, the two figures, together, support the notion that large institutions have lower spreads because of implicit government guarantees. That is, large financial institutions enjoy lower spreads because of implicit government support, not because of their underlying risk profiles.

As before, we also examine the impact of risk on spreads comparing financials to corporates. The results are reported in columns 4, 5, and 6. We are interested in the $financial_{t-1}$ * $mertondd_{t-1}$* $size90_{t-1}$ variable. This triple interaction term captures the risk sensitivity of spreads for large financials compared to large corporates. We find that risk sensitivity declines more for large financials than for large corporates. In other words, when we add corporates as controls, we find the same reduction in risk sensitivity for large financials that we found in columns 1, 2, and 3.

2. Quantification of the Implicit Subsidy

As the above results show, major financial institutions enjoy a funding subsidy as a result of implicit government support. In this subsection, we quantify the value of that subsidy. We provide an estimate of the reduction in funding costs for TBTF financial institutions as a result of implied government support.

We estimate the implicit subsidy on a yearly basis. To compute the annual subsidy, we run the following regression for each year:

$$\begin{aligned} Spread_{i,b,t} = \propto &+ \beta^1 \times seniority_{i,b,t} + \beta^2 \times ttm_{i,b,t} + \beta^3 leverage_{i,t} + \beta^4 roa_{i,t} + \beta^5 mb_{i,t} \\ &+ \beta^6 mismatch_{i,t} + \beta^7 mertondd_{i,t} + \beta^8 def_t + \beta^9 term_t + \beta^{10} mkt_t \\ &+ \beta^{11} size90_{i,t} + \varepsilon_{i,b,t} \end{aligned} \quad (2)$$

where our variable of interest, *size90*, indicates a firm in the top 90th percentile of firms by assets. The coefficient on *size90* represents the subsidy accruing to large financial institutions as a result of implicit government insurance. The estimated subsidy is plotted, by year, in Figure 3. It depicts the estimated subsidy over the period from 1990-2011.

[7] It is important to note that the implicit guarantee does not prevent a financial institution from suffering significant losses, including having its equity wiped out and approaching the default boundary on its debt, before the implicit guarantee becomes explicit. Both distance to default and z-score capture these losses and, therefore, do not reflect the implicit guarantee itself.

The implicit subsidy provided large financial institutions a funding cost advantage of approximately 24 basis points per year, on average, over the 1990-2011 period. The subsidy skyrocketed to over 100 basis points in 2009. We also examine how the funding cost advantage has varied over time using corporates as controls. We use the same approach used to create the results in column 7 in Table 2. Instead of doing running the regression for the for the full time-period, we estimate the coefficients each week and plot the interaction of *financial* dummy with the systemic size measure *size90.* Figure 7 plots the coefficient estimates for the crisis and post crisis time periods. We see a similar pattern. There has been a substantial decrease in funding costs for large financial firms compared to large corporates during the crisis. Although the funding cost advantage has come down it remains positive after the crisis.

We also quantify the dollar value of the annual subsidy. We multiply the annual reduction in funding costs by total uninsured liabilities (in US$ millions) to arrive at the yearly dollar value of the subsidy, reported on the left axis of Figure 3.[8] The dollar value of the subsidy amounted to $30 billion per year, on average. The value of the subsidy peaked in 2009 at over $170 billion.

Despite the magnitude of the implicit subsidy, few studies have attempted to quantify it. Those studies that have attempted a quantification do not focus on the U.S. and instead examine a sample of banks worldwide (Ueda and di Mauro 2011; Rime 2005; Soussa 2000). Ueda and di Mauro (2011) estimate a 60 basis point subsidy existed in 2007 for banks worldwide and an 80 basis point subsidy existed in 2009. Studying the pre-crisis period, Rime (2005) finds a subsidy of 10 to 20 basis points for stronger banks and 20 to 80 basis points for weaker banks. These studies, however, use credit ratings to proxy for funding costs. That is, they measure reductions in funding costs only indirectly, by studying differences in credit ratings, not directly as we do using market price data. Market prices reflect the expectations of actual investors in the market and, for many institutions, are available almost continuously. As a result, while prior studies support the notion that an implicit guarantee exists worldwide, they do not provide a precise measure of it. In addition, they use limited controls for differences in bank characteristics and risk. They also examine limited time periods: Ueda and di Mauro examine only two cross

[8] We exclude deposits backed by explicit government insurance. It is also possible that investors have different expectations of a guarantee for different aspects of liabilities of a given firm. Total uninsured liabilities, therefore, provides a rough estimate of the dollar value of the implicit guarantee.

sections (year-end 2007 and year-end 2009) and Rime examines only the period from 1999-2003.

Instead of measuring implicit government support, prior research has mainly attempted to measure explicit government support. For instance, Laeven and Valencia (2010) estimate that the direct fiscal cost of the U.S. government's response to the financial crisis amounted to approximately 5% of GDP. Veronesi and Zingales (2009) estimate the direct cost to be between $21 and $44 billion.[9] Direct costs of bailouts have always caught the attention of the public (Stern and Feldman 2004). Indeed, there is a growing concern in the literature that bailouts may have grown so large that they are straining the public finances in many countries and governments cannot continue to afford them (e.g., Brown and Dinç 2011; Demirgüç-Kunt and Huizinga 2010).

But direct costs provide only a narrow quantification of bailouts and likely underestimate their actual cost. Estimates of the direct, or ex post, cost of government interventions overlook the ex ante cost of implicit support (i.e., the resource misallocation it induces), which is potentially far greater. While explicit support is relatively easy to identify and quantify, implicit support is more difficult and has received less attention. We have focused on quantifying the cost of implicit government support since it is the more comprehensive measure of the cost of bailouts. Our approach recognizes that, even when the banking system appears strong, safety net subsidies exist for large financial institutions.

V. Robustness

In this section, we address the potential for endogeneity in the relationship between spreads and TBTF status. First, we examine in greater detail the relationship between the size of a financial institution and its risk. Next, we examine credit ratings issued by Fitch, which provide third-party measures of an institution's credit risk and an institution's likelihood of receiving external support in a crisis. Third, we perform an event study to examine shocks to investor expectations of support. Fourth, we compare non-guaranteed bonds to bonds with explicit government guarantees. Finally, we control for bond liquidity. Throughout our results, we use large non-financial firms as controls in analyzing the implicit subsidy for financial firms.

[9] Veronesi and Zingales use bailout events to quantify the value of the subsidy. While that approach may reveal the change in the subsidy that a particular intervention produced, it does not capture the level of the subsidy, which can be substantial even during periods between crises.

1. The TBTF-Risk Relationship

It is often claimed that large financial institutions are considered less risky by investors. Large institutions might benefit from government guarantees, reducing their risk of loss. But large financial institutions, by virtue of their size, might benefit from other factors that reduce the level of their risk vis-à-vis other financial institutions. For instance, large financial institutions might benefit from better investment opportunities. If so, they may have inherently less risky portfolios. In addition, large financial institutions might enjoy superior economies of scale and be better diversified than smaller ones. A growing literature argues that economies exist in banking (Wheelock and Wilson 2001, 2012; Hughes and Mester 2011; McAllister and McManus 1993). However, economies are often attributed to advances in information and financial technology and regulatory changes that have made it less costly for financial institutions to become large, not increasing size itself (e.g., Stiroh 2000; Berger and Mester 1997). Moreover, most research has concluded that economies exist only for financial institutions that are not very large (Amel et al. 2004; Berger and Humphrey 1994; Berger and Mester 1997).[10] This suggests that economies disappear once a certain size threshold is reached, with diseconomies emerging due to the complexity of managing large institutions and implementing effective risk-management systems (e.g., Laeven and Levine 2007; Demirguc-Kunt and Huizinga 2011).

Nevertheless, in this subsection, we address the potential endogeneity concern. If investors believe risk-reducing benefits accompany large size for reasons other than TBTF guarantees, larger institutions should exhibit superior credit risk. Hence, we regress credit risk on size, with controls, as follows:

$$\text{Risk}_{i,t} = \propto + \beta^1 \text{TBTF}_{i,t\text{-}1} + \beta^2 \text{Financial}_{i,t\text{-}1} + \beta^3 \text{TBTF}_{i,t\text{-}1} + \beta^4 \text{Financial}_{i,t\text{-}1} \times \text{TBTF}_{i,t\text{-}1} + \beta^5 \text{ Macro Controls}_t + \beta^6 \text{Firm Controls}_{i,t\text{-}1} + \text{Year FE} + \varepsilon_{i,t} \quad (3)$$

We use distance to default as our measure of risk. We run the regression for the financial firms in our sample first. The results for the financial firms appear in columns 1 and 2 of Table 4. We find *size* to be significantly associated with lower risk. This relationship, however, is not significant at the top of the size distribution. *size90* does not significantly affect risk. As in the

[10] The literature generally finds a U-shaped cost curve with a minimum typically reached within a range of $10 billion to $100 billion in assets, depending on the sample, time period, and methodology.

previous section, we examine the impact of size on risk comparing financials to corporates. These results are reported in columns 3 and 4. We are interested in the $Financial_{i,t-1} \times TBTF_{i,t-1}$ variable. This interaction term captures the differential effect size has on risk for financials compared to corporates. The estimated coefficient is negative and economically and statistically significant using both the *size* and *size90* variables, suggesting that the effect of size on risk is smaller for financials.

Overall, our results provide support for a large literature that has failed to detect efficiency and risk-reduction benefits for very large banks (see, e.g., Demirguc-Kunt and Huizinga 2011; Demsetz and Strahan 1997). In short, Table 4 shows that larger financial institutions are not less risky than smaller ones. Hence, it is not because of a reduction in underlying default risk that large institutions experience a reduction in their spreads. By showing that larger size does not imply lower risk, Table 4 supports our main finding that the credit market prices an expectation of government support for large financial institutions.

2. Individual and Support Ratings

To further alleviate concerns about endogeneity, we exploit credit ratings and government-support ratings as alternative measures of credit risk and implicit support. In this subsection, we examine ratings issued by Fitch, which provide third-party measures of credit risk and potential external support.

In rating financial institutions, Fitch distinguishes between an institution's own financial strength and the support it might receive from external sources. Accordingly, Fitch assigns both an "issuer rating" and a "stand-alone rating" to financial institutions. Fitch's issuer rating is a conventional credit rating. It measures a financial institution's ability to repay its debts after taking into account all possible external support. In contrast, Fitch's stand-alone rating measures a financial institution's ability to repay its debts without taking into consideration any external support. The stand-alone rating reflects an institution's independent financial strength, or in other words, the intrinsic capacity of the institution to repay its debts. The difference between these two ratings reflects Fitch's judgment about expected government support for a financial institution.

We use Fitch's long-term issuer rating (*issuer rating*) and Fitch's stand-alone rating (*stand-alone rating*) as independent variables in the spread regression specified in equation (1) above. The issuer rating scale ranges from AAA to C- (ratings below C- are excluded from our dataset since they indicate defaulted firms). The stand-alone rating scale ranges from A to E. We transform the ratings into numerical values using the following rule: AAA=1, ..., C-=9 for the issuer rating and A=1, A/B=2, …, E=9 for the stand-alone rating.

Table 5 (Panel A) contains results of regressions similar to the spread regressions of Table 2, but with the addition of the rating variables. The stand-alone rating is employed in specification 1. It has only a weakly significant impact on spreads. Specification 2 employs the issuer rating. The issuer rating has a significant positive impact on spreads. The issuer rating incorporates implicit government support, and that expectation of government assistance has a significant downward impact on credit spreads. Financial institutions likely to receive government support pay lower spreads on their bonds.

In specification 3, both ratings are employed simultaneously. In that specification, the coefficient on the issuer rating remains significant and positive. Moreover, the effect of the issuer rating subsumes the effect of the stand-alone rating. In the presence of the issuer rating, the coefficient on the stand-alone rating loses significance, indicating that the independent risk profile of a financial institution does not significantly impact spreads. In sum, we find that issuer ratings (which incorporate expectation of support) impact spreads, but stand-alone ratings do not have a similar effect. Investors do not price the true, intrinsic ability of a financial institution to repay its debts, but instead price implicit government support for the institution. This result is consistent with the findings of Sironi (2003) using European data and supports our earlier conclusion that the expectation of government support for large financial institutions impacts the credit spreads on their bonds.

In Panel B, issuer and stand-alone ratings are regressed on TBTF measures, with control variables. Both TBTF measures (*size* and *size90*) have a significant negative effect on the issuer rating (better ratings are assigned lower numerical values). The issuer rating incorporates expectations of government support, and we see that larger institutions have significantly better issuer ratings. In contrast, the TBTF measures do not have a significant effect on the stand-alone rating. The stand-alone rating excludes potential government support, and we find that large institutions do not have significantly better stand-alone ratings. Size does not impact the stand-alone rating, but it does impact the issuer rating.

