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

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Abstract

Using unsecured bonds traded in the U.S. between 1990 and 2012, we find that bond credit spreads are sensitive to risk for most financial institutions, but not for the largest financial institutions. This "too big to fail" relation between firm size and the risk sensitivity of bond spreads is not seen in the non-financial sectors. The results are robust to using different measures of risk, controlling for bond liquidity, conducting an event study around shocks to investor expectations of government guarantees, examining explicitly and implicitly guaranteed bonds of the same firm, and using agency ratings of government support for financial institutions.

JEL Classifications: G21, G24, G28.
Keywords: Too big to fail, Dodd-Frank, bailout, implicit guarantee, moral hazard.

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1. Introduction

The financial sector in the United States received an unprecedented amount of government support during the 2007-2009 financial crisis. The nature and the magnitude of this support renewed concerns about moral hazard arising from investor expectations of government bailouts of large financial institutions. In this paper, we examine the overall cost and the risk sensitivity of debt in the financial and non-financial sectors in the U.S. over the 1990 to 2012 period. We find that while large firm size is associated with lower cost and lower risk sensitivity of debt in the financial sector, a similar relation is not present in non-financial sectors.

The differences we observe between the sectors are consistent with investors expecting a government guarantee to support unsecured creditors of large financial institutions in times of distress. This expectation of support can result from the government following a too-big-to-fail (TBTF) policy of not allowing large financial institutions to fail if their failure would cause significant disruption to the financial system and economic activity. The expectation by the market that the government may provide a bailout is commonly referred to as an implicit guarantee; implicit because the government does not have any explicit, ex-ante commitment to intervene. In the absence of an implicit government guarantee, market participants would evaluate an institution's financial condition and incorporate those assessments into securities' prices, demanding higher yields on uninsured debt in response to greater risk-taking by the financial institution. However, for the market to discipline financial institutions in this manner, debtholders must believe that they will bear the cost of an institution becoming insolvent or financially distressed. An implicit government guarantee weakens market discipline by reducing investors' incentives to monitor and price the risk taking of potential TBTF candidates. Anticipation of government support for major financial institutions could enable the institutions to borrow at costs that do not reflect the risks otherwise inherent in their operations compared to other industries.

The implicit nature of the TBTF guarantee implies that investors may not expect the government to always implement TBTF policies. The possibility of a bailout may exist in theory but not reliably in practice, and as a result, market participants may not price an implicit guarantee fully.[1] It is also possible that the introduction of recent financial laws and regulations, like the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 (Dodd-Frank Act), may have eliminated or dampened TBTF expectations. Hence, it is an empirical question as to whether the implicit TBTF guarantee is considered credible and appropriately priced by market participants at all points in time.

In this paper, we examine the relation between the risk profiles of U.S. financial institutions and the credit spreads on their unsecured bonds. We distinguish between large and small financial institutions based on the size of their balance sheet assets. We define institutions that are in the 90th percentile in terms of assets in a given year as large financial institutions. Our results are robust to using the top 10 firms in terms of assets, as well as using measures of systemic importance other than size, such as the Adrian and Brunnermeir (2011) CoVar measure, and the Acharya et al. (2010) SRISK measure. We use both accounting-based measures of risk, such as the z-score, and equity-based measures of risk, such as Merton's (1974) distance-to-default measure. Since implicit guarantees may affect both leverage and asset volatility and inflate equity values, for robustness, we also create an adjusted measure of distance-to-default by removing the effect of size on market leverage and standard deviation of equity returns. We find similar results using measures of risk adjusted for firm size.

Comparing financial firms to non-financial firms, we find that while a positive relation exists between risk and credit spreads for medium and small financial institutions, the risk-to-spread relation is significantly weaker for the largest institutions. Importantly, we show that the relation between firm size and the risk sensitivity of bond credit spreads is not present in

[1] The U.S. 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 typically announce their willingness to support institutions they consider too big to fail. Rather, they prefer to be ambiguous about which troubled institutions, if any, would receive support. Ever since the U.S. Comptroller of the Currency named 11 banks as "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 difficult for investors to rely on a government bailout. While this does not eliminate the subsidy, it does reduce its value.

non-financial firms.

Comparing financial firms to non-financial firms allows us to control for general advantages associated with firm size that may affect both the level of spreads and the pricing of risk. For instance, larger firms may have lower funding costs due to greater diversification, larger economies of scale, or easier access to capital markets and liquidity in times of financial turmoil. Such general size advantages are likely to affect the cost of funding for large firms in industries outside the financial sector.

First, we use a difference-in-differences approach and compare differences in spreads of large and small financial institutions to the differences in spreads of large and small firms in non-financial sectors.[2] If bond investors believe that all of the largest firms (both financial and non-financial) are too-big-to-fail, then large non-financial firms should enjoy a funding advantage similar to that of large financial firms. However, we find this is not the case. We find that a substantial size funding advantage exists for financial firms even after controlling for the effect of size on credit spreads for non-financial firms.

Next, we use the difference-in-differences approach to examine the sensitivity of credit spreads to changes in risk. We find that the risk sensitivity of spreads is substantially weaker for large financial firms than for large non-financial firms. We find that these differences between financial and non-financial firms are not due to differences in the liquidity of their bonds. Our results are robust to controlling for measures of bond liquidity.

The economic magnitudes of the risk-sensitivity results are significant. Figure 2 shows the sensitivity of spreads for firms in different size decile groups. The two lines show the coefficient estimates on the interaction of our risk measure (distance-to-default) with a dummy variable that takes on a value of one for firms that belong to each size decile. The solid line shows coefficient estimates for financial firms and the dotted line shows coefficient estimates for non-financial firms. One standard deviation increase in distance-to-default reduces spreads by

[2] For non-financial firms, we compute a similar size measure. We group non-financial firms separately when we rank these firms by size. We find similar results grouping non-financial firms into 5 or 10 Fama-French industry groups and then ranking them by size.

105 bps for financial firms that are in the 50-60th percentile in terms of size. For financial firms that are in 90-100th percentile in terms of size, the corresponding decline in spreads is only 21 bps. We do not observe a similar change in risk sensitivity for non-financial firms. For non-financial firms that are in the 50-60th percentile, a one standard deviation increase in distance-to-default reduces spreads by 56 bps. For large non-financial firms in the 90-100th size group, the impact is 49 bps.

The differences in cost of funding and risk sensitivity we observe for large financial institutions may be driven by unobserved heterogeneity and omitted variables. To address this concern, we conduct two additional analyses.

First, we examine credit rating agencies' expectations of government support. In rating financial institutions, the Fitch rating agency assigns both an "issuer rating" and a "stand-alone rating." The 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. The stand-alone rating measures a financial institution's ability to repay its debts without taking into consideration any external support. Using these third-party estimates of risk and support, we find that issuer ratings (which incorporate an expectation of support) impact spreads, but stand-alone ratings do not. We also find that larger firms have significantly better issuer ratings, but not stand-alone ratings.

Second, we conduct an event study around shocks to investor expectations of implicit guarantees. We find that, following the collapse of Lehman Brothers in 2008, larger financial institutions experienced greater increases in their credit spreads than smaller institutions. In contrast, the spreads of large financial institutions also became more risk sensitive after the collapse of Lehman. Following the government's rescue of Bear Stearns in 2008 and the adoption of the Troubled Asset Relief Program (TARP) and other liquidity and equity support programs, we find that larger financial institutions experienced greater reductions in credit spreads than smaller institutions; the spreads of large financial institutions also became less risk sensitive. Our event study results continue to hold when we use non-financial firms as controls.

Finally, we examine the impact of the passage of the Dodd-Frank Act in reducing investor expectations of government support. We conduct an event study around the passage of the Dodd-Frank Act using a short event window of 10 days, as well as a longer event window of 12 months. We use two event dates: June 29, 2010 when the House and the Senate conference committees reconciled the Dodd-Frank bill, and July 21, 2010, when the bill was signed into law. We find that passage of Dodd-Frank Act did not significantly alter investor expectations of future government support for large financial institutions. These results continue to hold when we use non-financial firms as controls. We also conduct the event study using bonds issued under the Federal Deposit Insurance Corporation's (FDIC) Temporary Liquidity Guarantee Program (TLG Program). The TLG Program was designed to help restore confidence in the financial institutions and provided a guarantee for senior unsecured debt issued after October 14, 2008 and before June 30, 2009 (later extended to October 31, 2009). The guarantee remained in effect until June 30, 2012 or the date the debt matured, if earlier. This approach allows us examine within-firm variation and compare *implicitly* guaranteed bonds to *explicitly* guaranteed bonds issued by the *same* firm.

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.[3] Using this approach, we find a *decline* in the value of the explicit FDIC guarantee after Dodd-Frank's adoption. We also find that the risk sensitivity of non-guaranteed debt *declined* following Dodd-Frank. If Dodd-Frank had been successful in eliminating TBTF expectations, we should have found an *increase* in both the value of the explicit guarantee and the risk sensitivity of non-guaranteed debt.

Consistent with these findings, we show that market discipline is less effective in curbing the risk-taking behavior of financial institutions. In particular, we find that, while the risk of a financial institution, on average, is responsive to various measures of market

[3] In particular, we examine the following firms that we identify as having issued bonds under the TLG program: Bank of America, Citigroup, Goldman Sachs, JPMorgan Chase, Morgan Stanley, Sovereign Bancorp, State Street, SunTrust, US Bancorp, Wells Fargo, PNC Bank, HSBC USA, Keycorp, MetLife, John Deere Capital, and GE Capital.

discipline (e.g., Duan, Moreau, and Sealy 1992), this is not the case for the largest financial institutions. We examine the sensitivity of leverage to changes in firm risk, and find that this relation breaks down for large financial institutions. We also examine the fair value of insuring firm liabilities in order to study the incentive of financial institutions to shift risk onto taxpayers. We find that large financial institutions have a greater ability to shift risk than their smaller counterparts. We find similar results when we repeat the analyses using non-financial institutions as a control.

Our results contribute to the literature in two important ways. First, we provide evidence that unsecured bond spreads are less sensitive to firm risk for large financial institutions.. Unlike prior work on the risk sensitivity of bank debt, we examine the risk sensitivity of debt separately for large versus small financial institutions. We also show that the leverage and capital ratios of large financial institutions are less sensitive to changes in risk, and that large financial institutions are able to engage in greater risk-shifting onto the public safety net. Our second contribution is to show that the relation between firm size and the risk sensitivity of bond spreads is not present in non-financial sectors and is robust to alternative approaches to address potential endogeneity of risk to size and unobserved heterogeneity between large and small financial firms.

In the next section, we discuss the related literature. In Section III, we describe the data and methodology. Our main results are described in Section IV. Section V contains robustness tests. In Section VI, we report the results of our analyses of the impact of the Dodd-Frank Act. Section VII contains market discipline results. We conclude in Section VIII.

2. Related Literature

A large literature examines whether the market can provide discipline against bank risk taking (Flannery 1998; Calomiris 1999; Levonian 2000; DeYoung et al. 2001; Jagtiani, Kaufman, and Lemieux 2002; Morgan and Stiroh 2000) by studying whether there is a relation between a bank's funding cost and its risk. These 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. However, the existence of risk-sensitive pricing does not necessarily mean that investors are not also pricing an implicit guarantee.

In contrast to the extensive literature on 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 relation changes as investor perceptions of implicit government support changes. The premise is that investors will price bank-specific risk to a lesser extent during periods of perceived liberal application of TBTF policies, but will price it to a greater extent during periods of perceived restricted application of TBTF policies.

Flannery and Sorescu (1996) examine yield spreads on the subordinated debt of U.S. banks over the 1983-1991 period. They postulate 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 supposedly weakened. They also find the effect of bank size to have a lower influence on spreads in the later time period. Sironi (2003) reaches a similar conclusion in his study of European banks during the 1991-2001 period.[4] Flannery and Sorescu (1996) and Sironi (2003) argue that as the implicit guarantee was diminished through policy and legislative changes, debt holders realized that they were no longer protected from losses and responded by more accurately pricing risk. But these researchers analyze the risk sensitivity of debt without explicitly differentiating potential TBTF candidates from other banks and without using non-financial firms as controls, and are thus subject to econometric issues from omitted

[4] Sironi (2003) argues that, during this period, implicit public guarantees diminished due to the loss of monetary policy by national central banks and budget constraints imposed by the European Union. Using yield spreads on subordinated debt at issuance to measure the cost of debt, the author finds that spreads became relatively more sensitive to bank risk in the second part of the 1990s, as the perception of government guarantees supposedly diminished.

variables and unobserved heterogeneity.

