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

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Abstract

Using 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 institutions. This "too big to fail" relationship between firm size and risk-sensitivity of bond spreads is not seen in non-financial sectors. We confirm the robustness of our results by employing 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.

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I. Introduction

The financial sector received unprecedented amount of government support during the 2007-2008 financial crisis. The nature and the magnitude of this support have renewed concerns about moral hazard arising from investor expectations of 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 over the 1990 to 2012 time period. While large firm size is associated with lower cost and lower risk sensitivity of debt in the financial sector, a similar relationship is not present in the non-financial sectors.

The differences we observe are consistent with investors expecting a government guarantee to support 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 a bank's financial condition and incorporate those assessments into securities' prices, demanding higher yields on uninsured debt in response to greater risk taking by the bank. However, for the market to discipline banks in this manner, debtholders must believe that they will bear the cost of a bank becoming insolvent or financially distressed. An implicit government guarantee dulls market discipline by reducing investors' 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.

On the other hand, investors may not expect the government to actually implement TBTF policies, as there is no formal obligation to do so. The possibility of a bailout may exist in theory but not reliably in practice, and as a result, market participants may not price implicit guarantees.[5] It is also possible that the introduction of new financial laws and

[5] 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

regulations, like the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 (Dodd-Frank), may have eliminated TBTF expectations. Hence, it is an empirical question whether the implicit guarantee is considered credible and priced in by market participants.

In this paper, we examine the relationship between the risk profiles of U.S. financial institutions and the credit spreads on their bonds. We show that while a positive relationship exists between risk and credit spreads for medium and small institutions, the risk-to-spread relationship is significantly weaker for the largest institutions. Because they pay a lower price for risk than other financial institutions, the large institutions receive a funding advantage as a result of the perceived guarantee.

We show that this relationship between firm size and risk sensitivity of bond spreads is not present in non-financial sectors. Comparing financial firms to non-financial firms allows us to control for general advantages associated with 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 better 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 beyond just the financial sector. We use a difference-in-differences approach and compare differences in spreads of large and small financial institutions to differences in spreads of large and small companies in non-financial sectors. 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 institutions. However, we find this is not the case. We find that a substantial size funding advantage exists for financial institutions even after controlling for the effect of size on credit spreads for non-financial firms.

We also use the difference-in-differences approach in examining the sensitivity of credit spreads to changes in risk. We find that the risk sensitivity of spreads is substantially weaker for large financial institutions than for large non-financial firms. These differences we observe between financial and non-financial firms are not due to differences in the liquidity of

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 eleven banks "too big to fail" in 1984, authorities have walked a thin line between supporting large institutions and declaring that support was neither guaranteed nor to be expected, permitting institutions to fail when possible to emphasize the point. This has led authorities to take a seemingly random approach to intervention, for instance by saving AIG but not Lehman Brothers, in order to make it difficult for investors to rely on a government bailout. While this does not eliminate the subsidy, it does reduce its value.

their bonds. Our results are robust to controlling for various measures of liquidity.

Consistent with these findings, we show that outside discipline is less effective in curbing 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 outside 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 relationship 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-financials as a control. These findings contradict the "charter value" hypothesis put forth by Bliss (2001, 2004) and others.

Our results are robust to using different measures of firm risk. In the analyses, we use both accounting and equity based measures. Implicit guarantees may affect both leverage and asset volatility which may inflate equity values, which in turn can affect equity based measures of risk, such as, the Merton (1974) distance-to-default measure. For robustness, we create an adjusted measure of distance-to-default by removing the effect of size on market leverage and standard deviation of equity returns.[6] We find similar results using measures of risk adjusted for firm size.

The differences in cost of funding and risk sensitivity we observe may be driven by omitted variables. To address this concern, we carry out two additional analyses. First, we examine credit rating agencies' expectations of government support. Certain rating agencies (such as Fitch) estimate a financial institution's stand-alone financial condition separate from its likelihood of receiving external support. Using these third-party estimates of risk and support, we find that investors price an institution's likelihood of receiving government support.

Second, we conduct an event study around shocks to investor expectations of implicit guarantees. We find that, following the collapse of Lehman Brothers, larger financial institutions experienced greater increases in their credit spreads than smaller

[6] In particular, we run a cross-sectional regression of equity volatility and market leverage on size in each time period. 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 and use these values to compute an adjusted distance-to-default measure (See section III).

institutions. The spreads of large financial institutions also became more risk sensitive after the collapse of Lehman. Following the government's rescue of Bear Stearns and the adoption of the Troubled Asset Relief Program (TARP) and other liquidity and equity support programs, larger financial institutions experienced greater reductions in credit spreads than smaller institutions experienced. The spreads of large financial institutions also became less risk sensitive after these events. These event study results continue to hold when we use a triple-differencing approach and use non-financial firms as controls. Although, we cannot completely rule out the possibility of omitted variables driving the differences we observe, the results provide compelling evidence of investors pricing in implicit guarantees.