3. Event Study

Next, we examine how credit spreads were impacted by events that might have changed investor expectations of government support. The events we examine and their corresponding dates are reported in Table 6. These events offer natural experiments to assess changes in TBTF expectations over time. For instance, prior to the financial crisis, investors may have been unsure about whether the government would guarantee the obligations of large financial institutions should they encounter financial difficulty, since there was no explicit commitment to do so. When Bear Stearns collapsed, its creditors were protected through a takeover arranged and subsidized by the Federal Reserve, despite the fact that Bear Stearns was an investment bank and not a commercial bank.[11] This intervention likely reinforced expectations that the government would guarantee obligations of large financial institutions. Similarly, the later decision to allow Lehman Brothers to fail, in contrast, served as a negative shock to those expectations. Although the Federal Reserve and the Treasury intervened the day after Lehman was allowed to collapse (including a rescue of AIG's creditors), the government adopted a series of unpredictable and confusing policies around Lehman's collapse, making future intervention increasingly uncertain. Hence, the Bear Stearns event and the Lehman event provide contrasting shocks to investor expectations of government support. We also examine other events that may have affected investor expectations positively. In particular, we examine the events surrounding the passage of the Troubled Asset Relief Program (TARP), as well as, other announcements of liquidity and financial support to the banking sector.

We examine events using a window of +/- 5 trading days around the event. We run the following regression:

$$\begin{aligned} Spread_{i,b,t} = \propto + \beta^1 post + \beta^2 TBTF_{i,t} \times post + \beta^3\, Risk_{i,t} \times post + \beta^4 TBTF_{i,t} \times Risk_{i,t} \\ \times post + \beta^5 Macro\ Controls_t + Issue\ FE + \varepsilon_{i,b,t} \end{aligned} \quad (4)$$

[11] In connection with Bear Stearns' merger with JP Morgan, the Federal Reserve provided JP Morgan with regulatory relief and nearly $30 billion in asset guarantees, and Bear Stearns with lending support under section 13(3) of the Federal Reserve Act of 1913, the first time since the Great Depression that the Federal Reserve directly supported a non-bank with taxpayer funds. The Fed also announced the Primary Dealer Credit Facility, which opened the discount window to primary dealers in government securities, some of which are investment banks, bringing into the financial safety net investment banks like Lehman, Merrill Lynch, and Goldman Sachs.

We use *size90* as our measure of systemic importance. We use a dummy variable, *post*, which equals one on the event date and the five subsequent trading days. We use issue fixed effects (*Issue FE*) and the regression corresponds to a difference-in-difference estimation. We examine the change in TBTF subsidy after the event, as well as the change in risk sensitivity after the event. These changes are captured by the coefficients on the $TBTF_{i,t} \times post$, and the $TBTF_{i,t} \times Risk_{i,t} \times post$ variables respectively.

As before, we introduce corporate firms as controls and examine changes in TBTF subsidy and risk sensitivity after the event with respect to corporate firms. Specifically, we run the following regression for a sample of firms that includes corporates as well as financials:

$$\begin{aligned} Spread_{i,b,t} = \propto &+ \beta^1 post + \beta^2 TBTF_{i,t} \times post + \beta^3 Fincancial_{i,t} \times post + \beta^4\, Risk_{i,t} \\ &\times post + \beta^5 TBTF_{i,t} \times Fincancial_{i,t} \times post + \beta^6 TBTF_{i,t} \times Risk_{i,t} \times post \\ &+ \beta^7 Fincancial_{i,t} \times Risk_{i,t} \times post + \beta^8 TBTF_{i,t} \times Fincancial_{i,t} \times Risk_{i,t} \\ &\times post + \beta^9 Macro\ Controls_t + Issue\ FE + \varepsilon_{i,b,t} \end{aligned} \tag{5}$$

The coefficient on the $TBTF_{i,t} \times Fincancial_{i,t} \times post$ variable captures the impact of the event on spreads for large financial institutions compared to large corporates. Similarly, the $TBTF_{i,t} \times Fincancial_{i,t} \times Risk_{i,t} \times post$ variable captures the effect of the event on the spread-risk relationship for large financials compared to large corporates.

The results are reported in Table 6. To save space, we only report variables that are of interest discussed above. We find that announcements of government financial and liquidity support have been associated with a decrease in spreads for larger financial institutions. In particular, the bailout of Bear Stearns and the revised TARP bill passing the House of Representatives led to decreases in spreads in excess of 100 bps (column 1). Large financial institutions also saw a decrease in the risk sensitivity of their debt to changes in risk (column 2). We find similar results when we use corporate firms as controls. These triple-difference results are provided in the last two columns of Table 6.

Next, we examine a negative shock to investor expectations of government support, namely the collapse of Lehman Brothers on September 15, 2008. Again, our variable of interest is the term interacting *post* with *size90*. The coefficient on the interaction term is significant and positive for the Lehman event (column 1). The result indicates that larger institutions saw greater increases in their spreads after the government allowed Lehman to collapse.[12] The increase is economically significant at over 100 bps. In response to the Lehman collapse, large institutions also saw their spreads become significantly more sensitive to risk. The coefficient on the triple-interaction is significant and negative (column 2), indicating an increase in risk sensitivity for large institutions following that event. The results are similar when we use corporates as controls (columns 3 and 4).

These results suggest that market participants revised their expectations of government intervention during these events. By analyzing recent shocks to investor expectations of government assistance, we find additional evidence consistent with our main finding that credit markets price expectations of government support for large financial institutions.

We also examine two regulatory reforms that have been proposed to address problems associated with too-big-to-fail institutions. The first is the adoption of the Dodd-Frank Wall Street Reform and Consumer Protection Act (Dodd-Frank). One of the main purposes of the legislation was to end investors' expectations of future government bailouts. Table 6 shows results for June 29, 2010, the date the House and Senate conference committees issued a report reconciling the bills of the two chambers, and July 21, 2010 when the bill passed the U.S. House of Representatives. The coefficient on the term interacting *size90* and *post* for the first event is significant and negative. This indicates that Dodd-Frank actually lowered spreads for the very largest financial institutions relative to the others (though the 3 basis point effect is economically small). The coefficient on *size90*mertondd*post* is significant and negative. This suggests that Dodd Frank increased the risk sensitivity of spreads for large institutions (though the effect again is economically very small). We find a small positive increase using the July 21, 2010 event date when the bill passed the U.S. House of Representatives. As there has been uncertainty surrounding the information regarding Dodd-Frank and its implementation, we also employ a longer event window of 132 trading days (6 months). Results using this longer window are shown in Table BI of Appendix B. The relevant coefficients are largely insignificant statistically and economically. In all, these results suggest that Dodd-Frank has been unimportant in changing investors' expectations of future support for major financial institutions. Dodd-Frank

[12] We recognize that, in addition to signaling a reduced likelihood of bailouts, Lehman's collapse might have exerted a more direct effect on financial institutions. Hence, we tried controlling for institutions' exposure to Lehman by including an indicator variable (*exposure*) that takes the value of one for an institution that declared direct exposure to Lehman in the weeks following its collapse, and zero otherwise (following Raddatz 2009). We obtained results similar to the reported results.

designates certain companies as “systemically important” if their failure will cause instability of the financial system. Bank holding companies with assets of more than $50 billion are automatically designated as systemically important. Similar to the Comptroller of the Currency naming eleven banks “too big to fail” in 1984, Dodd-Frank’s designation of certain institutions as systemically important may have had the unintended consequence of firming market expectations that these institutions are likely to receive government support should they encounter financial problems.

We also examine FDIC’s recently proposed Single Point of Entry (SPOE) strategy to implement its Orderly Liquidation Authority (OLA) set out in Title II of the Dodd-Frank Act. This authority provides the FDIC with the ability to resolve large financial firms when bankruptcy would have serious adverse effects on financial stability in the United States. We use as the event date December, 10, 2012 when FDIC released a white paper and a press release describing the SPOE strategy. We find an increase spreads in large financial institutions in response to this event. The results continue to hold when we use corporates as controls. The reaction has not been, however, economically significant.

4. FDIC Guarantee

We also compare *implicitly* guaranteed bonds to *explicitly* guaranteed bonds that have been issued by the *same firm*.

To help restore confidence in financial institutions, the government issued a temporary explicit guarantee for certain new debt that financial institutions issued during the financial crisis. The Temporary Liquidity Guarantee Program (TLG Program) provided an FDIC guarantee for senior unsecured debt that was issued after October 14, 2008 and before June 30, 2009 (later extended to October 31, 2009). The guarantee continued in effect until June 30, 2012 (or the date the debt matured, if earlier). The TLG Program was available to insured depository institutions and financial holding companies that opted to participate in the program.[13]

[13] Not all debt of these institutions was eligible to be guaranteed under the TLG Program. To be eligible, the debt had to be newly-issued during the period from October 2008 to October 2009. Moreover, the debt had to be senior unsecured debt. In addition, institutions could only issue new debt under the TLG Program in an amount up to 125% of its senior unsecured debt that was outstanding on September 30, 2008 and scheduled to mature on or before the October 31, 2009. The FDIC charged issuers a fee for the guarantee, and institutions could opt out of the program.

We examine the institutions in our data set that issued bonds under the FDIC's TLG Program and that also had similar bonds outstanding outside the TLG Program.[14] For a given firm, we look at the difference between spreads on bonds backed by the FIDC guarantee and spreads on bonds without the FDIC guarantee. Figure 4 shows the difference in spreads for each of the top 6 financial institutions. Figure 4 is computed without using control variables.

We introduce controls by regressing spreads on a dummy that takes a value of one if the bond is backed by the FDIC guarantee. We control for various bond characteristics. We also control for firm-trading day fixed effects (to examine within-company variation on a given trading day).[15] Results appear in Table BII of Appendix B.

Figure 5 displays the results graphically, by running the regressions contained in Table BII (column 4) on a daily basis. It shows how the value of the FDIC guarantee varied over the June, 2009 to June 2011 period. Over that time period, the value of the FDIC guarantee declined. In the middle of the time period (June, 2010), Dodd-Frank was adopted. We do see a slight increase in the value of the FDIC guarantee in the months preceding Dodd-Frank's adoption. At that time, it was unclear what the final language of the legislation would be. After Dodd-Frank was finalized, however, the value of the FDIC guarantee resumed its downward trend. Dodd-Frank does not appear to have changed investors' expectations of support for non-guaranteed bonds of major financial institutions.

We confirm our finding by conducting an event study around Dodd-Frank. We run a regression similar to that in Table BII (column 4), but with an additional variable, *post*. *Post* is a dummy equal to one during the 5 trading days (or 132 trading days) following the adoption of Dodd-Frank. *Post* is interacted with an indicator variable (*non-guarantee*) that equals one if a bond is not guaranteed under the FDIC guarantee, and zero if it is guaranteed. This interaction term captures whether Dodd-Frank impacted investor expectations of support for non-guaranteed bonds relative to FDIC guaranteed bonds. Results appear in Table 7. The coefficient on the

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[14] The following companies issued both bonds under the FDIC guarantee and non-guaranteed bonds listed in the TRACE/FISD databases: Bank of America, Citigroup, Goldman Sachs, JP Morgan Chase, Morgan Stanley, Sovereign Bancorp, State Street, Suntrust, US Bancorp, Wells Fargo, PNC Bank, HSBC USA, Keycorp, Metlife, John Deere Capital, and GE Capital.

[15] Our sample includes bonds of all institutions that have issued both types of bonds. We address bonds with extreme yields by winsorizing at the 99th percentile values separately for guaranteed and non-guaranteed bonds. We eliminate extreme one-day moves (>30%) that reverse the next day. We also eliminate bond with maturities less than 90 days and greater than 30 years. If we do not observe both the guaranteed and non-guaranteed bonds trading on a given day for a given company, we delete all observations for that company on that day.

interaction term is significant and negative during the 10 trading day window (column 1). The result indicates that, after Dodd-Frank, spreads on bonds that lacked the FDIC guarantee decreased relative to spreads on bonds of the same firm that had the FDIC guarantee. In other words, Dodd-Frank lowered the spread differential between FDIC-guaranteed bonds and non-FDIC guaranteed bonds of the same firm. As investors viewed it, Dodd-Frank made a firm's implicitly guaranteed debt more like its explicitly guaranteed debt. While this effect may not be economically significant, and no statistically significant effect is detected using the 264 trading day window (column 3), we should observe a *significant positive effect* if Dodd-Frank had been successful in eliminating TBTF.