Later studies do attempt to identify TBTF banks and reach a different conclusion about the spread-risk relation. These studies define TBTF banks using the 11 banks that were declared “too big to fail” by the Comptroller of the Currency in 1984. Morgan and Stiroh (2005) determine that the spread-risk relation was flatter for the named TBTF banks than it was for other banks. They find that this flat relation for the TBTF banks existed during the 1984 bailout of Continental Illinois and persisted into the 1990s, even after the passage of FDICIA in 1991, contrary to the findings of Flannery and Sorescu (1996). Similarly, Balasubramnian and Cyree (2011) suggest that the spread-risk relation flattened for the TBTF banks following the rescue of Long-Term Capital Management in 1998.

In these studies, however, a TBTF institution is defined using the Comptroller’s list from 1984. Consequently, the usefulness of the definition is confined to a particular historical period. In contrast, we identify TBTF institutions by employing various measures of size and systemic risk. Our TBTF definition captures time variation and is relevant throughout our sample period. Using this approach, we are able to analyze TBTF institutions over a longer period of time (1990-2012), including the recent financial crisis. Further, we conduct a more detailed analysis of the role TBTF status plays in the spread-risk relation than prior studies have done. In addition to comparing larger financial institutions to smaller financial institutions, we also compare larger non-financial firms to smaller non-financial firms. We show that the effect of firm size on the risk sensitivity of bond spreads is present in the financial sector, but not in the non-financial sector. Moreover, our results are robust to controls for liquidity and multiple measures of risk. We also address endogeneity issues by performing event studies that enable within firm identification of changes in the risk sensitivity of bond spreads.

Other studies in the literature have taken different approaches to measuring funding cost differentials arising from expectations of support, using credit ratings or interest rates on deposits. Credit rating studies focus on the rating “uplift” that a financial institution receives from a rating agency as a result of expectations of government support. The uplift in ratings is then translated into a basis point savings in bond yields (Rime 2005; Ueda and Mauro

2012). These studies, however, measure reductions in funding costs only indirectly, by studying differences in credit ratings, not directly 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 these studies might support the notion that an implicit guarantee exists, they do not provide a precise measure of it.

Deposit studies focus on differences in interest rates paid on uninsured deposits for banks of different sizes (e.g., Jacewitz and Pogach 2013). This approach, however, relies on the assumption that interest rate differentials are attributable to expectations of government support. Other factors could affect uninsured deposit rates, such as the wider variety of services that large banks can offer relative to those offered by small banks, and the lower cost at which they can provide those services.

Finally, Tsesmelidakis and Merton (2015) and Tsesmelidakis and Schweikhard (2015), using a model calibrated to the pre-crisis regime, show that there was a structural break in the pricing of bank debt and CDS prices during the recent financial crisis. This approach assumes there is correct pricing prior to the crisis and the calibrated parameters are constant over time.

Although most research on implicit government guarantees has examined debt prices, there is also work investigating 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. More recently, Ghandi and Lustig (2015) examine equity data to investigate implicit support of banks. Other studies suggest that shareholders benefit from mergers and acquisitions that result in a bank achieving TBTF status (e.g., Kane 2000). Brewer and Jagtiani (2007) and Molyneux, Schaeck, and Zhou (2010) find that greater premiums are paid in larger M&A transactions, reflecting safety net subsidies. Similarly, Penas and Unal (2004) show that bond spreads also tend to decline after a bank merger when the resulting entity attains TBTF status.

3. Data and Methodology

3.1 Corporate Bond Sample

We collect data for financial firms and non-financial firms that have bonds traded during the 1990-2012 period. Financial firms are classified using Standard Industrial Classification (SIC) codes 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 1990–2012 period. Bond data come from three separate databases: the Lehman Brothers Fixed Income Database (Lehman) for the 1990-1998 period, the National Association of Insurance Commissioners Database (NAIC) for the 1998-2006 period, and the Trade Reporting and Compliance Engine (TRACE) system dataset for the 2006-2012 period. 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.

Our sample includes all unsecured bonds issued in the U.S. by firms in the above datasets that satisfy common selection criteria in the corporate bond literature (e.g., Anginer and Yildizhan 2010; Anginer and Warburton 2014). 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 the results are not heavily influenced by outliers, we set all observations higher than the 99^{th} percentile value of a given variable to the 99^{th} 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 over 300 unique financial institutions with 45,000 observations, and about 1,000 non-financial firms with 75,000 observations, that have corresponding credit spread and total asset information (Table 1). For each firm, we compute the end-of-month credit spread on its bonds (*spread*), defined as the difference between the yield on its bonds and that of the corresponding maturity-matched Treasury bond.

3.2 Measures of Systemic Importance

We are interested in systemically important financial institutions, as they will be the beneficiaries of potential TBTF interventions. While we focus on large institutions, we recognize that factors other than size may cause an institution to be systemically important. For instance, a large firm with a simple transparent structure (such as a manager of a family of mutual funds) might fail without imposing significant consequences on the financial system, while a relatively small entity (such as a mortgage insurer) that fails might cause substantial stress to build up within the system (Rajan 2010). Characteristics that tend to make an institution "too systemic to fail" include interconnectedness, number of different lines of business, transparency, and complexity of operations. But these characteristics tend to be highly correlated with the size of a financial institution's balance sheet. 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. The Dodd-Frank Act also emphasizes size in defining systemically important financial institutions. Large size even without significant interconnectedness may carry political influence (Johnson and Kwak 2010). Hence, we employ multiple measures of firm size. One is the 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 institutions in terms of size in a given year (*size_top_10*).[5] These latter two measures are meant to capture very large institutions, which are likely to benefit most from TBTF policies. For robustness, we also examine TBTF in relation to systemic importance by using two commonly-utilized measures of systemic importance: the Adrian and Brunnermeir (2011) CoVar measure (*covar*), and the Acharya et al. (2010) and Acharya, Engle, and Richardson (2012) systemic risk measure (*srisk*). The computation of these systemic importance measures is in Appendix A.

3.3 Measures of Bank Risk

There are a number of different measures of credit risk that have been used in the

[5] For non-financial firms, we compute similar measures. Since financial firms make up close to 40% of the sample, we group non-financial firms separately when we rank these firms by size and assign a dummy variable if they are in the top 90th percentile in terms of size. We found similar results grouping non-financial firms into 5 or 10 Fama-French industry groups and then ranking them by size.

literature. We use Merton's distance-to-default (*mertondd*) as our primary risk measure. Distance-to-default is based on Merton's (1974) structural credit risk model. In his model, the equity value of a firm is modeled as a call option on the firm's assets, which is used to compute asset values and asset volatility. 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. We follow Hillegeist et al. (2004) and Campbell, Hilscher, and Szilagyi (2008) in calculating Merton's distance-to-default. The details of the calculation are in Appendix A. A higher distance-to-default number signals a lower probability of insolvency.

There are limitations to using Merton's original distance-to-default model for financial institutions (Lucas and MacDonald 2006; Nagel and Purnanandam 2015,).[6] Also, implicit guarantees may affect equity values resulting in underestimation of risk using the Merton (1974) distance-to-default model. To address these concerns, we verify our results using alternative measures of risk:

i) First, we compute an adjusted distance-to-default measure by removing the effect of size on market leverage, as well as the standard deviation of equity returns. For each month, we run a cross-sectional regression of equity volatility and market leverage on *size*. Market leverage is computed as total liabilities divided by the sum of market equity and total liabilities. We then compute adjusted market leverage and volatility values by multiplying the coefficient on the size variable from the regression by the median firm size in a given month. We run the regression and compute the median values separately for the financial and non-financial firms. We use adjusted market leverage and adjusted volatility to compute an adjusted distance-to-default measure (*adj-mertondd*).[7]

ii) We use z-score (*zscore*), an accounting-based measure of risk, computed as the sum of return on assets and equity ratio (ratio of book equity to total assets), averaged over four years,

[6] Note that we are not trying to price corporate bonds using a particular option pricing framework. We are interested in examining the difference between large and small financial institutions, and unless particular modeling choices affect large and small institutions differently, our results should be robust to these modeling choices.

[7] We also computed a distance-to-default measure that uses scaled standard deviation values as an input. In particular, the standard deviations of banks in the top 90th percentile in terms of size are scaled to equal those of all other banks. We obtain similar results using this risk measure.

divided by the standard deviation of return on assets over four years (Roy 1952). 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.

iii) To make sure that the results are not sensitive to a particular specification, we also create a second alternative measure of distance-to-default, which places more weight on recent equity returns in computing standard deviations.[8] Following Longerstaey et al. (1996), we use a weighting coefficient of 0.94. We use the exponential moving average method (EWMA) to compute standard deviations, which are then used to construct this alternative distance-to-default measure (*ewma-mertondd*).

iv) We also use equity return volatility (*volatility*), without imposing any structural form, as a risk measure.[9] Volatility is computed using daily data over the past 12 months.

v) Finally, we use credit risk beta, *dd-beta*, to capture exposure to systematic credit risk shocks. It is obtained by regressing a firm's monthly change in distance-to-default on the monthly change in the value-weighted average distance-to-default of all other firms using 36 months of past data. In computing dd-beta, we require the company to have at least 24 non-missing monthly changes in distance-to-default over the previous 36 months.

3.4 Controls and Liquidity Measures

Following Flannery and Sorescu (1996) and Sironi (2003), our firm-level controls include leverage, return on assets, market-to-book ratio, and maturity mismatch. Our bond-level controls include time-to-maturity and seniority of the bonds. For the firm-level controls, 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. Market-to-book ratio (*mb*) is the ratio of the market value of total equity to the book value. Maturity mismatch (*mismatch*) is the ratio of short-term debt minus cash to total debt. Bond level controls include time-to-maturity (*ttm*) in years and a

[8] Exponentially weighted moving average standard deviations are computed as: $\sigma_{i,t}^2 = \lambda\sigma_{i,t-1}^2 + (1-\lambda)\varepsilon_{i,t-1}^2$.
[9] Atkeson, Eisfeldt and Weill (2014) show theoretically that one can approximate a firm's distance to insolvency using data on the inverse of the volatility of that firm's equity returns.

dummy variable that indicates whether the bond is senior (*seniority*). We also include three 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 in Appendix A.

We also compute two sets of corporate bond liquidity measures based on transaction data availability. First, liquidity measures are computed for the time period starting in 2003, after the introduction of TRACE. We use all bond transactions to compute four liquidity measures:

i) The first measure is based on Amihud (2002) and measures the price impact of trading a particular bond. The *amihud* measure is computed as the average absolute value of daily returns divided by total daily dollar volume.

ii) We also use a range-based measure (*range*) to proxy for price impact, following Jirnyi (2010). *range* is computed as the average of the high and low price differential in a given day scaled by the square root of dollar volume.

iii) The *roll* measure captures transitory price movements induced by lack of liquidity and proxies for the bid-ask spread of a bond, based on the work of Roll (1984). The *roll* measure is computed as the covariance of consecutive price changes.

iv) The fourth measure, *zeros*, is based on trading activity and is computed as the percentage of days during a month in which the bond did not trade.

Finally, we compute an aggregate liquidity measure, *lambda*, that combines the four liquidity measures described above. Following Dick-Nielsen, Feldhutter, and Lando (2012), we standardize the liquidity measures for each bond each month and then aggregate these standardized measures to compute *lambda*.

For the full time period (including years prior to 2003), we compute a liquidity measure based on bond characteristics following Longstaff, Mithal, and Neis (2005). We compute this *liquidity* measure based on four bond characteristics: amount outstanding, age, time-to-maturity, and rating. The maximum liquidity value assigned to a bond is four and the minimum liquidity value is zero. The construction of the liquidity variables is described in detail in Appendix A.

Summary statistics are reported in Table 1. Panel A reports summary statistics for financial firms and Panel B reports summary statistics for non-financial firms. Although it is larger financial institutions that issue public debt, we see significant dispersion in asset size.