Table 7 also examines Dodd-Frank's impact on the risk sensitivity of guaranteed and non-guaranteed bonds. This is captured by the triple-interaction term (*mertondd*non-guarantee*post*). The coefficient is significant and positive. The risk sensitivity of non-guaranteed debt declined following Dodd-Frank. We find this result using both 10 and 264 trading day windows (columns 2 and 4).

Figure 6 displays these results graphically, by running the regressions contained in Table 7 (column 4) on a daily basis. It shows how the risk sensitivity of non-guaranteed debt varied over the long event window around Dodd-Frank. Over that window, risk sensitivity declined, except for a brief spike in risk sensitivity in the weeks prior to Dodd-Frank's adoption. Figure 6 again shows that Dodd-Frank did not have much of an impact of investor expectations with respect to TBTF.

5. Additional Robustness Checks

Since we are examining bonds, it is conceivable that our results might be affected by the liquidity of those bonds that we study. Hence, in this section we explicitly control for liquidity. In Table 8, we show that our main results from Table 2 are robust to controls for liquidity. Since we do not have bond trades for the full sample period, we create a liquidity measure based on bond characteristics following Longstaff et al. (2005). This liquidity measure (*liquidity*) is an index constructed based upon the characteristics of the bond (as further described in Appendix A). In column 1, the *size90* variable retains its significance in the presence of the liquidity measure. In column 2, we use bond turnover (*turnover*) as our liquidity control. The *turnover* variable is constructed using data after 2003 from the TRACE dataset which includes trade information, as further described in Appendix A. The *size90* variable retains its significance in the presence of *turnover*.

We also define TBTF firms using measures of systemic risk. In column 3, following Adrian and Brunnermeier (2011), we use an institution's contribution to systemic risk (*covar*) to identify systemic importance. Higher values of covar indicate greater systemic risk contribution. Results show a significant negative relationship between *covar* and *spread*. That is, the greater an institution's contribution to systemic risk, the lower its spread. The second systemic risk measure we use (*srisk*) is based on the expected capital shortfall framework developed by Acharya, Engle and Richardson (2012). Results in column 4 show a significant negative relationship between *srisk* and *spread*. The greater the institution's systemic risk, the lower its spread. Overall, our results suggest a negative relationship between systemic importance and the cost of debt.

VI. Policy Implications

As Figure 3 shows, expectations of government bailouts for large financial institutions persist over time. Even when the banking system appears strong, large financial institutions benefit from expectations of too-big-to-fail assistance. Bailout expectations exist not only in times of crisis, but also in times of relative tranquility, and vary with government policies and actions.

The 1980s were a time of high expectations of government support for troubled institutions. In 1984, the U.S. government rescued Continental Illinois, once the seventh largest bank, in what constituted the largest bank bailout in U.S. history at the time. The bailout resulted in no losses for bank depositors or investors. While testifying on the bailout before Congress shortly thereafter, the Comptroller of the Currency formalized the previously implicit TBTF policy by declaring that eleven financial institutions were "too big to fail."

In the early 1990s, the government took steps to erode the perception that it backed large financial firms. In 1991, Congress passed the FDIC Improvement Act (FDICIA). It was believed that FDICIA would limit regulators' discretion to support distressed banks and enable regulators to save insured depositors without saving uninsured investors.[16] Accordingly, Figure

[16] FDICIA obligated regulators to take "prompt corrective action" against severely distressed banks, limited regulators' discretion to support distressed banks, and mandated "least-cost" resolution of failed banks. These

3 shows a decline in the implied subsidy during this period, reflecting diminishing expectations of government support for the largest financial institutions.

In contrast, expectations of government support increased during the late 1990s. In 1997 and 1998, the government responded to perceived threats to financial stability that emanated from currency crises in emerging economies. In 1998, the Federal Reserve brokered a bailout of hedge fund Long-Term Capital Management. Accordingly, the implicit subsidy spiked and remained elevated for several years as expectations of government bailouts became embedded in the market. In November, 1999, Congress formally repealed Glass-Steagall's separation of commercial banks from investment banks, enabling banks to engage in a wider range of activities and to merge with other financial firms, potentially bringing new activities and entities under the government's watchful eye. The Federal Reserve flooded the banking system with liquidity to prepare for the possibility of technical problems in connection with the year 2000 conversion and then the bursting of the tech bubble in 2000. In response to the terrorist attacks of September 11, 2001, the Federal Reserve provided an unusual amount of liquidity and reduced the federal funds rate. As Figure 3 shows, the implicit subsidy reached a record level at the time.

In 2003 and 2004, the implicit subsidy declined, as the economy recovered from recession and the market's appetite for risk re-emerged. As the economy expanded, investors exhibited a growing risk tolerance, lowering the credit spreads they required from smaller financial institutions relative to the largest. This period of diminished expectations of support, however, was short lived.

The financial crisis began during the summer of 2007, as liquidity dried up as a result of uncertainty about financial institutions' exposure to "toxic assets." The financial crisis was at its most intense during 2008-2009 (during which time CDS spreads on financial institutions grew considerably and reached record peaks). In responding to the crisis, government actions nearly formalized the implicit public guarantee of the financial sector. As Figure 3 shows, investor expectations of government assistance surged to unprecedented levels.

In the post-crisis period after 2009, the implicit subsidy remained at an elevated level. The passage of the Dodd-Frank in the summer of 2010 did not eliminate investors' expectations of government support. Dodd-Frank makes no attempt to price implicit guarantees. The

provisions imposed a relatively stringent process on the FDIC before it could extend protection in a failed-bank resolution beyond insured deposits.

centerpiece of Dodd-Frank is the creation of the Financial Stability Oversight Council whose objective is, in part, to "promote market discipline, by eliminating expectations on the part of shareholders, creditors, and counterparties of [large financial] companies that the government will shield them from losses in the event of failure." In pursuit of this objective, the Council is empowered to designate certain companies as "systemically important" if their failure will cause instability of the financial system and to subject them to additional oversight, including liquidation. While bank holding companies with assets of more than $50 billion are automatically designated as systemically important, the designation is otherwise highly discretionary and reflects a judgment that the institution is too big to fail. Because market participants believe every effort will be made to support systemically important institutions should they suffer financial distress, these companies have advantages over competitors in obtaining credit.[17] As a result, the credit market doubts whether Dodd-Frank will mitigate TBTF, believing instead that it will likely exacerbate the problem.

As Figure 3 shows, the value of the implicit subsidy provided to too-big-to-fail financial institutions is substantial. Expectations of state support for TBTF institutions has provided them with a sizable reduction in their cost of debt, which misaligns risk and return for their owners and managers and encourages them to take on more risk. A spiral can therefore develop - the implicit guarantee encourages institutions to take more risk, which increases the probability and cost of bank failure, which in turn increases the subsidy. Since any resulting bailouts are conducted using public funds, the implicit guarantee produces a transfer of resources from the government, and ultimately taxpayers, to major financial institutions.[18] As a result, to the extent TBFT institutions do not pay for this implicit guarantee, expectations of state support constitute a form of wealth redistribution. This redistribution is not a temporary event that exists only during

[17] Despite Dodd-Frank's explicit no-bailout pledge, the Act leaves open many avenues for future TBTF rescues. For instance, although Dodd-Frank grants new authority to officials to resolve large institutions, President of the Federal Reserve Bank of Kansas City, Thomas Hoenig, noted: "The final decision on solvency is not market driven but rests with different regulatory agencies and finally with the Secretary of the Treasury, which will bring political considerations into what should be a financial determination." Moreover, prior to any resolution, the Federal Reserve can offer a "broad-based" lending facility to a group of financial institutions to provide an industry-wide bailout or a single-firm bailout in disguise. In addition, Congress may at any time decide to abandon Dodd-Frank by explicitly amending or repealing the statute or by allowing regulators to interpret their authority in order to protect creditors and partner with large financial institutions (see, e.g., Skeel 2011; Wilmarth 2011; Standard & Poor's 2011).

[18] Dodd-Frank seeks to end this wealth transfer by requiring that the costs of resolving failed financial institutions be imposed on the surviving ones, not taxpayers. But during a systemic crisis, it is unlikely that the solvent part of the sector will be used to cover the losses of the failed part of the sector. Since capital is needed most during a crisis, taxpayer funds are likely to be used instead.

times of crisis; it persists even during times of relative tranquility. That is, the subsidy generates an ongoing wealth transfer from taxpayers to TBTF institutions.

Governments are generally not required to make any apparent commitment or outlay, or request funds from legislatures or taxpayers, when they implicitly guarantee too-big-to-fail institutions. Since it happens implicitly, the transfer lacks the transparency and accountability that accompany explicit policy decisions. Taxpayer interests would be better served, in both good times and bad, by estimating on an ongoing basis the accumulated value of this subsidy.

Ideally, the government would simply foreswear bailouts and end the subsidy. However, evidence and experience show that such a no-bailout policy lacks credibility. Instead, public accounting of accumulated TBTF costs might restrain those government actions and policies that encourage TBTF expectations. Because the cost of implicit insurance is not fully visible to policymakers or taxpayers, insufficient attempts are made to reign in TBTF expectations. Requiring ongoing estimation and disclosure of the subsidy would generate feedback for regulators and policymakers about the consequences of their actions and might generate pushback from taxpayers when they see the size of the subsidy in dollar terms.

In addition to public accounting and disclosure, large financial institutions could be made to bear responsibility for the implicit taxpayer insurance they enjoy. These institutions could be charged a Pigovian-style tax designed to compensate for the underpricing of risk that results from the implicit guarantee. That is, the funding subsidy that big institutions enjoy could be neutralized by imposing a corrective levy, tax, or premium that extracts the value of the subsidy. This charge would act as a form of compensation for the public support large financial institutions are expected to receive in the event of a crisis. The goal is not to make institutions pre-pay future rescue costs, but to realign incentives among beneficiaries of the implicit guarantee.[19] By pricing the implicit guarantee and internalizing its cost, policymakers could require financial institutions to bear the true cost of their debt, resulting in a more proper alignment of risk and return for owners and managers. Effective funding costs would more fully reflect the risk taking of the financial institution, helping to reduce excessive risk taking. Such a

[19] In contrast to Dodd-Frank's ex post tax on financial institutions, recent proposals have called for an ex ante tax on financial institutions intended to recoup future bailout costs. Most of the proposed taxes are not particularly sophisticated in design (i.e., levied at a uniform rate on total assets or total liabilities net of insured deposits, see IMF 2010) and may result in simply transferring funds from well-managed institutions to reckless ones instead of mitigating moral hazard. We propose instead a tax designed specifically to capture the subsidy a financial institution enjoys as a result of an implicit government guarantee. Such a tax is intended to better align risk and return for bank owners and managers.

Pigovian tax would be more straightforward and transparent than extensive government supervision and regulation that attempts to manage risk taking (the Dodd-Frank Act required 2,319 pages of legislation and mandates hundreds of additional rules, yet it does not directly address mispricing of conjectural government guarantees, leaving expectations of support to persist). If the cost of the implicit guarantee is instead internalized through a Pigovian tax, market discipline could then work with supervisory discipline to create a more stable and efficient financial system.

Similar recommendations have been put forth in papers examining systemic risk externalities. Contingent capital proposals have been popular among both academics and policymakers as way to limit systemic crises and TBTF expectations (see Acharya, Kulkarni and Richardson 2011). A form of debt that converts automatically into equity as credit quality deteriorates, contingent capital ensures that the institution maintains a sufficient level of capitalization, reducing the likelihood of default when an adverse shock materializes. By imposing losses on creditors, contingent capital would partially restore market discipline and reduce the need for government intervention. But, with its emphasis on reducing ex post distress, the contingent capital solution suffers from an important limitation, namely its ability to limit ex ante risk taking and buildup of systemic risk. Beneath contingent capital will remain debt that is implicitly (and explicitly) guaranteed by the government. The cost of this debt in good times will not reflect the true risk of the institution, and so long as this is the case, contingent capital and equity capital will continue to find it desirable to undertake excessive risk at the expense of guaranteed debt. Hence, contingent capital should complement measures that attempt to directly control ex ante risk by internalizing its external cost, such as the Pigovian-style tax we propose, not substitute for such measures.