3.5 Methodology

The primary model we estimate is based on Campbell and Taksler (2003) and Gopalan, Song, and Yerramilli (2014). We estimate the following regression using a panel with one observation for each bond-month pair:

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

In equation (1), the subscripts i, b, and t indicate the firm, the bond, and the time (month), respectively, and *Year FE* denotes year fixed effects. The dependent variable (*spread*) is the credit spread. To measure the systemic importance of an institution (*TBTF*), we use multiple measures of an institution's size and systemic risk contribution, but focus mainly on the *size90* measure discussed above. Bond level controls include time-to-maturity in years and a dummy variable indicating whether the bond is senior. Firm-level controls are leverage, return-on-assets, market-to-book ratio, and maturity mismatch. We also include three macro factors: the market risk premium, the default spread, and the term spread. In equation (1), we expect the coefficient on the *TBTF* variable to be significantly greater than zero, with $\beta^1 < 0$.

The second primary model we estimate is designed to study whether the risk sensitivity of corporate bond spreads varies with the systemic importance of a financial institution:

$$\begin{aligned} Spread_{i,b,t} = &\propto + \beta^1 TBTF_{i,t-1} + \beta^2 Risk_{i,t-1} + \beta^3 TBTF_{i,t-1} \times Risk_{i,t-1} \\ &+ \beta^4 Bond\ Controls_{i,b,t} + \beta^5 Firm\ Controls_{i,t-1} + \beta^6 Macro\ Controls_t \\ &+ Year\ FE + \varepsilon_{i,b,t} \end{aligned} \quad \text{(2a)}$$

The variable of interest is the term interacting risk with systemic importance - $TBTF_{i,t-1} \times Risk_{i,t-1}$. An implicit government guarantee weakens market discipline by reducing investors' incentives to monitor and price the risk taking of TBTF institutions. Since our main measure of risk (distance-to-default) is inversely related to risk, we expect the coefficient on the interaction term to be positive, $\beta^3 > 0$. To explore the effect of size on the risk sensitivity of bond spreads for different size groups, we interact the risk variable with dummy variables that take on a value of one if a particular firm is in a given size decile:

$$spread_{i,b,t} = \propto + \sum_{j=1}^{9} \delta^j size\ decile_{i,t-1}^{j} + \sum_{k=1}^{10} \gamma^k size\ decile_{i,t-1}^{k} \times Risk_{i,t-1} + \beta^1 Bond\ Controls_{i,b,t} + \beta^2 Firm\ Controls_{i,t-1} + \beta^3 Macro\ Controls_t + Year\ FE + \varepsilon_{i,b,t} \quad (2b)$$

Above, $size\ decile_{i,t-1}^{k}$ are ten dummy variables that take on a value of one if a firm belongs to one of the size deciles. We exclude the smallest *size decile* in the controls to avoid perfect multicollinearity. The variables of interest are the coefficients (γ^k) on the interaction of risk and size decile dummies. We run this regression separately for financial and non-financial firms. We expect the relation between size and risk sensitivity to be weaker for non-financial firms in the largest size decile. We also expect the relation between size and risk sensitivity to be more flat for non-financial firms as we go from the highest size decile to the lowest.

Finally, we use non-financial firms as a control and examine the differential effect of size on spreads between financial and non-financials:

$$\begin{aligned} Spread_{i,b,t} = \propto &+ \beta^1 TBTF_{i,t-1} + \beta^2 Risk_{i,t-1} + \beta^4 Financial_{i,} + \beta^5 Financial_i \times TBTF_{i,t-1} \\ &+ \beta^8 Bond\ Controls_{i,b,t} + \beta^9 Firm\ Controls_{i,t-1} + \beta^{10} Macro\ Controls_t \\ &+ Year\ FE + \varepsilon_{i,b,t} \end{aligned} \quad (3)$$

If investors expect government support only for failing financial firms, then we expect the TBTF effect on spreads to be significantly lower for non-financial firms. That is we expect the coefficient on the interaction term of the financial dummy and the TBTF measure, which captures the differential effect of size on spreads for financial firms compared to non-financial firms, to be negative with $\beta^5 < 0$.

We also compare financial institutions to non-financial institutions when examining the impact of risk on credit spreads. We use non-financial as controls and include interactions with the *financial* dummy in the regression model (2) above:

$$Spread_{i,b,t} = \propto + \beta^1 TBTF_{i,t-1} + \beta^2 Risk_{i,t-1} + \beta^3 TBTF_{i,t-1} \times Risk_{i,t-1} + \beta^4 Financial_{i,} + \beta^5 Financial_i \times TBTF_{i,t-1} + \beta^6 Financial_i \times Risk_{i,t-1} + \beta^7 Financial_i \times Risk_{i,t-1} \times TBTF_{i,t-1} + \beta^8 Bond\ Controls_{i,b,t} + \beta^9 Firm\ Controls_{i,t-1} + \beta^{10} Macro\ Controls_t + Firm\ FE + Year\ FE + \varepsilon_{i,b,t} \quad (4)$$

We are interested in the $Financial_i \times Risk_{i,t-1} \times TBTF_{i,t-1}$ variable. This triple interaction term captures the risk sensitivity of the credit spreads of large financial institutions compared to that of large non-financials. We expect the risk sensitivity to be lower for large financial institutions than for large non-financial institutions, with the coefficient on the interaction term $\beta^7 > 0$.

4. Results

4.1. Expectations of Government Support

To determine whether bondholders of major financial institutions expect government support, we estimate how the size of a financial institution affects the credit spread on its bonds, using equation (1). The results in Table 2 show a significant inverse relation between credit spreads and systemic importance. First, we use asset size (*size*) to identify systemic importance. In column 1, *size* has a significant negative effect on *spread*, with larger institutions having lower spreads. Next, we identify systemic importance as a financial institution in the top 90th percentile in terms of size (*size90*) (column 2). The coefficient on the *size90* dummy variable is significant and negative, indicating that very large institutions have lower credit spreads. This amounts to about a 32 bps funding advantage over smaller institutions. We define a systemically important institution as one of the ten largest institutions in terms of size in a given year (*size_top_10*). The results in column 3 show that TBTF status has a significant negative effect on spreads. Next, following Adrian and Brunnermeier (2011), we use an institution's contribution to systemic risk (*covar*) to identify systemically important financial institutions. In column 4, higher values of *covar* indicate greater systemic risk contribution. The results show a significant negative relation between *covar* and credit spreads. That is, the greater an institution's contribution to systemic risk, the lower its spread. The results in column 5 show a significant negative relation between our second measure of systemic risk, *srisk*, and credit spreads. The greater an institution's systemic risk, the lower its credit spread.

We also look at whether the size-spread relation varies by type of financial institution. We interact *size* with a dummy variable indicating whether the financial institution is a bank, insurance company or broker-dealer (based on its SIC code). The results appear in column 6 of Table 2. The effect of size on credit spreads is the most significant for the banks. Size does not reduce credit spreads as much when the financial institution is an insurance company or a broker-dealer, nor is the effect of size statistically significant in these cases.

There may be advantages associated with size that are not fully captured by the control variables. As mentioned earlier, larger firms may have lower funding costs due to greater diversification, larger economies of scale, or better access to capital markets and liquidity in times of financial turmoil. We control for such general size advantages in estimating investor expectations of government support by using non-financial firms as controls. We use a difference-in-differences approach and compare the differences in the credit spreads of large and small financial institutions to differences in the credit spreads of large and small companies in non-financial sectors. If investors expect government support only for financial firms, then the estimate of the large-small difference in the financial sector compared to the large-small difference in non-financial sectors (without an expectation of government support of large firms) would provide a measure of the advantage large financial firms have from expectations of government support.[10] Therefore, for robustness, we include non-financial companies (Panel A

[10] If there is an expectation of a government support for non-financial firms (such as General Motors; see Anginer and Warburton 2014), then we would be underestimating the funding advantage to large financial institutions.

of Table 3) in the regressions as controls. 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*. This interaction term captures the differential effect size has on the credit spreads for financial firms compared to non-financial firms. The estimated coefficient is negative and statistically and economically significant, which indicates that the effect of firm size on credit spreads is larger for financial firms than for non-financial firms.

In addition to indicating a relation between credit spreads and the size of a financial institution, Table 2 also shows that there is a significant relation 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 credit spreads on their bonds.

Does a financial institution's size affect this relation between credit spreads and risk? To answer that question, we interact the size and risk variables. In particular, we run the regression in equation (2b) separately for financial and non-financial firms. The results are reported in Panel B of Table 3. Columns 1 and 2 report regression results for the sample of financial firms and non-financial firms respectively. For brevity, we only report the coefficient on the interaction of the risk and size decile dummies. We find the relation between size and risk sensitivity to be weaker for the largest financial institutions. This indicates that the spread-to-risk relation diminishes with TBTF status. For institutions that achieve systemically important status, credit spreads are less sensitive to risk. This result is consistent with investors pricing an implicit government bailout guarantee for the largest financial institutions. These relations can be seen in Figure 1. Panel A of Figure 1 shows that there is a negative relation between the size of a financial institution and the credit spreads on its bonds: larger institutions have lower credit spreads. Why? Are they less risky than smaller ones? In Panel B, the size of a financial institution is plotted against its risk (distance-to-default). There does not appear to be any observable relation between firm size and risk. That is, larger institutions do not offer lower risk of large losses than smaller institutions.

We also find the relation between size and risk sensitivity to be flatter for non-financial firms as we go from the highest size decile to the lowest. Figure 2 displays a plot of these coefficient estimates. A one standard deviation increase in distance-to-default reduces credit spreads by 105 bps for financial firms that are in the 50-60th percentile in terms of size; for financial firms in the 90-100th percentile, the decline is only 21 bps. We do not observe a similar change in risk sensitivity for non-financial firms. For non-financial firms that are in the 50-60th percentile, a one standard deviation increase in distance-to-default reduces credit spreads by 56 bps; for large non-financial firms in the 90-100th percentile, the decline is 49 bps.

Moreover, these results are robust to different measures of risk. In Panel A of Table 4, we report regression results from the model specified in (2a) using different risk measures. For brevity, we only report variables of interest in this table. There is a significant and positive coefficient on the term interacting *size90* and *mertondd* (column 1) as expected. In place of *mertondd*, we employ z-score (*zscore*) in the regression for column 2 and volatility (*volatility*) in the regression for 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-to-risk relation diminishes for the largest institutions.

We construct two alternative measures of distance-to-default to address potential issues with our specific model. As mentioned earlier, implicit guarantees might affect equity values resulting in underestimation of risk using Merton's (1974) distance-to-default model. First, we compute an adjusted distance-to-default measure, *adj-mertondd*, by removing the effect of size on market leverage and volatility (the two inputs into the Merton model) as described in Section 2. We replicate the risk sensitivity analyses using *adj-mertondd* as our measure of risk. The results in column 4 of Table 3 are consistent with those in column 1, where we use the unadjusted distance-to-default measure, *mertondd*, in the regression. The second alternative measure of distance-to-default employs standard deviations computed using the exponential moving average method (EWMA), *ewma-mertondd.* The results in column 5 are consistent with those in column 1.

Instead of distance-to-default, we also use credit risk beta, *dd-beta*, as our measure of risk. It is obtained by regressing a firm's monthly change in distance-to-default on the monthly change in value-weighted average distance-to-default of all other firms using 36 months of past data. If the implicit guarantee takes effect only if banks fail at the same time, then they will have incentives to take on correlated risks (Acharya and Yorulmazer 2007; Acharya, Engle, and Richardson 2012) so as to increase the value of the implicit bailout guarantee. Investors will then price in idiosyncratic but not systematic risk, since the guarantee will only take effect if a bank fails when others are failing at the same time. If the guarantee applies only to large banks, systematic risk would be priced negatively for larger banks and positively for smaller banks. Kelly, Lustig, and Van Nieuwerburgh (2012), using options on individual banks and on a financial sector index, show evidence of a collective guarantee on the financial sector. They also show that larger financial institutions benefit relatively more than smaller ones from implicit guarantees. The interaction results using *dd-beta,* reported in column 6 of Table 3, support this notion. *dd-beta* is positive for smaller banks but turns negative for the largest financial institutions.[11]

As before, we also compare financial institutions to non-financial institutions when examining the impact of risk on credit spreads. We use the regression specified in equation (4). The results are reported in Panel B of Table 4. For brevity, we do not report coefficients on the control variables. We are interested in the $financial_{t\text{-}1} \times Risk_{t\text{-}1} \times size90_{t\text{-}1}$ variable. This triple interaction term captures the risk sensitivity of credit spreads of large financial institutions compared to that of large non-financials. We use the same six risk variables we used in Panel A: *mertondd*, *z-score*, *volatility*, *adj-mertondd*, *ewma-mertondd*, and *dd-beta*. We find that risk sensitivity declines more for large financial institutions than for large non-financial institutions. In other words, when we add non-financials as controls, we find the same reduction in risk sensitivity for large financials that we found in Panel A.