In the aftermath of the crisis, there has been a growing consensus that some elements of macro-prudential regulation should work like Pigovian taxes in order to discourage banks from pursuing strategies that contribute to the risk of the financial system as a whole (e.g., Acharya et al. 2010; Perotti and Suarez 2009; Brunnermeier et al. 2009; Financial Stability Forum 2009a, 2009b). A number of recent papers develop novel methods to measure and quantify systemic risk in the banking sector (Adrian and Brunnermeier 2011; Huang, Zhou, and Zhou 2009; Chan-Lau and Gravelle 2005; Avesani, Garcia Pascual and Li 2006; Elsinger and Lehar 2008). These papers use a portfolio credit risk approach to compute the contribution of an individual bank to the risk of a portfolio of banks. However, they examine the systemic risk contribution of each financial institution ex-post. Our results show that, as a result of the implicit guarantee, risk is not being priced appropriately on an ex-ante basis. Nevertheless, despite our different approaches, we arrive at similar policy recommendations – namely, that Pigovian-style taxes should be imposed on larger financial institutions to correct for the negative externalities they generate.[20]

VII. Conclusion

We find that expectations of state support are embedded in credit spreads on bonds issued by large U.S. financial institutions. While credit spreads are risk sensitive for most financial institutions, credit spreads lack risk sensitivity for the largest financial institutions. In other words, we find that bondholders of large financial institutions have an expectation that the government will shield them from losses and, as a result, they do not accurately price risk. This expectation of public support constitutes an implicit subsidy of large financial institutions, allowing them to borrow at government-subsidized rates. The cost of this implicit insurance should be internalized to enable financial institutions to compete on a level playing field. In addition, requiring large financial institutions to bear the true cost of their debt would better align risk with return for their owners and managers, promoting a more stable and efficient financial system.

Until it is internalized, implicitly-guaranteed institutions will have an incentive to take actions that promise rewards to their owners and managers while imposing costs on the rest of society. The privatization of gains and socialization of losses arising out of TBTF policies can undermine the public's faith that the capitalist system is responsible and fair.

[20] We recognize that, even in an efficient market without any guarantees, it is possible for there to be externalities associated with being systemically important that will not be fully internalized (see, for instance, Zingales 2009).

Appendix A

Bond characteristics	
spread (%)	The difference between the yield on a financial institution's bond and the yield on a treasury bond with similar maturity.
ttm	Year to maturity.
seniority	Dummy variable indicating whether the bond is senior.
rating	S&P issue rating, which is a number between 1 and 21, with 1 indicating the highest issue quality.
age	Age of the bond since issuance in years.
puttable	Dummy variable set equal to 1 if the bond is puttable.
redeemable	Dummy variable set equal to 1 if the bond is redeemable.
exchangeable	Dummy variable set equal to 1 if the bond is exchangeable.
fixrate	Dummy variable set equal to 1 if the bond has fixed rate coupons.
non-guarantee	Dummy variable set equal to 1 if the bond does not have a special FDIC guarantee and was not issued as part of the "The Temporary Liquidity Guarantee Program."
Firm characteristics	
size	Size of a financial institution defined as the log value of total assets.
size90	Dummy variable which equals 1 if an issuer's size is greater than the 90th percentile of its distribution in that fiscal year and 0 otherwise.
size60	Dummy variable which equals 1 if an issuer's size is greater than the 60th percentile of its distribution in that fiscal year but less than or equal to the 90th percentile and 0 otherwise.
size30	Dummy variable which equals 1 if an issuer's size is greater than the 30th percentile of its distribution in that fiscal year but less than or equal to the 60th percentile and 0 otherwise.
size_top_10	Dummy variable which equals 1 if an issuer ranks in the top ten in terms of size in that fiscal year and 0 otherwise.
financial	Dummy variable which equals 1 if the company is a financial firm defined as having an SIC code starting with 6.
covar	CoVaR measure of systemic fragility, as described below.
srisk	Systemic risk based on expected capital shortfall, as described below.
leverage	Total liabilities divided by total assets.
roa	Return on assets, measured as net income divided by total assets.
std roa	Standard deviation of roa computed over 5 years.
mb	Market value of total equity divided by book value of total equity.
mismatch	Short-term debt (minus cash) divided by total liabilities.
mertondd	Merton's distance-to-default measure, calculated using firm-level fiscal year financial and stock return data, as described below.
zscore	Z-score, calculated as the sum of roa and equity ratio (ratio of book equity to total assets), averaged over four years, divided by the standard deviation of roa over four years.
volatility	Stock return volatility computed using returns over the past 24 months .
liquidity	Bond liquidity measure based on Longstaff et al. (2005). A dummy variable is given each month a value of one or zero depending on the characteristics of the underlying bond. We then add up the dummy variables to come up with an overall liquidity score. The first proxy is used to measure general availability of the bond issue in the market.

	If the outstanding market value of a bond is larger than the median value of all bonds, then the dummy variable is assigned a value of one. The second proxy is the age of the bond and parallels the notion of on-the-run and off-the-run bonds in treasury markets, with on-the-run bonds being more liquid. If the age of a bond is less than the median age of all bonds then the dummy variable is assigned a value of one. The third proxy is the time to maturity of the bond. It has been shown that there exist maturity clienteles for corporate bonds and that shorter-maturity corporate bonds tend to be more liquid than longer-maturity bonds. If the time to maturity of a bond is less than seven years then the dummy variable is assigned a value of one. The fourth proxy that we use is a dummy variable for bonds rated by AAA/AA. As Longstaff et al. (2005) show, highly rated bonds tend to be more marketable and liquid in times distress when there is a "flight-to-quality." The maximum liquidity value assigned to a bond is four and the minimum liquidity value is zero.
turnover	Bond turnover computed using the past three months of trading data. This variable is computed using the TRACE database and is available after 2003.
Macro controls	
mkt	Market risk premium.
term	Term structure premium, measured by the yield spread between long-term (10-year) treasury bonds and short-term (three-month) treasuries.
def	Default risk premium, measured by the yield spread between BAA-rated and AAA-rated corporate bonds.
Other variables	
exposure	Financial institution's exposure to Lehman, which equals 1 if an institution disclosed its exposure to Lehman in the weeks following Lehman's bankruptcy and 0 otherwise. Data comes from the Daily List of Companies Reporting Lehman Exposure, published by the Dow Jones News Service between Sept. 15, 2008 and Oct. 15, 2008.
bank dummy	Dummy variable that takes on a value of one for firms with SIC codes that start with 60 and 61 and firms with SIC code 6712.
insurance dummy	Dummy variable that takes on a value of one for firms with SIC codes that start with 63 and 64.
broker dummy	Dummy variable that takes on a value of one for firms with SIC codes that start with 62.
stand-alone rating	Fitch individual rating, which is a number between 1 and 9, with 1 indicating the highest issue quality.
issuer rating	Fitch long term issuer rating, which is a number between 1 and 9, with 1 indicating the highest issue quality.

Merton Measure of Default

We follow Campbell, Hilscher and Szilagyi (2008) and Hillegeist et al. (2004) in calculating Merton's distance to default. The market equity value of a company is modeled as a call option on the company's assets:

$$V_E = V_A e^{-dT} N(d_1) - X e^{-rT} N(d_2) + \left(1 - e^{-dT}\right) V_A$$
$$d_1 = \frac{\log\left(\frac{V_A}{X}\right) + \left(r - d + \frac{s_A^2}{2}\right)T}{s_A\sqrt{T}}; d_2 = d_1 - s_A\sqrt{T} \quad \text{(A1)}$$

V_E is the market value of a bank. V_A is the value of the bank's assets. X is the face value of debt maturing at time T. r is the risk-free rate and d is the dividend rate expressed in terms of V_A. s_A is the volatility of the value of assets, which is related to equity volatility through the following equation:

$$s_E = \frac{V_A e^{-dT}\, N(d_1) s_A}{V_E} \quad \text{(A2)}$$

We simultaneously solve the above two equations to find the values of V_A and s_A. We use the market value of equity for V_E and total liabilities to proxy for the face value of debt X. We have found similar results using short-term debt plus the currently due portion of long-term liabilities plus demand deposits as the default barrier. Since the accounting information is on an annual basis, we linearly interpolate the values for all dates over the period, using end of year values for accounting items. The interpolation method has the advantage of producing a smooth implied asset value process and avoids jumps in the implied default probabilities at year end. s_E is the standard deviation of weekly equity returns over the past 12 months. In calculating standard deviation, we require the company to have at least 36 non-zero and non-missing returns over the previous 12 months. T equals one year, and r is the one-year treasury bill rate, which we take to be the risk-free rate. The dividend rate, d, is the sum of the prior year's common and preferred dividends divided by the market value of assets. We use the Newton method to simultaneously solve the two equations above. We use the Newton method to simultaneously solve the two equations above. For starting values for the unknown variables, we use $V_A = V_E + X$ and $s_A = s_E V_E/(V_E+X)$. After we determine asset values V_A, we follow Campbell, Hilscher and Szilagyi

(2008) and assign asset return *m* to be equal to the equity premium (6%).[1] Merton's distance-to-default (*dd*) is finally computed as:

$$Mertondd = \frac{log\left(\frac{V_A}{X}\right) + \left(m - d - \frac{s_A^2}{2}\right)T}{s_A\sqrt{T}} \qquad \text{(A3)}$$

The default probability is the normal transform of the distance-to-default measure, defined as: $PD = F(-MertonDD)$.

CoVaR Measure of Systemic Fragility

Following Adrian and Brunnermeier (2011), we compute a conditional value-at-risk measure (CoVaR) for each of the financial institutions in our sample using quantile regression. Quantile regression estimates the functional relationship among variables at different quantiles (Koenker and Hallock 2001) and allows for a more accurate estimation of credit risk co-dependence during stress periods by taking into account nonlinear relationships when there is a large negative shock. As in Adrian and Brunnermeier (2011), we estimate a time series CoVaR measure using a number of state variables. We run the following quantile regressions over the sample period:

$$\Delta BankDD_{i,t} = \propto_i + \gamma_i M_{t-1} + \varepsilon_{i,t}$$

$$\Delta SystemDD_t = \propto_{system|i} + \beta_{system|i}\, \Delta BankDD_{i,t} + \gamma_{system|i} M_{t-1} + \varepsilon_{system|i,t} \qquad \text{(A4)}$$

where $\Delta BankDD_{i,t}$ is the change in the Merton distance-to-default variable for bank *i* in week t and $\Delta SystemDD_t$ is similarly the change in the value-weighted Merton distance-to-default variable for all financial institutions in the sample. M_{t-1} are lagged state variables and include the change in the term spread (*term*), the change in the default spread (*def*), the CBOE implied volatility index (*vix*), the S&P 500 return (*spret*) and the change in the 3 month t-bill rate (*rate*). The CoVaR variable is then computed as the change in the VaR of the system when the

[1] We obtain similar distance-to-default values if we compute asset returns (V_A), as max($\frac{V_{A,t}}{V_{A,t-1}} - 1, r$), following Hillegeist et al. (2004).

institution is at the q^{th} percentile (or when the institution is in distress) minus the VaR of the system when the institution is at the 50% percentile:

$$\Delta CovarSystem_t^q = \hat{\beta}_{system|i}^q \left(\Delta \widehat{BankDD}_{i,t}^q - \Delta \widehat{BankDD}_{i,t}^{50\%}\right) \quad \text{(A5)}$$

Finally, we invert the *covar* variable, so that higher values of *covar* indicate greater systemic risk.

SRISK Measure of Systemic Expected Shortfall

The second systemic risk measure we use is based on the expected capital shortfall framework developed by Acharya, Engle and Richardson (2012). The systemic expected shortfall of an institution describes the capital shortage a financial firm would experience in case of a systemic event. The capital short fall depends on the firm's leverage and equity loss conditional on an aggregate market decline:

$$\begin{aligned} SRISK_t^i &= E\big((k(Debt + Equity) - Equity|Crisis)\big) \\ &= k\big(Debt_t^i\big) - (1-k)\big(1 - MES_t^i\big)Equity_t^i \end{aligned} \quad \text{(A6)}$$

Marginal Expected Shortfall (MES_t^i) of a firm, *i*, is the expected loss an equity investor in a financial firm would experience if the market declined substantially. Following Acharya et al (2010), we use the bivariate daily time series model of equity returns of firm, *i*, and the aggregate market index and simulate returns 6 months into the future. The simulation allows volatilities and correlations to change over time and samples from the empirical distribution such that empirical tail dependence is maintained. Crisis is defined as the aggregate index falling by 40% over the next six months. Marginal expected shortfall is the equity decline in such a scenario.