[11] In unreported results, we allow the risk variable to have a non-linear relation with the bond spread. In particular, we include an interaction term of the squared *mertondd* variable with the *size90* variable. We compute the sensitivity of spread to risk for the largest banks at their mean risk values, after taking the derivative of spread with respect to risk and then with respect to size. Inclusion of the squared interaction term does not change the results. The effect of risk on spreads is still lower for the largest banks after accounting for non-linear effects.

4.2. Time Series Variation of Implicit Subsidy

In this subsection, we estimate the value of the implicit TBTF subsidy on a yearly basis. To compute the annual subsidy, we run the regression specified in equation (1) each year using *size90* as our indicator of TBTF. 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. The implicit subsidy provided large financial institutions a funding cost advantage of approximately 30 bps over the 1990-2012 period. The subsidy increased during the crisis and remains at elevated levels. We also quantify the dollar value of the annual implicit subsidy accruing to major financial institutions. We multiply the reduction in funding costs by the average total uninsured liabilities (in US$ millions) to determine the annual dollar value of the subsidy, reported in Figure 3.[12] The subsidy amounts to an average $30 billion per year and rose above $100 billion during the financial crisis.

Despite the magnitude of the implicit government subsidy for failing financial institutions, few studies have attempted to quantify it, although some have attempted to measure explicit government support (e.g., Laeven and Valencia 2010; Veronesi and Zingales 2010). Direct costs of bailouts have always drawn the public's attention. But direct costs provide only a narrow quantification of bailouts and likely underestimate their actual costs. 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.

Moreover, our approach recognizes that, even when the banking system appears strong, safety net subsidies exist for large financial institutions. Figure 3 shows that expectations of government support for large financial institutions persist over time. These expectations exist despite economic conditions, and vary with government policies and actions. In the post-crisis

[12] We exclude deposits backed by 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, provide a rough estimate of the dollar value of the implicit guarantee.

period after 2009, the implicit subsidy has remained at positive levels.

5. Robustness

In this section, we conduct a number of robustness checks on the results reported in the previous section. First, we examine the impact of liquidity of bonds on our results to make sure that the spread differences are not due to differences in liquidity. Second, we examine credit ratings issued by Fitch. Third, we perform an event study to examine shocks to investor expectations of support. The purpose of these robustness checks is to control for omitted variables such as liquidity that may drive bond spread differences, and to do within-firm analysis that helps control for unobserved heterogeneity between large and small firms.

5.1. Impact of Liquidity

It is possible that our results might be affected by the liquidity of the bonds we study. In examining investor expectations of support, we have used a differences-in-differences approach using non-financials as a control. We now test to see whether there are significant differences in the liquidity of bonds issued by financial and non-financial firms. Since we do not have all bond trades for the full sample period, we create a liquidity measure (*liquidity*) based on bond characteristics following Longstaff, Mithal, and Neis (2005), which is described in Section 3 and in detail in Appendix A. For the time period starting in 2003 (for which we have all bond transactions), we create four liquidity measures (*amihud*, *roll*, *range* and *zeros*) and an aggregate measure (*lambda*) constructed by summing up the standardized values of these four liquidity measures.

To test to see if there are difference between financial and non-financial firms, we use the same specification and controls used to generate the results in Table 2, but use the four measures of liquidity (*amihud*, *roll*, *range*, *zeros*) and the aggregate liquidity measure (*lambda*) as the dependent variable. The results are reported in Panel A of Table 5. As expected, we find that the bonds of large financial institutions have significantly higher liquidity compared to their smaller counterparts (columns 1 to 5). However, when we examine the differences in liquidity of bonds between large financials and large non-financials, we do not find a significant difference. The coefficient on the interaction term, *financial*×*size90*, lacks statistical and economic significance (columns 6 to 10), suggesting that our prior results are unlikely to be driven by differences in liquidity.

In Panel B of Table 5, we show that our main results in Table 2 are robust to controls for liquidity. For brevity, we only report coefficients on the variables of interest. The results in column 1 in Panel B of Table 5 show that the *size90* variable retains its significance when we control for liquidity. The risk sensitivity results in column 2 are also similar to those reported earlier. Using non-financials as control, we again find similar results with respect to lower risk sensitivity of bond spreads and lower cost of funding for large financial institutions. These results are reported in columns 3-8.

Finally, for the time period starting in 2003 (for which we have all bond transactions), we use the four liquidity measures (*amihud*, *roll*, *range*, *zeros*) and the aggregate measure (*lambda*). In the regression for columns 2 and 3 of Table 5 Panel B, we use *lambda* as our liquidity control. The *size90* variable and the interaction of *size90* with *Risk* retain their economic and statistical significance in the presence of *lambda*.

5.2. Stand-Alone and Support Ratings

To alleviate potential concerns about the endogeneity of risk measures to TBTF status, we use credit ratings and government support ratings as alternative measures of credit risk and implicit support. We examine Fitch credit ratings. In rating financial institutions, Fitch assigns both an "issuer rating" and a "stand-alone rating." An issuer rating is a conventional credit rating measuring 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 government support should the financial institution encounter severe financial distress. We use Fitch's long-term issuer rating (*issuer rating*) as well as their stand-alone rating (*stand-alone rating*) as independent variables in the credit spread regression specified in equation (1).[13]

Panel A of Table 6 contains results similar to the spread regression results in Table 2, but with rating variables added to the regressions. The stand-alone rating is employed in the regression for column 1, while the issuer rating is employed in the regression for column 2. Although both ratings significantly affect spreads, the issuer rating has a greater economic impact. When both ratings are employed in the regression for column 3, 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 sum, we find that issuer ratings (which incorporate an expectation of support) impact spreads, but stand-alone ratings do not. Investors significantly price implicit government support for the institution.[14]

In Panel B of Table 6, issuer and stand-alone ratings are regressed on lagged TBTF measures and 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 bailout. The results show 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, thus we find that large institutions do not have significantly better stand-alone ratings.

5.3. Event Studies

Next, we examine how credit spreads are impacted by events that might have changed investor expectations of government support. The events and their corresponding dates are in Table 7. These events offer natural experiments to assess changes in TBTF expectations within-

[13] The issuer rating scale ranges from AAA to C- (ratings below C- are excluded 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.

[14] This result is consistent with the findings of Sironi (2003), who uses European data, and supports our conclusion that the expectation of government support for large financial institutions impacts the credit spreads on their bonds.

firm over time. For instance, prior to the recent 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, not a commercial bank.[15] This intervention likely reinforced expectations that the government would guarantee the obligations of large financial institutions. Similarly, the later decision to allow Lehman Brothers to fail served as a negative shock to those expectations. While the Federal Reserve and the Treasury intervened the day after the Lehman 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, both the Bear Stearns and Lehman events are 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.[16]

We examine a window of ± 5 trading days around the event. We run the following regression:

$$Spread_{i,b,t} = \propto + \beta^1 post + \beta^2 TBTF_{i,t} \times post + \beta^3\, Risk_{i,t} \times post + \beta^4 TBTF_{i,t} \times Risk_{i,t} \times post + \beta^5 Macro\ Controls_t + Issue\ FE + \varepsilon_{i,b,t}. \tag{5}$$

We use *size90* as our measure of systemic importance. We also use a dummy variable, *post*,

[15] In connection with Bear Stearns' merger with JPMorgan Chase in 2008, the Federal Reserve provided JPMorgan Chase 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 institutions like Lehman, Merrill Lynch, and Goldman Sachs.

[16] The event dates are obtained from the St. Louis Fed: https://www.stlouisfed.org/financial-crisis/full-timeline.

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-differences estimation. We examine the change in the TBTF subsidy after the event, as well as the change in the risk sensitivity of bond spreads. 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 non-financial institutions as controls and examine changes in both the TBTF subsidy and risk sensitivity after the event. Specifically, we run the following regression for a sample that includes both financial institutions and non-financial institutions:

$$Spread_{i,b,t} = \propto + \beta^1 post + \beta^2 TBTF_{i,t} \times post + \beta^3 financial_{i,t} \times post + \beta^4 \, Risk_{i,t} \times post + \beta^5 TBTF_{i,t} \times financial_{i,t} \times post + \beta^6 TBTF_{i,t} \times Risk_{i,t} \times post + \beta^7 financial_{i,t} \times Risk_{i,t} \times post + \beta^8 TBTF_{i,t} \times financial_{i,t} \times Risk_{i,t} \times post + \beta^9 Macro\ Controls_t + Issue\ FE + \varepsilon_{i,b,t}. \qquad (6)$$

The coefficient on the $TBTF_{i,t} \times financial_{i,t} \times post$ variable captures the impact of the event on the bond spreads for large financial institutions compared to large non-financials.[17] Similarly, the $TBTF_{i,t} \times financial_{i,t} \times Risk_{i,t} \times post$ variable captures the effect of the event on the spread-risk relation for large financials compared to large non-financials.

In Panel A of Table 7, we find that announcements of government financial and liquidity support are associated with a decrease in credit spreads for larger financial institutions. In particular, the bailout of Bear Stearns and the passage of the revised TARP bill by 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 non-financial institutions as controls. These triple-difference results are provided in columns 3 and 4.

Next, we examine a negative shock to investor expectations of government support,

[1717] The regression specified in equation (6) includes all combinations of *TBTF*, *financial Risk*, and *post* variables. We did not include the combinations that would drop out in running the regression such as TBTF*financial which doesn't vary over the event window.

namely the bankruptcy filing by Lehman Brothers on September 15, 2008. These results are reported in Panel B of Table 7. 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 credit spreads after the Lehman collapse.[18] The increase is economically significant at over 100 bps. In response to the Lehman collapse, large institutions also saw their credit spreads become significantly more sensitive to risk. The coefficient on the triple-interaction term 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 non-financials as controls (columns 3 and 4).

These results indicate 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 the impact of the Dodd-Frank Act, which was designed to address problems associated with TBTF institutions. One of the main purposes of the legislation was to end investors' expectations of future government bailouts. Panel C of Table 7 shows the 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 President Barak Obama signed the bill into law. The coefficient on the term interacting *size90* and *post* for the first event is significant and negative. This indicates that the Dodd-Frank Act actually *lowered* credit spreads for the very largest financial institutions relative to the others (although the 3 bps effect is economically small). The coefficient on *size90*×*mertondd*×*post* is significant and positive, indicating that Dodd-Frank Act decreased the risk sensitivity of credit spreads for large institutions (although the effect again is economically very small). We find a small positive

[18] 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.

increase in spreads using the July 21, 2010 event date.

6. Impact of the Dodd-Frank Act

The results from the previous section suggest that the adoption of Dodd-Frank Act has not significantly altered investors' perceptions of implicit government support. In this section, we examine the impact of Dodd-Frank Act in more detail by conducting two additional analyses. First, as there has been uncertainty surrounding the information regarding Dodd-Frank and its implementation, we employ a longer event window of 132 trading days (6 months). The results are shown in Table BI of Appendix B. The relevant coefficients are largely insignificant statistically and economically. Overall, the results indicate that Dodd-Frank has been insignificant in changing investors' expectations of future support for major financial institutions.

Second, we repeat the event study analyses using bonds issued under the FDIC'S Temporary Liquidity Guarantee Program (TLG Program). This approach allows us examine within-firm variation and compare *implicitly* guaranteed bonds to *explicitly* guaranteed bonds 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 TLG Program provided a guarantee for senior unsecured debt issued after October 14, 2008 and before June 30, 2009 (later extended to October 31, 2009). The guarantee remained 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 participating in the program; however, not all of their debt was eligible to be guaranteed. To be eligible, the debt had to be senior unsecured debt issued from October 2008 to October 2009. In addition, an institution 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 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 TLG Program and also had similar bonds outstanding outside the Program. The following companies in the TRACE/FISD databases issued bonds under the FDIC guarantee as well as non-guaranteed bonds: Bank of America, Citigroup, Goldman Sachs, JPMorgan Chase, Morgan Stanley, Sovereign Bancorp, State Street, SunTrust, U.S. Bancorp, Wells Fargo, PNC Bank, HSBC USA, Keycorp, MetLife, John Deere Capital, and GE Capital. 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. This approach allows us to examine the effect of an implicit guarantee after controlling for time-varying firm effects.

To maximize sample size, we include all bonds issued by the firms covered under the TLG Program, and control for bond characteristics by regressing spreads on a dummy variable (*guarantee*) that takes a value of one if the bond is backed by the FDIC guarantee:

$$\begin{aligned} &Spread_{i,b,t} = \propto \\ &+ \beta^1 Bond\ Controls_{i,b,t} + \beta^2 guarantee_{i,t-1} + \ Firm \times Trading\ Day\ FE + \varepsilon_{i,b,t}. \end{aligned} \tag{7}$$

We control for the age of the bond since issuance in years (*age*) and the time to maturity in years (*ttm*), and include dummies set to one if the bond is *puttable*, *redeemable*, *exchangeable*, or if the bond has fixed-rate coupons (*fixrate*). We also include firm-trading day fixed effects (to examine within-company variation on a given trading day).[19]

Panel A of Figure 4 shows the raw difference (without controlling for bond characteristics) in spreads between bonds backed by the FIDC guarantee and the spreads on bonds without the FDIC guarantee for each of the top six financial institutions. Panel B displays the coefficient on the *guarantee* variable obtained by running the regression specified in (7) on a daily basis. In the middle of the time period (June 2010), the Dodd-Frank Act was adopted. We see a slight increase in the value of the FDIC guarantee in the months preceding Dodd-Frank's

[19] Our sample includes the bonds of all institutions that issued both types of bonds. We address bonds with extreme yields by winsorizing at the 99th percentile values 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.

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 government support for the non-guaranteed bonds of major financial institutions.

We confirm our finding by conducting an event study around the adoption of Dodd-Frank. We run a regression similar to (7) above, but with an additional variable, *post*. *Post* is a dummy equal to one during the five trading days (or 132 trading days) following the adoption of Dodd-Frank. *post* is interacted with an indicator variable (*guarantee*) that equals one if a bond is guaranteed under the TLG Program, and zero if it is not. This interaction term captures whether Dodd-Frank impacted investor expectations of support for non-guaranteed bonds relative to FDIC guaranteed bonds. In Table 8, the coefficient on the interaction term is significant and positive 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 the 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 negative effect* if Dodd-Frank had been successful in eliminating TBTF expectations. This is not what the data shows.

In Table 8, we also examine Dodd-Frank's impact on the risk sensitivity of guaranteed and non-guaranteed bonds, which is captured by the triple-interaction term (*mertondd*×*guarantee*×*post*). For both the 10- and 264-trading day windows (columns 2 and 4), the coefficient is significant and negative, which indicates that the risk sensitivity of non-guaranteed debt declined following Dodd-Frank.

Despite Dodd-Frank's explicit no-bailout pledge, the Act leaves open many avenues for future TBTF rescues. For instance, the Federal Reserve can offer a broad-based lending facility to a group of financial institutions in order to provide a disguised bailout to the industry or a single firm. In addition, Congress can sidestep Dodd-Frank by amending or repealing it or by allowing regulators to interpret their authority in ways that protect creditors and support large financial institutions (e.g., Skeel 2010; Standard & Poor's 2011; Wilmarth 2011).[20]

7. Market Discipline

We have established the presence of implicit government guarantees in the price of unsecured debt of large financial institutions. The presence of guarantees should weaken the market discipline of large financial institutions. We document that consistent with our results on the risk sensitivity of bond spreads, large financial institutions are able to take on more leverage and increase risk.

We use two methods to examine market discipline's effect on financial institutions' risk. In the first method, we examine the sensitivity of leverage to changes in bank risk. We follow Duan, Moreau, and Sealey (1992) and Hovakimian and Kane (2000) and assume a linear relation between changes in market leverage and changes in risk as measured by changes in asset volatility. Since we are interested in cross-bank differences, we also interact change in asset volatility with our *TBTF* measure. In particular, we estimate the following empirical model:

$$\Delta D/V_{i,t} = \propto + \beta^1 \Delta s_{A_{i,t}} + \beta^2 TBTF_{i,t} + \beta^3 TBTF_{i,t} \times \Delta s_{A_{i,t}} + Year\ FE + \varepsilon_{i,t}, \quad (8)$$

where D is the book value of debt, V is the market value of assets, and s_A is the volatility of the market value of assets. V and s_A are computed using the structural model of Merton (1974) described in Appendix A. In equation (8), a negative coefficient on asset volatility ($\beta^1 < 0$) would indicate a moderating effect of market discipline in response to changes in risk. As risk increases, financial institutions are pressured by the market to reduce their leverage. Similar to the sensitivity of credit spreads to risk, weaker market discipline would imply that leverage is less sensitive to changes in risk. That is, a positive coefficient on the interaction of asset

[20] Former 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."

volatility and our *TBTF* measure ($\beta^3 > 0$) would imply that the leverage of larger financial institutions is less responsive to changes in risk.

The results are reported in Table 9. Consistent with Duan, Moreau, and Sealey (1992), we find evidence of market discipline. An increase in risk reduces leverage (column 1). We use *size* and *size90* as our measures of *TBTF*. The results from interacting these measures with asset volatility are reported in columns 2 and 3, respectively. The coefficients on both interaction terms are positive, indicating that TBTF status impedes market discipline and reduces the sensitivity of leverage to changes in asset volatility. Finally, following our prior approach, we use large non-financial firms as controls in examining the impact of size on the relation between leverage and risk. We interact the *size90* variable with asset volatility and the *financial* dummy. The results from the triple interaction regression are reported in column 4. The coefficient on the triple interaction term is positive (but not statistically significant), suggesting that the discipline effect is weaker for large financial firms compared to large non-financial firms.

The second method is based on the deposit insurance pricing model of Merton (1977). Using this approach, we compare the restraining effect of market discipline to the strength of financial institutions' incentives to take on risk. In particular, the model can be used to assess the risk-shifting behavior of financial institutions — whether they can increase risk without adequately compensating taxpayers by increasing their capital ratios or by paying higher premiums for government guarantees. Merton (1977) shows that the value of a government guarantee to the shareholders of a bank increases with asset risk and leverage. Holding the premium on a government guarantee fixed, bank shareholders can extract value from the government by increasing asset risk or leverage. To examine this relation empirically, we follow Duan, Moreau, and Sealey (1992) and use the following reduced-form specification:

$$\Delta IPP_{i,t} = \propto + \gamma^1 \Delta s_{A_{i,t}} + \gamma^2 TBTF_{i,t} + \gamma^3 TBTF_{i,t} \times \Delta s_{A_{i,t}} + Year\ FE + \varepsilon_{i,t}, \qquad (9)$$

where *IPP* is the fair insurance premium per dollar of liabilities. The coefficient γ^1 captures two offsetting effects: the risk-shifting incentives of financial institutions and outside discipline. We assume a linear relation between the value of the liabilities put option and leverage and asset volatility, $IPP_{i,t} = \propto + \theta^1 D/V_{i,t} + \theta^2 s_{A_{i,t}}$, and plug in the value of $D/V_{i,t} = \delta + \beta^1 \Delta s_{A_{i,t}}$ from the relation in equation (9). After substitution, $\gamma^1 = \frac{\partial IPP}{\partial s_A} + \frac{\partial IPP}{\partial D/V} \beta^1$. The first term captures the incentives of financial institutions to increase risk, while the second term captures the offsetting effect of market discipline (given $\beta^1 < 0$) in moderating risk taking. A positive γ^1 is consistent with the ability of financial institutions to risk-shift, since the disciplining effect does not completely neutralize incentives to increase risk. As before, we interact asset volatility with our *TBTF* measures, and use large non-financial institutions as controls. The results are reported in Table 9. On average, financial institutions are able to risk-shift, as evidenced by the positive coefficient on asset volatility (column 5). This risk-shifting effect is stronger for larger financial institutions (columns 6 and 7). When we use large non-financial institutions as controls, we find the risk-shifting incentives of large financial institutions to be greater than those of large non-financial institutions (column 8).

8. Conclusion

In this paper, we find that expectations of a government support are embedded in the credit spreads of unsecured bonds issued by large U.S. financial institutions. We find that credit spreads are risk sensitive for most financial institutions, yet 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 in the event of failure and, as a result, they do not accurately price risk. This expectation of government support constitutes an implicit subsidy of large financial institutions, allowing them to borrow at subsidized rates. This relation between firm size and the risk sensitivity of bond spreads is not present in non-financial sectors and is robust to non-risk-related reasons for bond spreads being lower for the largest financial institutions, such as liquidity.

We confirm the robustness of our results by conducting an event study examining shocks to investor expectations and using ratings of government support. We also show that recent financial regulations that seek to address too-big-to-fail financial institutions have not had a significant impact in eliminating investors' expectations of government support. In the post-financial crisis period after 2009, the implicit subsidy has remained at positive levels. We find that the passage of the Dodd-Frank Act in the summer of 2010 did not significantly alter investors' expectations of government support.

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Figure 1: Size, Spreads, and Risk

Panel A shows the relation 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 given 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. Panel B shows the relation 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 the average distance-to-default of a financial institution in a given year, computed as described in Appendix A.

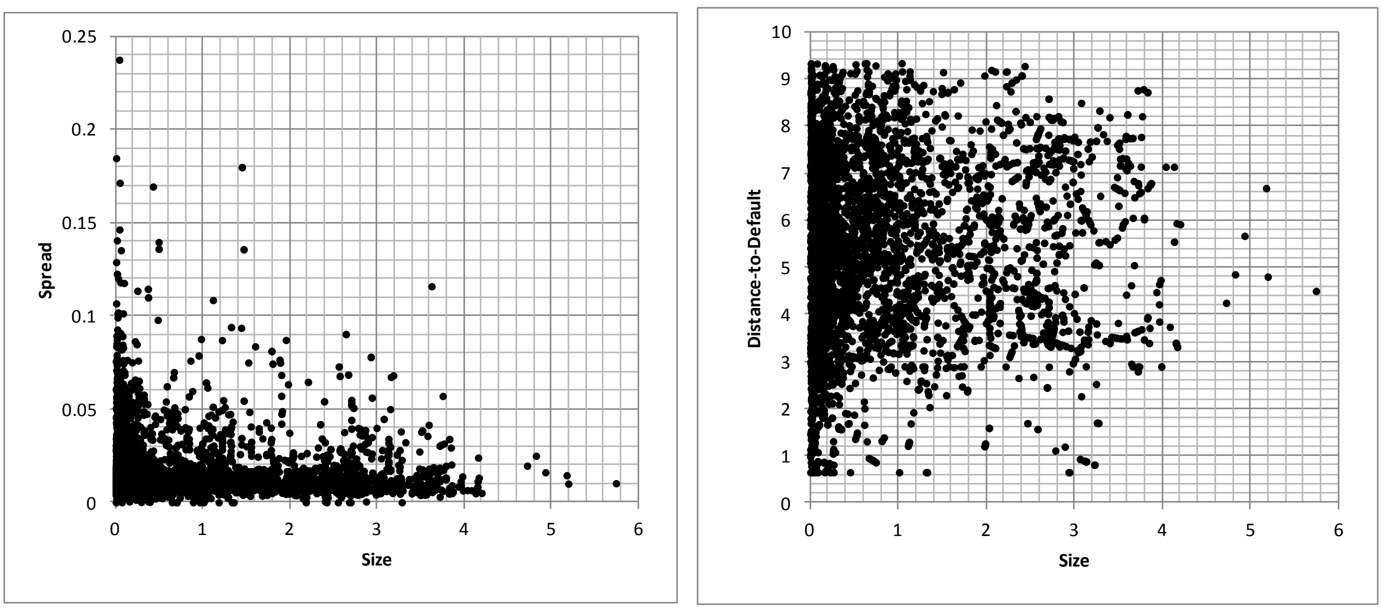


Figure 2: Risk Sensitivity of Bonds for Financial and Non-financial firms

This figure shows the risk sensitivity of spreads for firms in different size decile groups. The two lines show the coefficient estimates on the interaction of our risk measure, *mertondd*, and a dummy variable that takes on a value of one for firms that belong to each size decile. The solid line shows coefficient estimates for financial firms and the dashed line shows coefficient estimates for non-financial firms. The estimation of the coefficients is described in Table 3.