Appendix B. Additional Results

Table BI: Impact of Dodd-Frank

Regression results for the model, $Spread_{i,b,t} = \propto + \beta^1 post + \beta^2 TBTF_{i,t} \times post + \beta^3 Risk_{i,t} \times post + \beta^4 TBTF_{i,t} \times Risk_{i,t} \times post + \beta^5 Macro\ Controls_t + Issuer\ FE + \varepsilon_{i,b,t}$. The event date is June 29, 2010 (Dodd-Frank). The variable *post* equals 1 if the transaction date is the event date or one of the 132 trading days following the event date, and 0 if the transaction date is one of the 132 trading days prior to the event date. Other variables are defined in Appendix A. Standard errors are reported in parentheses below their coefficient estimates and are adjusted for both heteroskedasticity and within correlation clustered at the issuer level. ***, ** and * indicate significance at 1%, 5% and 10% two-tailed level, respectively.

VARIABLES	(1) spread	(2) spread
ttm	0.031*	0.031*
	(0.018)	(0.018)
seniority	-0.213	-0.212
	(0.203)	(0.204)
leverage $_{t-1}$	4.951***	4.425***
	(1.568)	(1.343)
roa $_{t-1}$	-2.395	-2.738
	(4.138)	(3.517)
mb $_{t-1}$	0.059	0.244
	(0.145)	(0.173)
mismatch $_{t-1}$	-1.705***	-0.993
	(0.592)	(0.842)
def	0.512*	0.547*
	(0.277)	(0.280)
term	-0.130	-0.124
	(0.102)	(0.102)
mkt	2.377	2.481
	(3.406)	(3.427)
mertondd $_{t-1}$	-0.012	-0.266
	(0.111)	(0.179)
size90 $_{t-1}$	-0.722***	-0.499**
	(0.130)	(0.191)
post	-0.225**	-0.591***
	(0.102)	(0.217)
size90 $_{t-1}$* post	0.077	0.550*
	(0.094)	(0.276)
mertondd $_{t-1}$* post		0.237*
		(0.123)
size90 $_{t-1}$* mertondd $_{t-1}$ *post		-0.370*
		(0.187)
Constant	1.939**	2.130***
	(0.755)	(0.701)

Firm FE	Y	Y
Year FE	Y	Y
Rating Dummies	Y	Y
Observations	1,810	1,810
R-squared	0.547	0.548

Table BII: FDIC Guarantee Estimation

Regression results for the model, $Spread_{i,b,t} = \propto + \beta^1 Bond\ Controls_{i,b,t} + \beta^2 guarantee_{i,t-1} + Firm - Firm \times Trading\ Day\ FE + \varepsilon_{i,b,t}$, for financial institutions that issued under the Temporary Liquidity Guarantee program. Variables are defined in Appendix A. Standard errors are reported in parentheses below their coefficient estimates and are adjusted for both heteroskedasticity and within correlation clustered at the issuer level. ***, ** and * indicate significance at the 1%, 5% and 10% two-tailed level, respectively.

VARIABLES	(1) spread	(2) spread	(3) spread	(4) spread
guarantee	-0.023***	-0.020***	-0.022***	-0.021***
	(0.002)	(0.003)	(0.003)	(0.002)
fixed rate		-0.016***	-0.011***	-0.011***
		(0.003)	(0.002)	(0.002)
seniority		-0.005**	-0.007***	-0.006***
		(0.002)	(0.001)	(0.001)
putable		0.008*	0.002	0.003**
		(0.004)	(0.002)	(0.001)
exchangeable		0.054***	0.052***	0.051***
		(0.005)	(0.005)	(0.004)
redeemable		0.005	0.001	-0.001
		(0.003)	(0.002)	(0.001)
ttm		0.001***	0.001***	0.000***
		(0.000)	(0.000)	(0.000)
age		-0.001**	-0.001***	-0.000***
		(0.000)	(0.000)	(0.000)
constant	0.026***	0.044***	0.041***	0.041***
	(0.002)	(0.002)	(0.001)	(0.001)
Specification	OLS	OLS	Firm FE	Firm*Day FE
Observations	90,528	90,528	90,528	90,528
R-squared	0.233	0.275	0.329	0.782

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Figure 1: Size and Spreads

This figure shows the relationship between the size of a financial institution and the credit spread on its bonds. Size (x-axis) is the relative size of a financial institution, computed as size (log of assets) in a year divided by the average size of all financial institutions in that year. Spread (y-axis) is the difference between the yield on a financial institution's bond and that on a corresponding maturity-matched treasury bond.

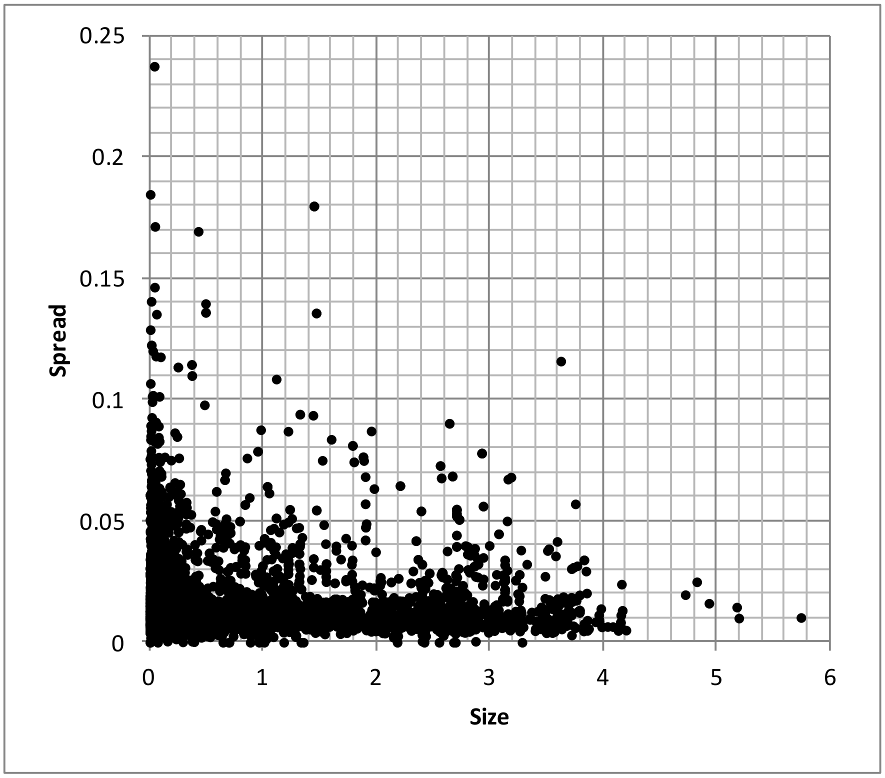


Figure 2: Size and Risk

This figure shows the relationship between the size of a financial institution and its risk. Size (x-axis) is the relative size of a financial institution, computed as its size (log of assets) in a year divided by the average size of all financial institutions in that year. Risk (y-axis) is distance to default of a financial institution, computed as defined in Appendix A.

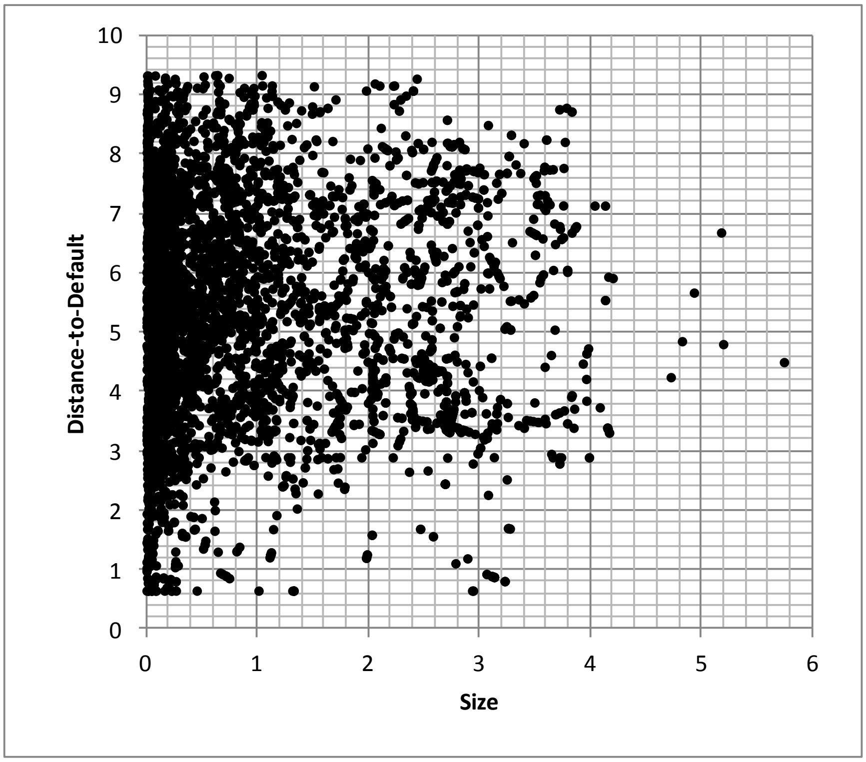


Figure 3: Value of the Implicit Subsidy (1990-2011)

This figure plots the annual subsidy to large financial institutions due to the implicit state guarantee. To compute the annual subsidy, we run the following regression each year: $Spread_{i,b,t} = \propto + \beta^1 \times seniority_{i,b,t} + \beta^2 \times ttm_{i,b,t} + \beta^3 leverage_{i,t} + \beta^4 roa_{i,t} + \beta^5 mb_{i,t} + \beta^6 mismatch_{i,t} + \beta^7 mertondd_{i,t} + \beta^8 def_t + \beta^9 term_t + \beta^{10} mkt_t + \beta^{11} size90_{i,t} + \varepsilon_{i,b,t}$. Variables are defined in Appendix A. The coefficient on *size90* (right axis) represents the subsidy accruing to large financial institutions as a result of implicit government insurance. We also quantify the dollar value of the annual subsidy. We multiply the annual reduction in funding costs by total uninsured liabilities (in US$ millions) to arrive at the yearly dollar value of the subsidy (left axis).

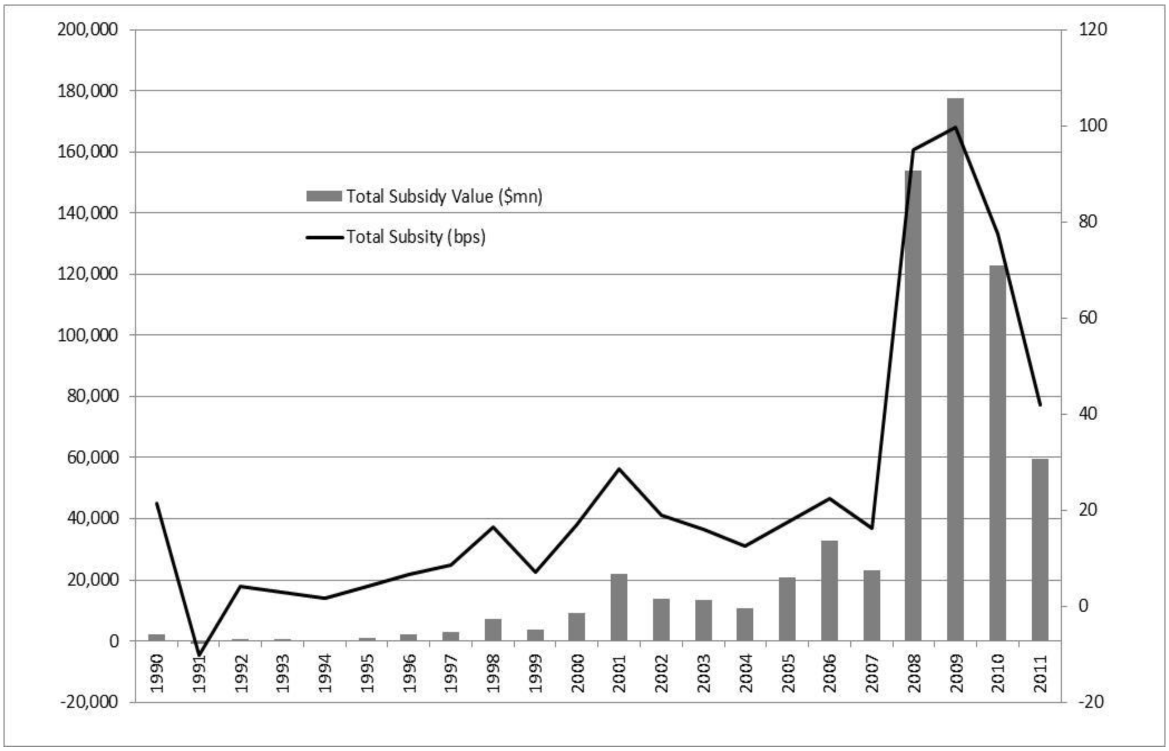


Figure 4: Non-Guarantee and FDIC-Guarantee Spread Difference

This figure plots the difference between FDIC guaranteed and non-guaranteed bonds for six individual financial institutions. We plot averages for each month for each company if there are more than 10 daily trading observations.