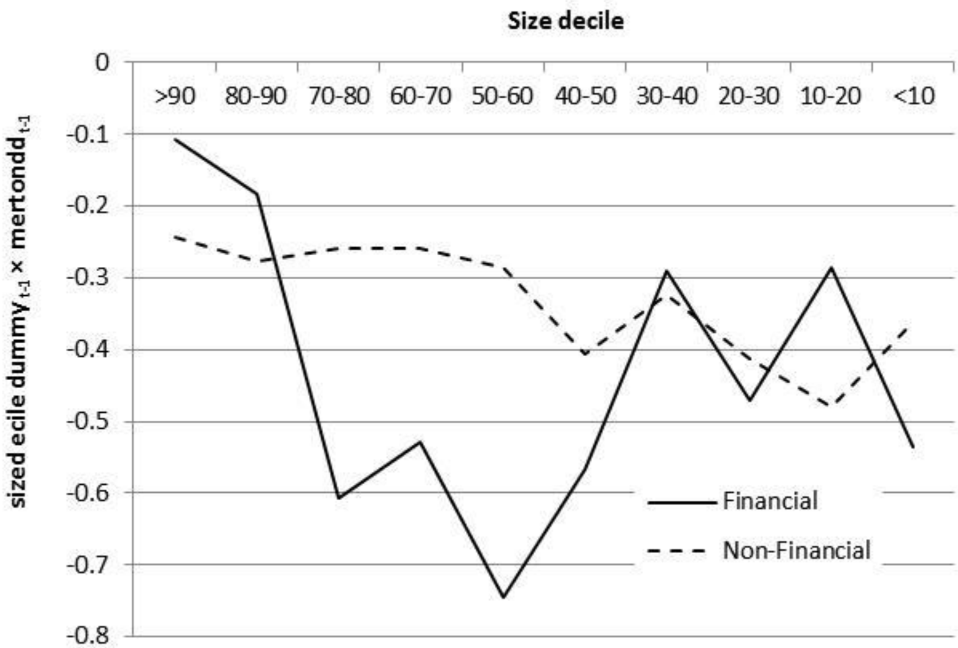


Figure 3: Value of the Implicit Subsidy over Time

This figure shows the estimates of annual subsidy accruing to large financial institutions as a result of the implicit government guarantee. To compute the annual subsidy, we run the following regression for each year: $Spread_{i,b,t} = \propto + \beta^1 seniority_{i,b,t} + \beta^2 ttm_{i,b,t} + \beta^3 leverage_{i,t} + \beta^4 roa_{i,t} + \beta^5 mb_{i,t} + \beta^6 mismatch_{i,t} + \beta^7 mertondd_{i,t} + \beta^8 def_t + \beta^9 term_t + \beta^{10} mkt_t + \beta^{11} size90_{i,t} + \varepsilon_{i,b,t}$. All the variables are defined in Table 1 and Appendix A. The coefficient on *size90* (z-axis) represents the subsidy accruing to large financial institutions. 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 (y-axis). The dollar amounts are adjusted for inflation and are in constant 2010 dollars.

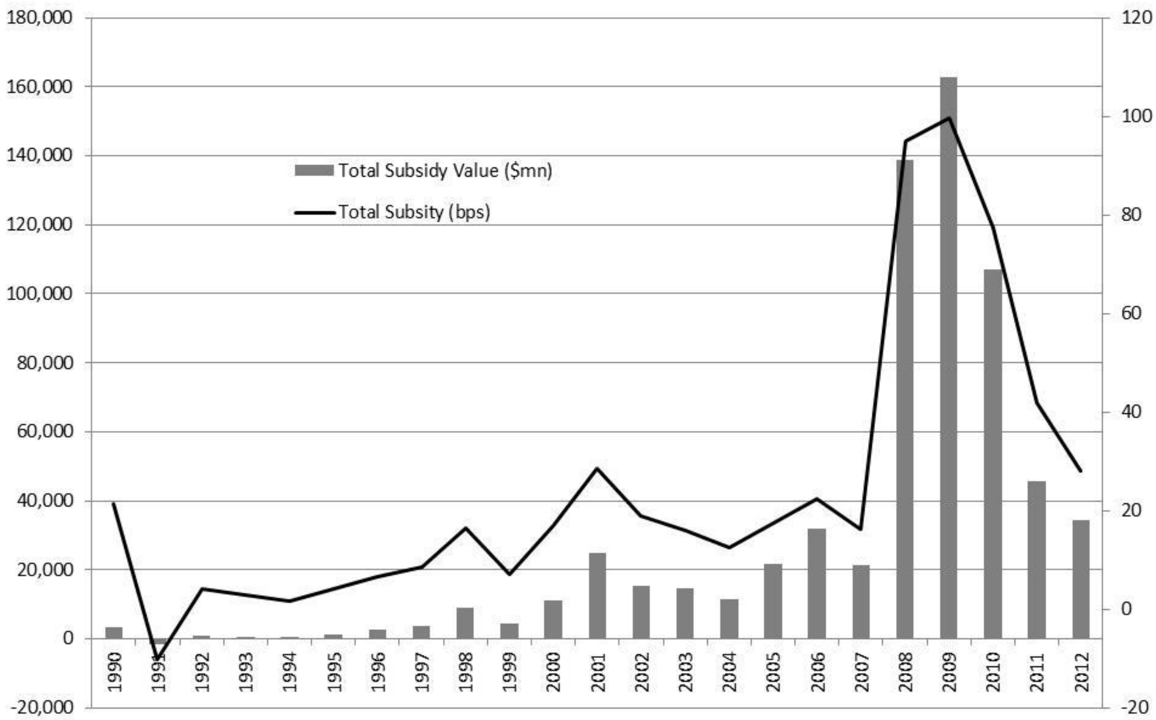
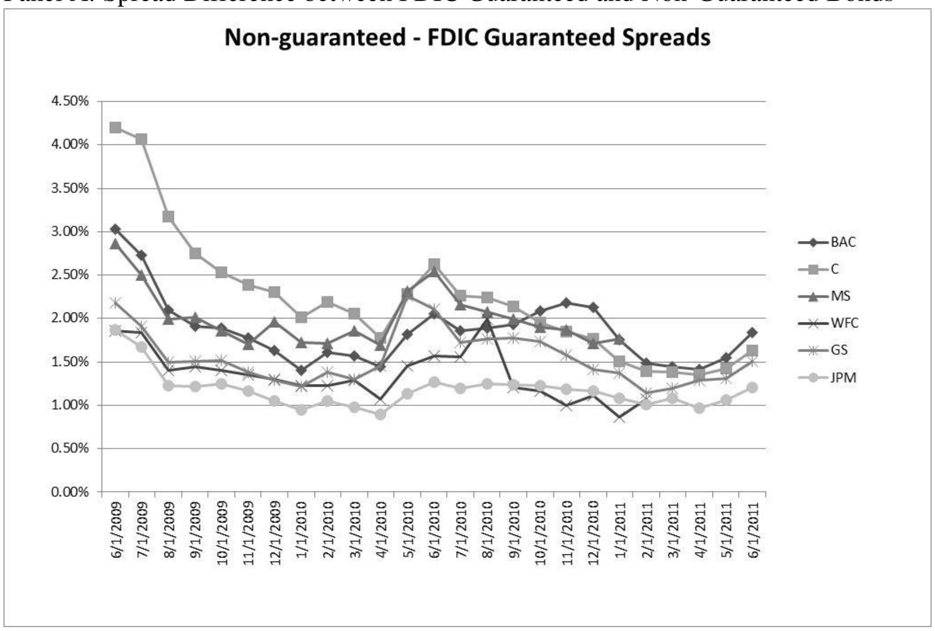


Figure 4: Explicit and Implicit Guarantee Spread Difference
Panel A shows the difference in spreads between FDIC guaranteed and non-guaranteed bonds for six financial institutions. *BAC* is Bank of America, *C* is Citibank, *MS* is Morgan Stanley, *WFC* is Wells Fargo, *GS* is Goldman Sachs, and *JPM* is JPMorgan Chase. We plot averages for each month for each company if there are more than 10 daily trading observations. Panel B shows the estimated FDIC guarantee premium. To compute the premium, we run the regression specified in equation (7). The sample includes financial institutions that issued bonds under the FDIC's Temporary Liquidity Guarantee Program. The regression includes firm fixed effects. We run the regression daily and then average the coefficient on the *guarantee* variable each week. When plotting, we invert the guarantee variable so that reduction corresponds to a positive premium.

Panel A: Spread Difference between FDIC Guaranteed and Non-Guaranteed Bonds



Panel B: Estimated FDIC Gurantee Premium

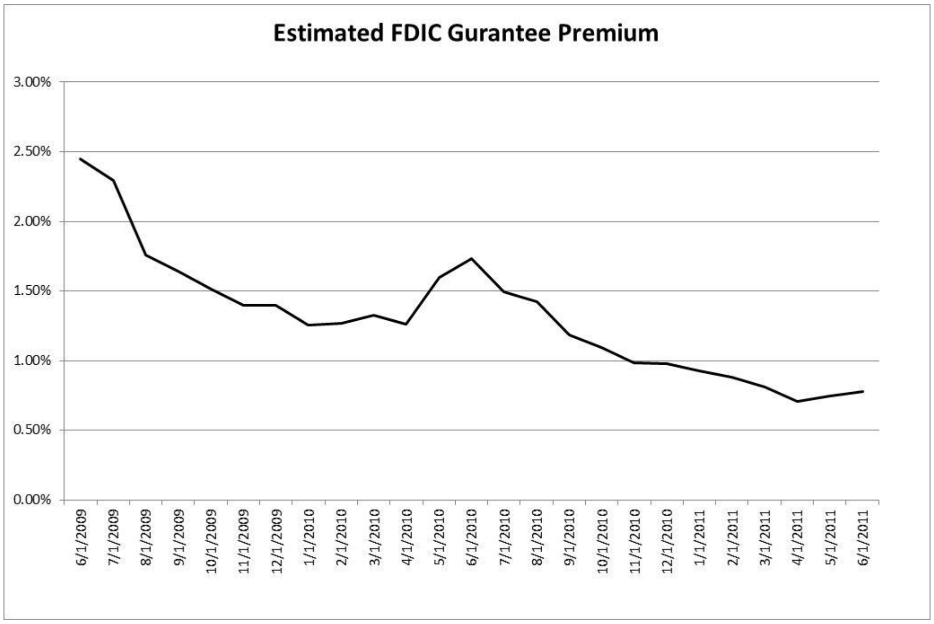


Table 1: Summary Statistics

This table presents summary statistics for the variables; Panel A for financial firms and Panel B for non-financial firms. *ttm* is the time-to-maturity for a bond. *seniority* is a dummy variable indicating whether the bond is senior. *spread* is the difference between the yield on a given firm's bond and the yield on a maturity-matched Treasury bond. *spread* is in percentages. *size* is the size of an institution defined as the log value of total assets. *roa* is the return on assets, measured as net income divided by total assets. *mismatch* measures maturity mismatch and is computed as short-term debt minus cash divided by total liabilities. *leverage* is total liabilities divided by total assets. *mb* is the market-to-book ratio computed as the value of total equity divided by book value of total equity. *mertondd* is Merton's (1974) distance-to-default measure, calculated using firm-level financial and stock return data, described in Appendix A. *z-score* is a financial distress measure 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* is stock return volatility computed using daily returns over the past 12 months. In calculating *volatility*, we require the company to have at least 90 non-zero and non-missing returns over the previous 12 months. Variables are defined in Appendix A.

Panel A: Financial Firms						
Variables	*N*	Mean	Std. Dev.	P25	P50	P75
ttm	45616	6.960	5.876	3.056	5.375	8.747
seniority	45616	0.695	0.460	0.000	1.000	1.000
spread	45616	2.371	11.221	0.703	1.019	1.776
size	45616	11.459	1.693	10.405	11.430	12.636
roa	45616	0.012	0.025	0.005	0.010	0.014
mismatch	45207	0.068	0.182	-0.031	0.046	0.151
leverage	45616	0.896	0.092	0.895	0.919	0.943
mb	45542	1.632	0.892	1.093	1.450	1.969
mertondd	45616	5.278	1.999	3.976	5.601	6.839
zscore	43869	37.267	40.670	13.901	24.975	46.487
volatility	45616	0.365	0.248	0.211	0.280	0.397
Panel B: Non-Financial Firms						
Variables	*N*	Mean	Std. Dev.	P25	P50	P75
ttm	78698	11.106	10.747	4.061	7.817	15.733
seniority	78698	0.975	0.155	1.000	1.000	1.000
spread	78698	2.072	4.441	0.674	0.998	1.760
size	78469	9.294	1.296	8.379	9.328	10.126
roa	78469	0.043	0.064	0.016	0.043	0.074
mismatch	78462	0.012	0.169	-0.056	0.001	0.071
leverage	78465	0.660	0.137	0.568	0.652	0.744
mb	78084	3.005	12.310	1.290	1.987	3.243
mertondd	78698	5.929	2.204	4.405	5.835	7.366
zscore	77097	29.524	40.890	10.172	18.549	35.816
volatility	78698	0.321	0.143	0.226	0.279	0.359

Table 2: TBTF-Spread Regressions

Results for the regression in equation (1) are in columns 1 to 6. *spread* is the difference between the yield on a given firm's bond and the yield on a maturity-matched Treasury bond. s*ize90* is a dummy variable equal to one if a given financial institution's size is in the top 90th percentile. *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. *covar* is the Covar measure of Adrian and Brunnermeir (2011). *srisk* is the systemic risk measure of Acharya et al. (2010) and Acharya, Engle, and Richardson (2012). *bank, insurance* and *broker* dummies are variables set to one if the firm belongs to the corresponding industry based on its SIC code. *mkt* is the market risk premium, computed as the value-weighted stock market return minus the risk-free rate. *term* is the term structure premium, measured by the yield spread between long-term (10-year) Treasury bonds and short-term (three-month) Treasuries. *def* is the default risk premium, measured by the yield spread between BAA-rated and AAA-rated corporate bonds. Other control variables are defined in Table 1 and in Appendix A. Standard errors are in parentheses below their coefficient estimates and are adjusted for both heteroscedasticity and within correlation clustered at the issuer level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% two-tailed levels, respectively.