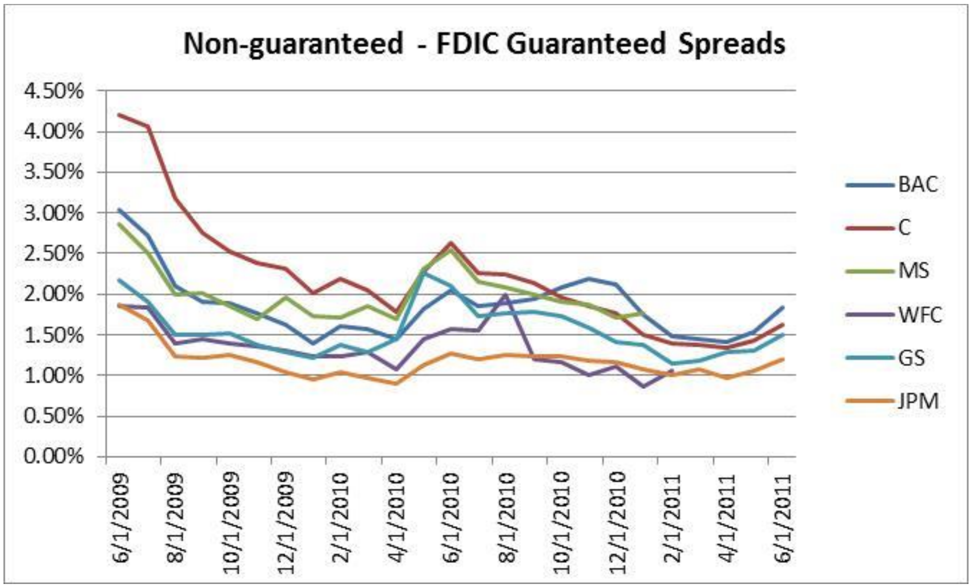


Figure 5: Explicit Guarantee Premium

This figure plots the estimated FDIC guarantee premium. To compute the premium, we run the following regression each day: $Spread_{i,b,t} = \propto + \beta^1 \times seniority_{i,b,t} + \beta^2 \times ttm_{i,b,t} + \beta^3 \times fixed\ rate_{i,b,t} + \beta^4 \times puttable_{i,b,t} + \beta^5 \times exchangeable_{i,b,t} + \beta^6 \times redeemable_{i,b,t} + \beta^7 \times Gurantee_{i,b,t} + Firm\ FE + \varepsilon_{i,b,t}$. Variables are defined in Appendix A.

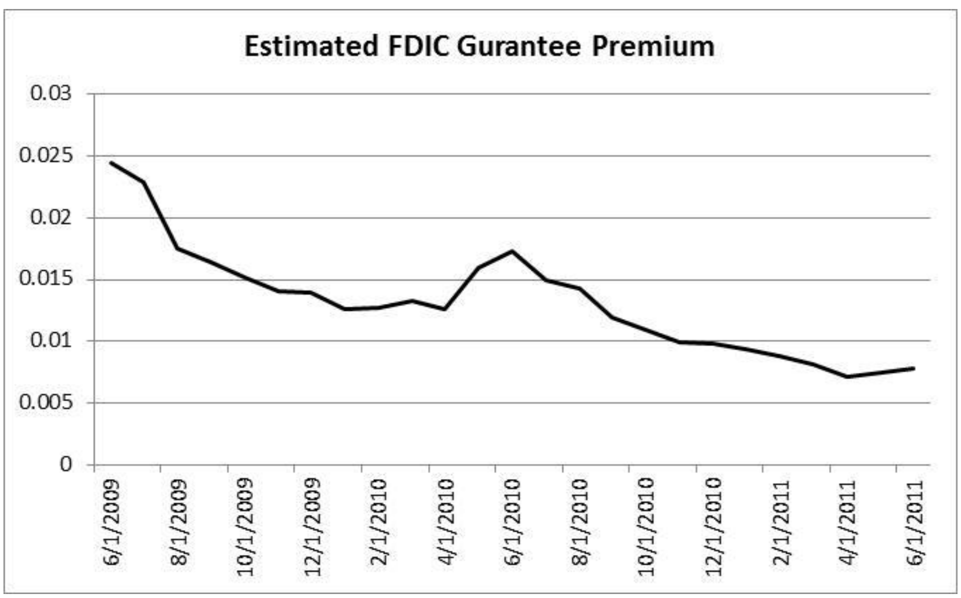


Figure 6: Risk Sensitivity of Non-Guaranteed Debt

This figure plots the estimated risk sensitivity of bonds of financial institutions that were issued under the Temporary Liquidity Guarantee program. The figure plots the daily non-gurantee * mertondd coefficient estimates from the following regression:

$$Spread_{i,b,t} = \propto + \beta^1 \times Bond\ controls_{i,b,t} + \beta^2 \times non - gurantee_{i,b,t} + \beta^3 \times non - gurantee_{i,b,t} \times mertondd_{i,t-1} + Firm\ FE + \varepsilon_{i,b,t}.$$

The coefficient estimates are then averaged each week. Variables defined in Appendix A.

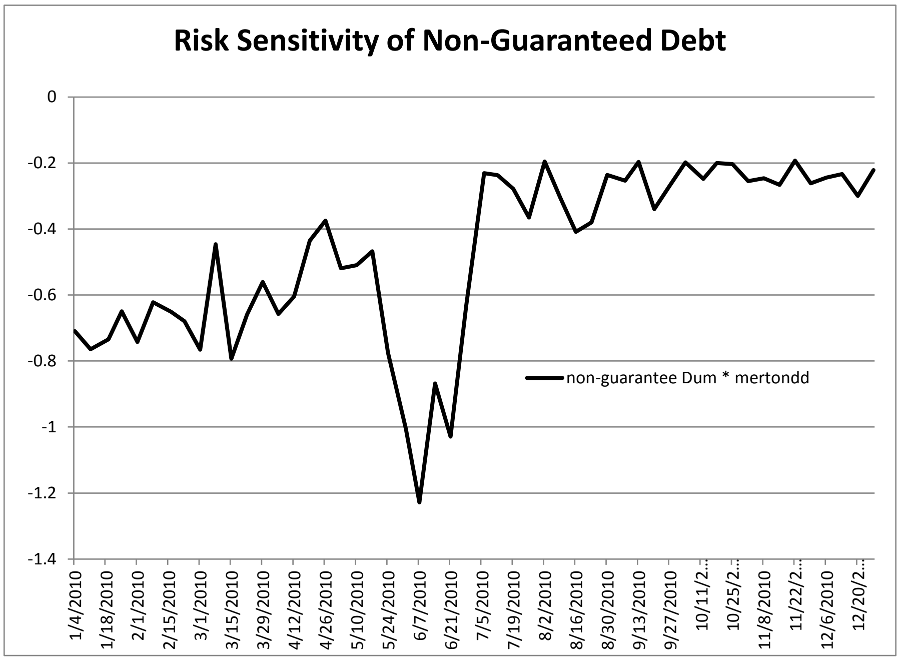


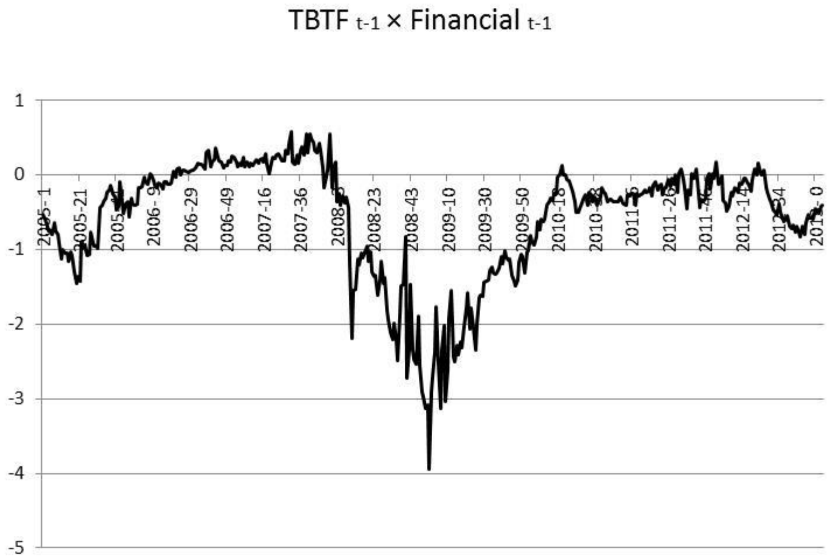
Figure 7: Financial-Corporate size subsidy over time

This figure plots the coefficient on the $TBTF_{i,t-1} \times Financial_i$ variable estimated from the following regression:

$$Spread_{i,b,t} = \propto + \beta^1 TBTF_{i,t-1} + \beta^2 Risk_{i,t-1} + \beta^3 Bond\ Controls_{i,b,t} + \beta^4 Firm\ Controls_{i,t-1} + \beta^4 Macro\ Controls_t + \beta^5 Financial_i + \beta^6 TBTF_{i,t-1} \times Financial_i + Year - Week\ FE + \varepsilon_{i,b,t}.$$

The coefficients are estimated each week. The second graph plots the estimates for the post 2010 time period. Variables defined in Appendix A.

Full time period:



Post-crisis period:

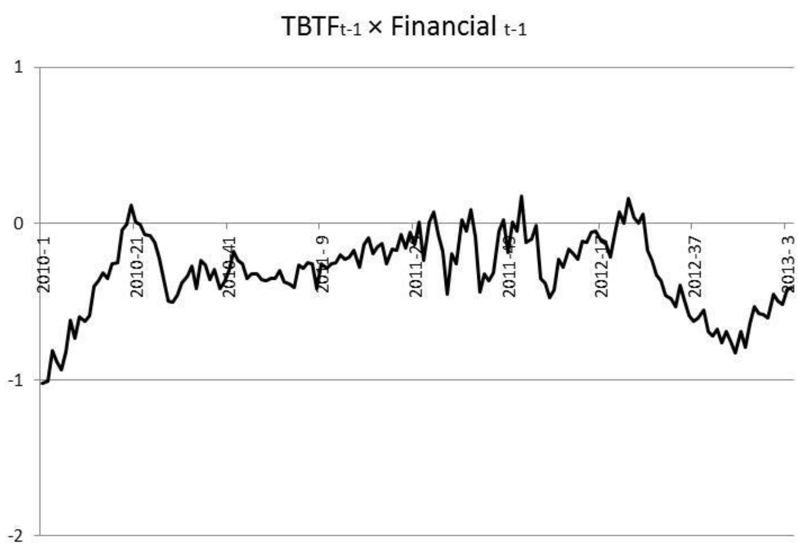


Table 1: Summary Statistics

Panel A presents the number of firms and the number of observations included in the sample, by type of institution and by time period. Panel B presents the summary statistics for the variables used in this study. Variables are defined in Appendix A. * indicates significance at the 1% level.

Panel A	# of Firms	# of Obs
Depository Institutions	228	34,719
Nondepository Credit Institutions	80	22,819
Brokers, Dealers, Exchanges & Services	61	12,839
Insurance Carriers	125	10,315
Holding and Other Investment Offices	73	3,365
1990-1994	141	14,211
1995-1999	252	26,051
2000-2004	230	17,310
2005-2010	188	26,485

Panel B	N	Mean	Std Dev	P25	P50	P75
size	84,057	1.061	0.129	0.992	1.092	1.160
mertondd	84,057	5.513	2.043	4.095	5.725	7.189
zscore	75,538	37.120	39.547	14.669	24.080	47.615
spread	84,057	0.016	0.021	0.007	0.010	0.017
rating	84,057	6.032	2.541	5.000	6.000	7.000
leverage	84,057	0.342	0.223	0.179	0.280	0.521
roa	84,057	0.013	0.017	0.007	0.011	0.016
mb	84,057	2.038	1.504	1.298	1.767	2.419
mismatch	84,057	0.074	0.684	-0.006	0.070	0.204
idiovol	84,057	1.953	0.474	1.655	1.870	2.156
issue_size	84,057	12.294	1.237	11.918	12.324	13.122
ttm	84,057	6.217	5.525	2.664	4.631	7.819

Table 2: TBTF-Spread Regressions

Regression results for the model, $Spread_{i,b,t} = \propto + \beta^1 TBTF_{i,t-1} + \beta^2 Financial_{i,t-1} + \beta^3 Risk_{i,t-1} + \beta^4 TBTF_{i,t-1} \times Financial_{i,t-1} + \beta^5 Bond\ Controls_{i,b,t} + \beta^6 Firm\ Controls_{i,t-1} + \beta^7 Macro\ Controls_t + Firm\ FE + Year\ FE + \varepsilon_{i,b,t}$, are reported in this table. We measure the systemic importance (*TBTF*) of an institution using a number of different proxies. *size* log of assets of a financial institution. *size90* is a dummy variable equal to one if a given financial institution's size is in the top 90th percentile. *size60* is a dummy variable equal to one if a given financial institution's size is between the 60th and 90th percentiles. *size30* is a dummy variable equal to one if a given financial institution's size is between the 30th and 60th percentiles. *size_top_10* is a dummy variable equal to one if a given financial institution is ranked in the top ten in terms of size in a given year. *bank*, *insurance* and *broker* dummies are variables set to one if the firm belongs to the corresponding industry based on its SIC code. Variables are defined in Appendix A. Standard errors are reported in parentheses below their coefficient estimates and are adjusted for both heteroskedasticity and within correlation clustered at the issuer level. ***, ** and * indicate significance at the 1%, 5% and 10% two-tailed level, respectively.