Variables	(1) spread	(2) spread	(3) spread	(4) spread	(5) spread	(6) spread
ttm	0.018**	0.020***	0.020***	0.019**	0.103**	0.020***
	(0.007)	(0.008)	(0.008)	(0.008)	(0.046)	(0.008)
seniority	-0.128	-0.121	-0.123	-0.044	0.020***	-0.154
	(0.127)	(0.132)	(0.132)	(0.133)	(0.007)	(0.154)
$leverage_{t-1}$	-0.230	-2.138***	-2.137***	-2.009***	-0.083	-2.114***
	(0.870)	(0.687)	(0.686)	(0.673)	(0.127)	(0.667)
roa_{t-1}	-5.839	-6.350	-6.362	-4.075	-2.596***	-6.370
	(4.037)	(4.256)	(4.264)	(3.006)	(0.682)	(4.243)
mb_{t-1}	-0.176**	-0.140*	-0.139*	-0.226**	-5.992	-0.148*
	(0.082)	(0.083)	(0.083)	(0.095)	(4.149)	(0.087)
$mismatch_{t-1}$	0.076	0.035	0.031	0.305	-0.150*	-0.087
	(0.319)	(0.318)	(0.319)	(0.340)	(0.087)	(0.313)
def	1.560***	1.540***	1.540***	1.622***	0.193	1.542***
	(0.200)	(0.197)	(0.198)	(0.186)	(0.314)	(0.195)
term	0.057	0.055	0.056	0.079	1.681***	0.054
	(0.047)	(0.046)	(0.047)	(0.050)	(0.210)	(0.045)
mkt	-0.653	-0.639	-0.645	-0.581	0.058	-0.640
	(0.516)	(0.513)	(0.516)	(0.519)	(0.041)	(0.513)
$mertondd_{t-1}$	-0.291***	-0.310***	-0.311***	-0.263***	-0.375	-0.308***
	(0.050)	(0.054)	(0.055)	(0.059)	(0.500)	(0.056)
$size_{t-1}$	-0.246***					
	(0.065)					
$size90_{t-1}$		-0.320**				
		(0.148)				
$size\_top\_10_{t-1}$			-0.331**			
			(0.148)			
$covar_{t-1}$				-9.316**		
				(3.625)		
$srisk_{t-1}$					-0.011**	
					(0.005)	
$size_{t-1}$ × bank dummy						-0.382**
						(0.183)

$size_{t-1}$ × insurance dummy						-0.296
						(0.334)
$size_{t-1}$ × broker dummy						-0.196
						(0.209)
constant	4.827***	4.075***	4.121***	3.112***		4.116***
	(1.038)	(1.032)	(1.033)	(0.854)		(1.043)
Year FE	Y	Y	Y	Y	Y	Y
Rating Dummies	Y	Y	Y	Y	Y	Y
Observations	39,125	39,125	39,125	36,219	36,504	39,125
R^2	0.432	0.423	0.423	0.444	0.422	0.423

Table 3: TBTF Effect in the Financial and Non-financial Sectors

In Panel A, we report regression results described in equation (3). In Panel B, we report results for the regression specified in equation (2b). *spread*, *mertondd*, *Bond Controls*, *Firm Controls*, and *Macro Controls* are the same as in equation (2a) and described in Tables 1 and 2. *financial* is a dummy variable set to one if the firm is a financial firm (SIC code starting with 6). $sizedecile_{i,t-1}^{k}$ are ten dummy variables that take on a value of one if a firm belongs to one of the specified size deciles. The variables of interest, γ^k, are the coefficients on the interaction of *mertondd* with *sizedecile* dummies. We exclude the smallest *sizedecile* in the controls in order to avoid perfect multicollinearity. We run the regression separately for the results of financial firms in column (1) and the results of non-financial firms are in column (2). For brevity, we do not report coefficients on the control variables and only report coefficients on the interaction terms, γ^k. Standard errors are in parentheses below their coefficient estimates and are adjusted for both heteroscedasticity and within correlation clustered at the issuer level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% two-tailed levels, respectively.

Panel A: TBTF-Spread relation for Financial and Non-Financial Firms

	(1) spread
$size90_{t-1}$	-0.022
	(0.116)
$financial_{t-1}$	-0.252**
	(0.161)
$financial_{t-1} \times size90_{t-1}$	-0.241**
	(0.121)
Year FE	Y
Rating Dummies	Y
Controls	Y
Observations	104,127
R^2	0.425

Panel B: Risk-sensitivity of Debt for Financial and Non-Financial Firms

	(1) Financial Firms spread	(2) Non-Financial Firms spread
$size90_{t-1} \times mertondd_{t-1}$	-0.108***	-0.243***
	(0.039)	(0.069)
$size80_{t-1} \times mertondd_{t-1}$	-0.184***	-0.277***
	(0.050)	(0.090)
$size70_{t-1} \times mertondd_{t-1}$	-0.606**	-0.260***
	(0.234)	(0.052)
$size60_{t-1} \times mertondd_{t-1}$	-0.530***	-0.259***
	(0.189)	(0.054)
$size50_{t-1} \times mertondd_{t-1}$	-0.746***	-0.286***
	(0.187)	(0.069)
$size40_{t-1} \times mertondd_{t-1}$	-0.566***	-0.406***
	(0.179)	(0.087)
$size30_{t-1} \times mertondd_{t-1}$	-0.290***	-0.324***
	(0.064)	(0.066)
$size20_{t-1} \times mertondd_{t-1}$	-0.470***	-0.413**
	(0.114)	(0.177)
$size10_{t-1} \times mertondd_{t-1}$	-0.285***	-0.479***
	(0.114)	(0.127)
Year FE	Y	Y
Rating Dummies	Y	Y
Controls	Y	Y
Observations	39,125	65,002
R^2	0.475	0.425

Table 4: Alternative Measures of Risk

Results for the regression in equation (3) are in Panel A. *size90* dummy variable, set equal to one if a given financial institution's size is in the top 90^{th} percentile. We use alternative measures of risk. Merton's distance-to-default (*mertondd*) is reported in column 1, z-score (*zscore*) in column 2, volatility (*volatility*) in column 3, the adjusted distance-to-default measure (*adj-mertondd*) in column 4, the distance-to-default measure computed using exponentially weighted moving average standard deviations (*ewma-mertondd*) in column 5, and credit risk beta (*dd-beta*) in column 6. *adj-mertondd* is the Merton's adjusted distance-to-default measure, calculated by removing the effect of size on market leverage and volatility as described in the text. *ewma-mertondd* is the Merton's distance-to-default measure, calculated using standard deviations computed using the exponentially weighted moving average method as described in the text. *dd-beta* is the Beta obtained from regressing a firm's monthly changes of distance-to-default on the monthly changes of value-weighted average distance-to-default of all other firms using 36 months of data. In computing *dd-beta*, we require the company to have at least 24 non-missing monthly changes in distance-to-default over the previous 36 months. *mertondd*, *zscore, volatility*, and the other control variables are defined in Table 1. We use negative (-) values for *volatility* and *dd-beta* so that higher values indicate lower risk consistent with the other risk measures. Panel B reports regression results for equation (4). We use the same controls and risk measures as in Panel A, but include non-financial firms as controls. *financial* is a dummy variable set to one if the firm is a financial firm (SIC code starting with 6). For brevity, we do not report coefficients on the control variables. Standard errors are in parentheses below their coefficient estimates and are adjusted for both heteroscedasticity and within correlation clustered at the issuer level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% two-tailed levels, respectively.

Panel A: Risk-sensitivity of Debt

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	mertondd	zscore	(-)volatility	adj-mertondd	ewma-mertondd	(-)dd-beta
$size90_{t-1}$	-2.022***	-1.305***	-0.876***	-1.819**	-1.211***	0.172*
	(0.568)	(0.401)	(0.256)	(0.896)	(0.384)	(0.091)
$risk\_measure_{t-1}$	-0.446***	-0.336***	-4.885***	-0.467***	-0.097***	-0.142*
	(0.082)	(0.082)	(1.106)	(0.112)	(0.021)	(0.076)
$size90_{t-1} \times risk\_measure_{t-1}$	0.332***	0.266**	3.342***	0.399**	0.104***	0.295**
	(0.091)	(0.115)	(0.824)	(0.187)	(0.034)	(0.131)
Year FE	Y	Y	Y	Y	Y	Y
Rating Dummies	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Observations	39,125	37,856	39,125	39,125	39,125	38,344
R^2	0.457	0.429	0.492	0.326	0.425	0.438

Panel B: Differences in Risk-sensitivity of Debt between Financial and Non-financial Firms

Variables	(1) mertondd	(2) zscore	(3) (-)volatility	(4) adj-mertondd	(5) ewma-mertondd	(6) (-)dd-beta
$size90_{t-1}$	-0.435	0.226	-0.055	-0.575	-0.390	0.211
	(0.442)	(0.398)	(0.301)	(0.423)	(0.280)	(0.210)
$risk\_measure_{t-1}$	-0.241***	-0.172**	-8.170***	-0.224***	-0.065***	0.080
	(0.046)	(0.070)	(0.824)	(0.048)	(0.016)	(0.072)
$size90_{t-1} \times risk\_measure_{t-1}$	0.071	-0.112	0.175	0.092	0.038	-0.141
	(0.063)	(0.125)	(1.018)	(0.062)	(0.025)	(0.162)
$financial_{t-1}$	0.482	0.162	-0.558*	0.268	0.011	0.540**
	(0.598)	(0.407)	(0.313)	(0.586)	(0.391)	(0.228)
$financial_{t-1} \times risk\_measure_{t-1}$	-0.149	-0.134	2.740***	-0.130	-0.040	-0.284**
	(0.091)	(0.101)	(1.057)	(0.091)	(0.032)	(0.114)
$financial_{t-1} \times size90_{t-1}$	-1.554**	-1.445**	-0.721*	-1.225*	-0.739	-0.092
	(0.746)	(0.579)	(0.377)	(0.725)	(0.476)	(0.241)
$financial_{t-1} \times size90_{t-1} \times risk\_measure_{t-1}$	0.259**	0.387**	3.106**	0.219*	0.069*	0.428*
	(0.113)	(0.171)	(1.310)	(0.114)	(0.042)	(0.225)
Year FE	Y	Y	Y	Y	Y	Y
Rating Dummies	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Observations	104,127	101,944	104,127	104,127	104,127	103,796
R^2	0.459	0.439	0.548	0.454	0.441	0.435