VARIABLES	(1) spread	(2) spread	(3) spread	(4) spread	(5) spread	(6) spread	(7) spread
ttm	0.018**	0.007	0.020***	0.018***	0.020***	0.020***	0.014***
	(0.007)	(0.004)	(0.008)	(0.007)	(0.008)	(0.008)	(0.003)
seniority	-0.128	-0.170**	-0.121	-0.133	-0.123	-0.154	-0.034
	(0.127)	(0.082)	(0.132)	(0.129)	(0.132)	(0.154)	(0.105)
$leverage_{t-1}$	-0.230	5.533***	-2.138***	-0.581	-2.137***	-2.114***	0.855
	(0.870)	(1.906)	(0.687)	(0.770)	(0.686)	(0.667)	(0.597)
roa_{t-1}	-5.839	-2.579*	-6.350	-6.161	-6.362	-6.370	-3.404***
	(4.037)	(1.356)	(4.256)	(4.221)	(4.264)	(4.243)	(0.811)
mb_{t-1}	-0.176**	-0.149***	-0.140*	-0.167**	-0.139*	-0.148*	0.000
	(0.082)	(0.044)	(0.083)	(0.082)	(0.083)	(0.087)	(0.001)
$mismatch_{t-1}$	0.076	-0.996***	0.035	0.037	0.031	-0.087	-0.723***
	(0.319)	(0.362)	(0.318)	(0.323)	(0.319)	(0.313)	(0.238)
def	1.560***	1.595***	1.540***	1.548***	1.540***	1.542***	1.292***
	(0.200)	(0.080)	(0.197)	(0.197)	(0.198)	(0.195)	(0.116)
term	0.057	0.078***	0.055	0.055	0.056	0.054	0.012
	(0.047)	(0.023)	(0.046)	(0.046)	(0.047)	(0.045)	(0.023)
mkt	-0.653	-0.691***	-0.639	-0.629	-0.645	-0.640	-0.440**
	(0.516)	(0.211)	(0.513)	(0.513)	(0.516)	(0.513)	(0.222)
$mertondd_{t-1}$	-0.291***	-0.208***	-0.310***	-0.295***	-0.311***	-0.308***	-0.254***
	(0.050)	(0.020)	(0.054)	(0.055)	(0.055)	(0.056)	(0.030)
$size_{t-1}$	-0.246***	-0.191**					
	(0.065)	(0.084)					
$size90_{t-1}$			-0.320**	-1.100***			-0.085
			(0.148)	(0.273)			(0.120)
$size60_{t-1}$				-0.870***			
				(0.263)			
$size30_{t-1}$				-0.373*			
				(0.218)			
$size\_top\_10_{t-1}$					-0.331**		
					(0.148)		
$size_{t-1}$ * bank dummy						-0.382**	
						(0.183)	
$size_{t-1}$ * insurance dummy						-0.296	
						(0.334)	
$size_{t-1}$ * broker dummy						-0.196	
						(0.209)	

financial $_{t-1}$							-0.414**
							(0.181)
size90 $_{t-1}$ * financial $_{t-1}$							-0.361**
							(0.178)
constant	4.827***	-1.238	4.075***	3.297***	4.121***	4.116***	0.192
	(1.038)	(1.613)	(1.032)	(1.039)	(1.033)	(1.043)	(0.619)
Firm FE	N	Y	N	N	N	N	N
Year FE	Y	Y	Y	Y	Y	Y	Y
Rating Dummies	Y	Y	Y	Y	Y	Y	Y
Observations	39,164	39,125	39,164	39,164	39,164	39,164	104,127
R-squared	0.432	0.509	0.423	0.428	0.423	0.423	0.439

Table 3: TBTF and Risk Interactions

Regression results for the model, $Spread_{i,b,t} = \propto + \beta^1 TBTF_{i,t-1} + \beta^2 Risk_{i,t-1} + \beta^3 TBTF_{i,t-1} \times Risk_{i,t-1} + \beta^4 Financial_{i,} + \beta^5 Financial_i \times TBTF_{i,t-1} + \beta^6 Financial_i \times Risk_{i,t-1} + \beta^7 Financial_i \times Risk_{i,t-1} \times TBTF_{i,t-1} + \beta^8 Bond\ Controls_{i,b,t} + \beta^9 Firm\ Controls_{i,t-1} + \beta^{10} Macro\ Controls_t + Firm\ FE + Year\ FE + \varepsilon_{i,b,t}$. where risk of a financial institution is measured by distance-to-default (in columns 1 and 4), z-score (in column 2, 5), volatility (in column 3 and 6). Variables are defined in Appendix A. Standard errors are reported in parentheses below their coefficient estimates and are adjusted for both heteroskedasticity and within correlation clustered at the issuer level. ***, ** and * indicate significance at the 1%, 5% and 10% two-tailed level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	spread	spread	spread	spread	spread	spread
ttm	0.021***	0.022**	0.023***	0.014***	0.014***	0.016***
	(0.007)	(0.009)	(0.007)	(0.003)	(0.003)	(0.002)
seniority	-0.103	-0.147	-0.092	0.003	-0.035	-0.020
	(0.123)	(0.129)	(0.108)	(0.107)	(0.115)	(0.092)
$leverage_{t-1}$	-2.015***	-1.402*	-1.847***	0.767	0.983*	1.056**
	(0.649)	(0.781)	(0.586)	(0.564)	(0.547)	(0.463)
roa_{t-1}	-4.378	-7.145	-3.884	-2.547***	-4.892***	-1.214*
	(3.361)	(5.132)	(2.632)	(0.799)	(1.063)	(0.699)
mb_{t-1}	-0.136*	-0.093	-0.087	-0.000	-0.002	-0.002
	(0.077)	(0.074)	(0.061)	(0.001)	(0.002)	(0.002)
$mismatch_{t-1}$	-0.188	0.289	-0.072	-0.759***	-0.590**	-0.323
	(0.341)	(0.276)	(0.332)	(0.246)	(0.234)	(0.212)
def	1.567***	1.778***	1.443***	1.431***	1.613***	1.249***
	(0.196)	(0.217)	(0.187)	(0.115)	(0.133)	(0.115)
term	0.067	0.112**	0.020	0.021	0.019	-0.006
	(0.042)	(0.049)	(0.043)	(0.024)	(0.026)	(0.024)
mkt	-0.788	-0.636	-0.883	-0.507*	-0.402*	-0.615**
	(0.519)	(0.505)	(0.551)	(0.260)	(0.244)	(0.260)
$size90_{t-1}$	-2.022***	-1.305***	0.876***	-0.435	0.226	0.055
	(0.568)	(0.401)	(0.256)	(0.442)	(0.398)	(0.301)
$mertondd_{t-1}$	-0.446***			-0.241***		
	(0.082)			(0.046)		
$size90_{t-1}$* $mertondd_{t-1}$	0.332***			0.071		
	(0.091)			(0.063)		
$zscore_{t-1}$		-0.336***			-0.172**	
		(0.082)			(0.070)	
$size90_{t-1}$* $zscore_{t-1}$		0.266**			-0.112	
		(0.115)			(0.125)	
$volatility_{t-1}$			4.885***			8.170***
			(1.106)			(0.824)
$size90_{t-1}$ * $volatility_{t-1}$			-3.342***			-0.175
			(0.824)			(1.018)
$financial_{t-1}$				0.482	0.162	0.558*
				(0.598)	(0.407)	(0.313)
$financial_{t-1}$ * $size90_{t-1}$				-1.554**	-1.445**	0.721*
				(0.746)	(0.579)	(0.377)
$financial_{t-1}$ * $mertondd_{t-1}$				-0.149		
				(0.091)		
$financial_{t-1}$ * $mertondd_{t-1}$* $size90_{t-1}$				0.259**		
				(0.113)		

financial $_{t-1}$ * zscore $_{t-1}$					-0.134	
					(0.101)	
financial $_{t-1}$ * zscore $_{t-1}$ *size90 $_{t-1}$					0.387**	
					(0.171)	
financial $_{t-1}$ * volatility $_{t-1}$						-2.740***
						(1.057)
financial $_{t-1}$ * volatility $_{t-1}$ *size90 $_{t-1}$						-3.106**
						(1.310)
constant	3.306***	1.517*	-0.512	-0.617	-1.642**	-4.119***
	(0.819)	(0.910)	(0.809)	(0.750)	(0.716)	(0.509)
Year FE	Y	Y	Y	Y	Y	Y
Rating Dummies	Y	Y	Y	Y	Y	Y
Observations	39,125	37,856	39,125	104,267	101,944	104,267
R-squared	0.457	0.429	0.492	0.459	0.439	0.548

Table 4: TBTF-Risk Relationship

Regression results for the model,

$Risk_{i,t} = \propto + \beta^1 TBTF_{i,t-1} + \beta^2 Financial_{i,t-1} + \beta^3 TBTF_{i,t-1} + \beta^4 Financial_{I,t-1} \times TBTF_{i,t-1} + \beta^5\ Macro\ Controls_t + \beta^6 Firm\ Controls_{i,t-1} + Year\ FE + \varepsilon_{i,t}$. Variables are defined in Appendix A. Standard errors are reported in parentheses below their coefficient estimates and are adjusted for both heteroskedasticity and within correlation clustered at the issuer level. ***, ** and * indicate significance at the 1%, 5% and 10% two-tailed level, respectively.

VARIABLES	(1) mertondd	(2) mertondd	(3) mertondd	(4) mertondd
def	-89.333***	-86.078***	-91.350***	-90.576***
	(6.431)	(6.195)	(2.203)	(2.325)
term	-12.792***	-12.971***	-0.092	0.329
	(3.033)	(3.076)	(1.294)	(1.333)
mkt	-0.098	-0.111	0.165***	0.120**
	(0.155)	(0.156)	(0.058)	(0.060)
roa	6.268***	6.324***	8.187***	9.083***
	(1.241)	(1.053)	(0.678)	(0.714)
mb	0.088**	0.066	0.008**	0.007**
	(0.038)	(0.040)	(0.003)	(0.003)
std roa	-9.368**	-11.392**	-3.410***	-4.812***
	(4.466)	(5.725)	(0.847)	(0.999)
leverage	-2.676***	-1.427**	-3.295***	-3.100***
	(0.560)	(0.599)	(0.305)	(0.311)
mismatch	-0.593**	-0.606*	-0.098	0.025
	(0.281)	(0.324)	(0.132)	(0.145)
size $_{t-1}$	0.222***		0.508***	
	(0.047)		(0.031)	
size90$_{t-1}$		0.066		1.021***
		(0.154)		(0.133)
financial $_{t-1}$			2.247***	0.543***
			(0.515)	(0.123)
financial $_{t-1}$* size $_{t-1}$			-0.257***	
			(0.052)	
financial $_{t-1}$* size90 $_{t-1}$				-0.482**
				(0.219)
Constant	6.604***	7.706***	3.409***	7.632***
	(0.659)	(0.606)	(0.346)	(0.233)
Year FE	Y	Y	Y	Y
Rating Dummies	Y	Y	Y	Y
Observations	10,762	10,762	88,213	88,182
R-squared	0.627	0.605	0.522	0.465

Table 5: Ratings as an Exogenous Measure

Panel A reports regression results for the model:
$Spread_{i,b,t} = \propto + \beta^1 issuer\ rating_{i,t-1} + \beta^2 stand\ alone\ rating_{i,t-1} + \beta^3 Bond\ Controls_{i,b,t} + \beta^4 Firm\ Controls_{i,t-1} + \beta^5 Macro\ Controls_t + Firm\ FE + Year\ FE + \varepsilon_{i,b,t}$. Panel B reports regression results for the model: $issuer\ /\ stand\ alone\ rating_{i,t-1} = \propto + \beta^1 TBTF_{i,t-1} + \beta^2 Firm\ Controls_{i,t-1} + Firm\ FE + Year\ FE + \varepsilon_{i,b,t}$. Variables are defined in Appendix A. Standard errors are reported in parentheses below their coefficient estimates and are adjusted for both heteroskedasticity and within correlation clustered at the issuer level. ***, ** and * indicate significance at 1%, 5% and 10% two-tailed level, respectively.