Table 5: Liquidity Regressions

Regression results for the model $Liquidity_{i,b,t} = \propto + \beta^1 TBTF_{i,t-1} + \beta^2 Risk_{i,t-1} + \beta^3 Bond\ Controls_{i,b,t} + \beta^4 Firm\ Controls_{i,t-1} + \beta^5 Macro\ Controls_t + \ Year\ FE + \varepsilon_{i,b,t}$ are in Panel A. We use alternative measures of liquidity, which are reported separately in each column. The *amihud* measure is computed as the monthly average absolute value of daily returns divided by total daily dollar volume. The *roll* measure is computed as two times the square root of the negative covariance between two consecutive price changes. The *range* measure is computed as the monthly average of the difference of high and low price of a given bond scaled by square root of volume in a given trading day. The *zeros* is computed as the percentage of days during a month in which the bond did not trade. *lambda* is computed by aggregating standardized values of these four liquidity measures. Regression results for the model $Spread_{i,b,t} = \propto + \beta^1 TBTF_{i,t-1} + \beta^2 Risk_{i,t-1} + \ \beta^3 TBTF_{i,t-1} \times Risk_{i,t-1} + \beta^4 Financial_{i,} + \ \beta^5 Financial_i \ \times TBTF_{i,t-1} + \beta^6 Financial_i \times Risk_{i,t-1} + \ \beta^7 Financial_i \times Risk_{i,t-1} \times TBTF_{i,t-1} + \beta^8 Bond\ Controls_{i,b,t} + \beta^9 Firm\ Controls_{i,t-1} + \beta^{10} Macro\ Controls_t + \ Year\ FE + \varepsilon_{i,b,t}$ are in Panel B. We use two alternative measures of bond liquidity as additional controls. *liquidity* is a bond liquidity measure based on Longstaff et al. (2005). It is computed based on four bond characteristics – amount outstanding, age, time-to-maturity and rating. *lambda* is a liquidity measure computed by aggregating the *amihud*, *roll*, *range* and *zeros* measures of liquidity. This variable is computed using the TRACE database and is available only after 2003. All the variables are described in detail in Appendix A. We use the same set of controls as in column 1 of Table 2. Only the relevant variables of interest are reported for brevity. Standard errors are in parentheses below their coefficient estimates and are adjusted for both heteroscedasticity and within correlation clustered at the issuer level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% two-tailed levels, respectively

Panel A: Differences in Liquidity of Bonds between Financial and Non-financial Firms

Variables	(1) amihud	(2) range	(3) roll	(4) zeros	(5) lambda	(6) amihud	(7) range	(8) roll	(9) zeros	(10) lambda
size90 $_{t-1}$	-0.138**	-0.528**	-0.313***	-0.218***	-1.150***	-0.133***	0.018	-0.282**	-0.197***	-1.056***
	(0.054)	(0.214)	(0.110)	(0.058)	(0.332)	(0.043)	(0.283)	(0.117)	(0.047)	(0.280)
financial $_{t-1}$						-0.124**	-0.737**	-0.430***	-0.106*	-1.139***
						(0.051)	(0.344)	(0.123)	(0.054)	(0.325)
financial $_{t-1}$ × size90 $_{t-1}$						0.002	-0.631	-0.057	-0.018	-0.114
						(0.073)	(0.480)	(0.159)	(0.076)	(0.439)
Constant	-0.189	3.368	2.363***	-0.089	-2.174	0.159	2.989***	1.843***	0.558***	-1.342
	(0.275)	(2.243)	(0.585)	(0.285)	(1.833)	(0.165)	(1.014)	(0.382)	(0.139)	(1.004)
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Rating FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	15,451	19,005	13,999	21,670	13,988	27,498	36,812	24,242	45,249	24,226
R-squared	0.113	0.113	0.319	0.210	0.273	0.143	0.137	0.320	0.266	0.327

Panel B: Controlling for Liquidity on Risk-Senstivity Regressions

Variables	(1) spread	(2) spread	(3) spread	(4) spread	(5) spread	(6) spread	(7) spread	(8) spread
$size90_{t-1}$	-0.428***	-2.645***	0.466***	-0.348	-0.256***	-1.971***	0.034	-0.355
	(0.138)	(0.950)	(0.153)	(0.879)	(0.071)	(0.629)	(0.060)	(0.492)
$risk\_measure_{t-1}$	-0.356***	-0.582***	-0.202***	-0.226**	-0.320***	-0.464***	-0.224***	-0.238***
	(0.037)	(0.145)	(0.040)	(0.100)	(0.028)	(0.086)	(0.019)	(0.047)
$size90_{t-1} \times risk\_measure_{t-1}$		0.443***		0.123		0.332***		0.066
		(0.157)		(0.109)		(0.100)		(0.070)
$financial_{t-1}$			-0.072	1.162			-0.273***	0.569
			(0.204)	(1.107)			(0.097)	(0.640)
$financial_{t-1} \times risk\_measure_{t-1}$				-0.259				-0.162*
				(0.161)				(0.098)
$financial_{t-1} \times size90_{t-1}$			-0.821***	-2.053			-0.306***	-1.631**
			(0.181)	(1.282)			(0.088)	(0.805)
$financial_{t-1} \times size90_{t-1} \times risk\_measure_{t-1}$				0.291*				0.266**
				(0.162)				(0.122)
$lambda_{t-1}$	0.090***	0.082***	0.032**	0.032				
	(0.015)	(0.021)	(0.015)	(0.023)				
$liquidity_{t-1}$					-0.218***	-0.208***	-0.043	-0.051
					(0.043)	(0.076)	(0.027)	(0.042)
Constant	3.955***	4.588***	-1.725***	-1.960	4.595***	3.763***	-0.703**	-0.750
	(0.918)	(1.499)	(0.646)	(1.443)	(0.662)	(0.804)	(0.354)	(0.793)
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Rating FE	Y	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Observations	13,988	13,988	24,226	24,226	39,125	39,125	104,127	104,127
R^2	0.562	0.607	0.573	0.595	0.428	0.447	0.440	0.449

Table 6: 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 $issuer/stand\ alone\ rating_{i,t-1} = \propto + \beta^1 TBTF_{i,t-1} + \beta^2 Firm\ Controls_{i,t-1} + \ Firm\ FE + Year\ FE + \varepsilon_{i,b,t}$. *issuer rating* is the Fitch long-term issuer rating, which is a number between 1 and 9, with 1 indicating the highest issuer quality. *stand-alone rating* is the Fitch individual company rating ,which excludes any potential government support. It takes on a number between 1 and 9, with 1 indicating the highest issuer quality. Control variables are described in Tables 1 and 2, and in Appendix A. Standard errors are in parentheses below their coefficient estimates and are adjusted for both heteroscedasticity and within correlation clustered at the issuer level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% two-tailed levels, respectively.

Panel A: Relationship between Fitch Ratings and Spreads

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^2	0.644	0.654	0.655

Panel B: Relationship between Fitch Ratings and Firm Size

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 $_{t-1}$	-32.744*	-35.547	-23.599	-23.952
	(18.217)	(21.865)	(15.001)	(15.519)
mb $_{t-1}$	-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^2	0.622	0.492	0.527	0.518

Table 7: Event Study

Regression results for the model in equations (5) and (6) are reported in this table. The variable *post* equals 1 if the transaction date is the event date or one of the five trading days following the event date, and 0 if the transaction date is one of the five trading days prior to the event date. We measure the systemic importance (*TBTF*) of an institution using the *size90* dummy variable, set equal to one if a given financial institution's size is in the top 90th percentile. Risk of a financial institution is measured by distance-to-default (*mertondd*). *financial* is a dummy variable set to one if the firm is a financial firm (SIC code starting with 6). *Issue FE* is an issue fixed effect included in the regression. Other variables are defined in Appendix A. For brevity, we only report the relevant variables. Standard errors are in parentheses below their coefficient estimates and are adjusted for both heteroscedasticity and within correlation clustered at the issuer level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% two-tailed levels, respectively.

Event Date	Event	(1) $size90_{t-1} \times post$	(2) $size90_{t-1} \times mertondd_{t-1} \times post$	(3) $size90_{t-1} \times financial_{t-1} \times post$	(4) $size90_{t-1} \times mertondd_{t-1} \times financial_{t-1} \times post$
	Panel A: Increase in TBTF expectations				
03/13/08	Bear Stearns bailout	-1.149***	0.251**	-1.141***	0.401**
		(0.224)	(0.103)	(0.228)	(0.182)
07/13/08	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)
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 $900 billion	-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)
11/12/08	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)
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)
	Panel B: Decrease in TBTF expectations				
09/15/08	Lehman Brothers files for bankruptcy	1.005***	-1.464***	1.086***	-1.437***
		(0.329)	(0.293)	(0.436)	(0.184)
	Panel C: Impact of the Dodd-Frank Act				
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	President Obama signs Dodd-Frank into law	0.027*	-0.019	0.017	-0.016
		(0.016)	(0.014)	(0.019)	(0.015)

Table 8: Impact of the Dodd-Frank Act

Results for the regression in equation (7) are reported in this table. *mertondd* is Merton's (1974) distance-to-default measure, calculated using firm-level financial and stock return data, described in Appendix A. *guarantee* is a dummy variable set equal to 1 if the bond had a special FDIC guarantee and was issued as part of the Temporary Liquidity Guarantee Program. The regression also includes additional bond controls. *age* is the age of the bond since issuance in years. *puttable* is a dummy variable set equal to 1 if the bond is puttable. *redeemable* is a dummy variable set equal to 1 if the bond is redeemable. *exchangeable* is a dummy variable set equal to 1 if the bond is exchangeable. *fixrate* is a dummy variable set equal to 1 if the bond has fixed-rate coupons. The event date is June 29, 2010 (enactment of 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 five 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 regression includes issuer-trading day fixed effects (*Issuer×Trading Day FE*). Other control variables are described in Table 1 and in Appendix A. Standard errors are in parentheses below their coefficient estimates and are adjusted for both heteroscedasticity and within correlation clustered at the issuer level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% two-tailed levels, 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)
guarantee	-1.780***	-2.712***	-1.413***	-2.190***
	(0.227)	(0.181)	(0.202)	(0.129)
guarantee × post	0.134***	0.700**	0.001	0.409**
	(0.022)	(0.259)	(0.065)	(0.129)
$mertondd_{t-1}$ × guarantee		0.887***		0.662***
		(0.220)		(0.181)
$mertondd_{t-1}$ × 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^2	0.687	0.703	0.594	0.595

Table 9: TBTF and Risk Shifting

Columns 1-4 report regressions results for the model in equation (8). We measure the systemic importance (*TBTF*) of an institution using log value of total assets (*size*), and the *size90* dummy variable set equal to one if a given financial institution's size is in the top 90^{th} percentile. *ΔD/V* is the annual change in the book value of debt divided by the market value of assets computed from the Merton model described in Appendix A. *Δ asset vol* is the annual change in the volatility of market value of assets computed using the Merton model described in Appendix A. *financial* is a dummy variable set to one if the firm is a financial firm (SIC code starting with 6). Columns 5-8 report regressions results for the model in equation (9). *ΔIPP* is the fair insurance premium per dollar of liabilities computed following Merton (1977). The estimation is described in Appendix A. Standard errors are in parentheses below their coefficient estimates and are adjusted for both heteroscedasticity and within correlation clustered at the issuer level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% two-tailed levels, respectively.

Variables	(1) Δ D/V	(2) Δ D/V	(3) Δ D/V	(4) Δ D/V	(5) Δ IPP	(6) Δ IPP	(7) Δ IPP	(8) Δ IPP
Δ asset vol	-0.183***	-1.075***	-0.207***	-0.445***	0.191***	-0.424***	0.155***	0.098***
	(0.070)	(0.318)	(0.074)	(0.028)	(0.016)	(0.072)	(0.017)	(0.009)
$size_{t-1}$		0.000				-0.001		
		(0.001)				(0.001)		
$size_{t-1}$ × Δ asset vol		0.096***				0.066***		
		(0.031)				(0.007)		
$size90_{t-1}$			-0.000	0.005*			-0.003	-0.000
			(0.003)	(0.003)			(0.003)	(0.000)
$size90_{t-1}$ × Δ asset vol			0.308**	0.252***			0.458***	-0.006
			(0.148)	(0.089)			(0.060)	(0.040)
$financial_{t-1}$				-0.003*				0.003***
				(0.002)				(0.001)
$financial_{t-1}$ × Δ asset vol				0.237***				0.057
				(0.079)				(0.041)
$financial_{t-1}$ × $size90_{t-1}$				-0.005				-0.003
				(0.004)				(0.003)
$financial_{t-1}$ × $size90_{t-1}$ × Δ asset vol				0.057				0.464*
				(0.173)				(0.275)
Constant	0.003*	0.001	0.003	0.006***	0.004***	0.010*	0.004***	0.001***
	(0.002)	(0.011)	(0.002)	(0.001)	(0.001)	(0.005)	(0.001)	(0.000)
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	2,131	2,131	2,131	12,817	2,131	2,131	2,131	12,817
R^2	0.018	0.041	0.022	0.083	0.060	0.095	0.086	0.078