Panel A:

VARIABLES	(1) spread	(2) spread	(3) spread
ttm	-0.021**	-0.014	-0.011
	(0.010)	(0.021)	(0.020)
seniority	-0.271**	-0.212	-0.208
	(0.105)	(0.216)	(0.216)
leverage $_{t-1}$	-14.418***	-5.450	-4.093
	(1.997)	(3.829)	(4.288)
roa $_{t-1}$	-55.024***	-42.518***	-46.346***
	(10.843)	(11.292)	(11.410)
mb $_{t-1}$	0.419***	0.526***	0.465***
	(0.105)	(0.161)	(0.164)
mismatch $_{t-1}$	2.971***	2.492**	2.385**
	(0.423)	(1.110)	(1.097)
def	1.344***	1.309***	1.298***
	(0.106)	(0.181)	(0.178)
term	0.031	0.048	0.044
	(0.038)	(0.054)	(0.055)
mkt	-0.555	-0.572	-0.528
	(0.369)	(0.439)	(0.427)
mertondd $_{t-1}$	-0.171***	-0.155***	-0.178***
	(0.040)	(0.046)	(0.059)
stand-alone rating $_{t-1}$	0.107*		-0.164
	(0.055)		(0.147)
issuer rating $_{t-1}$		0.271***	0.340***
		(0.071)	(0.107)
Constant	14.591***	4.759	3.335
	(2.012)	(3.812)	(4.143)
Year FE	Y	Y	Y
Observations	16,127	16,120	16,107
R-squared	0.644	0.654	0.655

Panel B

VARIABLES	(1) issuer rating	(2) issuer rating	(3) stand-alone	(4) stand-alone
leverage $_{t-1}$	-19.374**	-25.011***	-2.654	-3.474
	(8.490)	(6.312)	(5.209)	(4.786)
roa	-32.744*	-35.547	-23.599	-23.952
	(18.217)	(21.865)	(15.001)	(15.519)
mb	-0.410*	-0.137	-0.259*	-0.214
	(0.220)	(0.246)	(0.130)	(0.134)
mismatch $_{t-1}$	2.863**	3.106**	1.047	1.116*
	(1.337)	(1.281)	(0.676)	(0.642)
size $_{t-1}$	-0.753***		-0.130	
	(0.151)		(0.107)	
size90 $_{t-1}$		-1.892***		-0.344
		(0.439)		(0.299)
constant	30.062***	28.649***	6.559	6.153
	(7.237)	(5.780)	(4.558)	(4.400)
Year FE	Y	Y	Y	Y
Observations	16,120	16,120	16,127	16,127
R-squared	0.622	0.492	0.527	0.518

Table 6: Event Study

Regression results for the model,
$Spread_{i,b,t} = \propto + \beta^1 post + \beta^2 TBTF_{i,t} \times post + \beta^3 Fincancial_{i,t} \times post + \beta^4\, Risk_{i,t} \times post + \beta^5 TBTF_{i,t} \times Fincancial_{i,t} \times post + \beta^6 TBTF_{i,t} \times Risk_{i,t} \times post + \beta^7 Fincancial_{i,t} \times Risk_{i,t} \times post + \beta^8 TBTF_{i,t} \times Fincancial_{i,t} \times Risk_{i,t} \times post + \beta^9 Macro\ Controls_t + Issue\ FE + \varepsilon_{i,b,t}$ are reported in this Table. The variable *post* equals 1 if the transaction date is the event date or one of the 5 trading days following the event date, and 0 if the transaction date is one of the 5 trading days prior to the event date. Other variables are defined in Appendix A. We only report the relevant variables of interest to save space. Standard errors are reported in parentheses below their coefficient estimates and are adjusted for both heteroskedasticity and within correlation clustered at the issuer level. ***, ** and * indicate significance at 1%, 5% and 10% two-tailed level, respectively.

Event Date	Event	$size90_{t-1}$×post	$size90_{t-1}$ ×$mertondd_{t-1}$×post	$size90_{t-1}$ ×$financial_{t-1}$×post	$size90_{t-1}$×$mertondd_{t-1}$ ×$financial_{t-1}$*post
07/11/08	Paulson requests government funds for	-0.222**	0.074	-0.191*	0.049
	Fannie Mae and Freddie Mac	(0.106)	(0.091)	(0.110)	(0.093)
03/13/08	Bear Stearns bailout	-1.149***	0.251**	-1.141***	0.401**
		(0.224)	(0.103)	(0.228)	(0.182)
09/20/08	Paulson submits TARP proposal	-1.182***	-0.080	-1.259***	-0.050
		(0.308)	(0.352)	(0.309)	(0.356)
10/03/08	TARP passes the U.S. House of Representatives	-1.060***	1.951***	-1.268***	2.186***
		(0.292)	(0.420)	(0.363)	(0.439)
10/06/08	The Term Auction Facility is increased to $900bn	-0.686**	0.808***	-0.878**	1.063***
		(0.278)	(0.310)	(0.357)	(0.340)
10/14/08	Treasury announces $250 billion capital injections	-0.927**	0.201	-0.748*	0.269
		(0.362)	(0.281)	(0.382)	(0.291)
02/02/09	The Federal Reserve announces it is prepared to	-0.031	0.102	-0.297*	0.462***
	increase TALF to $1 trillion	(0.086)	(0.109)	(0.162)	(0.176)
11/13/08	Paulson indicates that TARP will be used to buy equity	-0.630**	0.925**	-0.614*	0.901**
	instead of troubled assets	(0.272)	(0.403)	(0.316)	(0.429)
09/15/08	Lehman Brothers files for bankruptcy	1.005***	-1.464***	1.086***	-1.437***
		(0.329)	(0.293)	(0.436)	(0.184)
06/29/10	The House and the Senate conference committees	-0.034*	0.039*	-0.003	0.033
	reconcile the Dodd-Frank bill	(0.019)	(0.021)	(0.022)	(0.023)
07/21/10	The Dodd-Frank bill passes the U.S. House of Representatives	0.027*	-0.019	0.017	-0.016
		(0.016)	(0.014)	(0.019)	(0.015)

12/10/12	The FDIC and the Bank of England release a white paper and press release describing SPOE	0.037*** (0.012)	-0.028** (0.014)	0.030** (0.014)	-0.029** (0.014)

Table 7: FDIC Guarantee

This table reports the results from the following regression: $Spread_{i,b,t} = \propto + \beta^1 \times Bond\ controls_{i,b,t} + \beta^2 \times non - gurantee_{i,b,t} + \beta^3 \times non - gurantee_{i,b,t} \times post + \beta^4 \times mertondd_{i,t-1} + \beta^5 mertondd_{i,t-1} \times post + \beta^6 \times non - gurantee_{i,b,t} \times mertondd_{i,t-1} + \beta^7 \times non - gurantee_{i,b,t} \times mertondd_{i,t-1} \times post + Issue \times Trading\ day\ FE + \varepsilon_{i,b,t}$. Variables defined in Appendix A. The event date is June 29, 2010 (Dodd-Frank). For specifications (1) and (2), the variable *post* equals 1 if the transaction date is the event date or one of the 5 trading days following the event date, and 0 if the transaction date is one of the 5 trading days prior to the event date. For specifications (3) and (4), *post* equals 1 if the transaction date is the event date or one of the 132 trading days following the event date, and 0 if the transaction date is one of the 132 trading days prior to the event date. The other variables are defined in Appendix A. Standard errors are reported in parentheses below their coefficient estimates and are adjusted for both heteroskedasticity and within correlation clustered at the issuer level. ***, ** and * indicate significance at 1%, 5% and 10% two-tailed level, respectively.

VARIABLES	(1) spread	(2) spread	(3) spread	(4) spread
fixed rate	-1.410***	-1.417***	-0.828***	-0.720***
	(0.095)	(0.047)	(0.194)	(0.181)
seniority	-0.190*	-0.233*	-0.259**	-0.285**
	(0.099)	(0.103)	(0.099)	(0.104)
puttable	-0.366*	-0.320	-0.227	-0.232
	(0.187)	(0.198)	(0.151)	(0.141)
redeemable	0.106	0.160*	-0.005	-0.019
	(0.160)	(0.082)	(0.166)	(0.126)
ttm	0.090***	0.085***	0.087***	0.083***
	(0.015)	(0.018)	(0.012)	(0.012)
exchangeable			1.450***	1.431***
			(0.231)	(0.217)
non-guarantee	1.780***	2.712***	1.413***	2.190***
	(0.227)	(0.181)	(0.202)	(0.129)
non-guarantee * post	-0.134***	-0.700**	-0.001	-0.409**
	(0.022)	(0.259)	(0.065)	(0.129)
$mertondd_{t-1}$ * non-guarantee		-0.887***		-0.662***
		(0.220)		(0.181)
$mertondd_{t-1}$ * non-guarantee * post		0.604**		0.387**
		(0.206)		(0.124)
Constant	1.617***	1.675***	1.125***	1.062***
	(0.227)	(0.174)	(0.284)	(0.277)
Issuer * Trading Day FE	Y	Y	Y	Y
Event days	10	10	132	132
Observations	2,537	2,090	31,338	30,011
R-squared	0.687	0.703	0.594	0.595

Table 8: Robustness Checks

Regression results for the model, $Spread_{i,b,t} = \propto + \beta^1 TBTF_{i,t-1} + \beta^2 Risk_{i,t-1} + \beta^3 Bond\ Controls_{i,b,t} + \beta^4 Firm\ Controls_{i,t-1} + \beta^5 Macro\ Controls_t + \beta^3 Bond\ Liquidity_{i,b,t} + \ Year\ FE + \varepsilon_{i,b,t}$, are reported in this table. Column (1) reports issue fixed effects regression results. In columns (1) and (2) we use alternative measures of bond liquidity. We use *covar* and *srisk* as alternative measures of systemic importance. Variables are defined in Appendix A. Standard errors are reported in parentheses below their coefficient estimates and are adjusted for both heteroskedasticity and within correlation clustered at the issuer level. ***, ** and * indicate significance at the 1%, 5% and 10% two-tailed level, respectively

VARIABLES	(1) spread	(2) spread	(3) spread	(4) spread
ttm	0.009*	0.019***	0.013***	0.010
	(0.005)	(0.006)	(0.004)	(0.006)
seniority	0.034	-0.238**	0.005	0.085
	(0.117)	(0.112)	(0.081)	(0.167)
leverage $_{t-1}$	0.542***	1.268***	0.280*	0.725**
	(0.180)	(0.454)	(0.151)	(0.309)
roa	-9.022**	-5.022	-8.671*	-9.373
	(4.102)	(5.653)	(5.225)	(6.024)
mb	0.005	-0.252**	-0.071	-0.134
	(0.043)	(0.112)	(0.057)	(0.089)
mismatch $_{t-1}$	-0.300	0.005	-0.219	-0.662
	(0.199)	(0.473)	(0.167)	(0.441)
def	1.653***	1.776***	1.668***	1.677***
	(0.110)	(0.014)	(0.124)	(0.124)
term	0.079***	0.194***	0.089***	0.118***
	(0.025)	(0.04)	(0.025)	(0.034)
mkt	0.370**	0.322	0.420**	0.325
	(0.155)	(0.333)	(0.178)	(0.250)
mertondd $_{t-1}$	-0.063***	-0.052***	-0.052***	-0.064**
	(0.019)	(0.019)	(0.015)	(0.025)
size90 $_{t-1}$	-0.168**	-0.293**		
	(0.067)	(0.145)		
liquidity $_{t-1}$	-0.100***			
	(0.027)			
turnover$_{t-1}$		-0.073***		
		(0.020)		
covar$_{t-1}$			-4.047**	
			(1.570)	
srisk$_{t-1}$				-0.857**
				(0.388)
Constant	-0.665**	1.889**	0.545**	10.142**
	(0.289)	(0.788)	(0.251)	(4.563)
Observations	46,308	14,003	43,185	27,943
R-squared	0.521	0.607	0.539	0.506