Finally, we examine the impact of the passage of Dodd-Frank in reducing investor expectations of government support. We conduct an event study around the passage of Dodd-Frank using a short event window of 10 days as well as a longer event window of 12 months. We find that passage of Dodd-Frank did not significantly alter investor expectations of future government support. These results continue to hold when we use a triple-differencing approach and 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. This approach allows us examine within-firm variation and compare *implicitly* guaranteed bonds to *explicitly* guaranteed bonds issued by the same firm. Using this approach, we do not find that Dodd-Frank altered the spread differential between FDIC-guaranteed bonds and non-FDIC guaranteed bonds of the same firm.

Our contribution to the literature is twofold. First, we provide evidence that bond spreads are less sensitive to firm risk for large financial institutions than for other 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 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 this relationship between firm size and risk sensitivity of bond spreads is not present in non-financial sectors and is robust to alternative approaches to address potential endogeneity.

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. We conclude in Section VI.

II. Related Literature

A large literature examines whether the market can provide discipline against bank risk taking (DeYoung et al. 2001; Jagtiani, Kaufman and Lemieux 2002; Morgan and Stiroh 2000; Calomiris 1999; Levonian 2000; and Flannery 1998). This literature examines whether there is a relationship between a bank's funding cost and its risk. Studies present some evidence that subordinated debt spreads reflect the issuing bank's financial condition and consequently propose that banks be mandated to issue subordinated debt. While these studies find that a bank's risk profile has some effect on credit spreads, 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 studying the spread-to-risk relationship in banking, a much smaller literature focuses on the role of implicit government guarantees in that relationship. These studies examine how the spread-to-risk relationship changes as investor perceptions of implicit government support changes. Their premise is that investors will price bank-specific risk to a lesser extent during periods of perceived liberal application of TBTF policies, and will price bank-specific risk to a greater extent during periods of perceived restricted application of TBTF policies. Flannery and Sorescu (1996) examine yield spreads on subordinated debt of U.S. banks over the 1983-1991 period. They believe that the perceived likelihood of a government guarantee declined over that period, which began with the public rescue of Continental Illinois in 1984 and ended with the passage of the FDIC Improvement Act (FDICIA) in 1991. They find that yield spreads were not risk sensitive at the start of the period, but came to reflect the specific risks of individual issuing banks at the end of the period, as conjectural government guarantees 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. Sironi believes 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, Sironi 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. In other words, these studies argue that as the implicit guarantee was diminished through policy and legislative changes, debt holders came to believe that they were no longer protected from losses and responded by more accurately pricing risk. But these studies analyze the risk-sensitivity of debt without explicitly differentiating potential TBTF candidates from other banks and without using non-financial firms as controls.

Later studies do attempt to identify TBTF banks and reach a different conclusion about the spread-risk relationship. These studies define TBTF banks using the eleven 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 relationship was flatter for the named TBTF banks than it was for other banks. They find that this flat relationship 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 relationship flattened for the TBTF banks following the rescue of Long-Term Capital Management in 1998. These studies, however, define a TBTF institution using the Comptroller's list from 1984. Consequently, the usefulness of their TBTF 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 period of analysis. Using this approach, we are able to analyze TBTF over a longer period of time (1990-2012), including the recent financial crisis. Further, we undertake a more detailed analysis of the role TBTF status plays in the spread-risk relationship than prior studies have done. In addition to comparing larger financial institutions to smaller financial institutions, we also compare larger non-financials to smaller non-financials. 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 and additional robustness tests.

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 (Ueda and Mauro 2012; Rime 2005). 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 structural break in the pricing of bank debt and CDS prices during the financial crisis. This approach assumed correct pricing prior to the crisis and the constancy of calibrated parameters.

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). Studies find that greater premiums are paid in larger M&A transactions, reflecting safety net subsidies (Brewer and Jagtiani 2007; Molyneux, Schaeck and Zhou 2010).[7] Equity studies conjecture that implicit support will impact a TBTF bank's stock price by reducing its cost of funds, thereby increasing profitability. But the immediate and most-valued beneficiaries of TBTF policies will be the institution's debtholders.

[7] Similarly, Penas and Unal (2004) show that bond spreads also tend to decline after a bank merger when the resulting entity attains TBTF status.

III. Data and Methodology

We collect data for financial firms and non-financial firms that have bonds traded during the 1990 to 2012 period. Financial firms are classified using Standard Industrial Classification (SIC) codes of 60 to 64 (banks, broker-dealers, exchanges, and insurance companies), and 67 (other financial firms). We exclude debt issued by government agencies and government-sponsored enterprises. Firm-level accounting and stock price information are obtained from COMPUSTAT and CRSP for the 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. In this paper, we focus on the 1990-2012 period.

Our sample includes all bonds issued in the U.S. by firms in the above datasets that satisfy selection criteria commonly used 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 statistical results are not heavily influenced by outliers, we set all observations higher than the 99th percentile value of a given variable to the 99th percentile value. There is no potential survivorship bias in our sample, as we do not exclude bonds issued by firms that have gone bankrupt or bonds that have matured. In total, we have 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. We are interested in systemically important financial institutions, as these firms 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. Dodd-Frank also emphasizes size in defining systemically important financial institutions. Large size even without significant interconnectedness may carry political influence (Johnson and Kwak 2010). We employ multiple measures of firm size. One is the size (log of assets) of a financial institution (*size*) in a given year. A second is whether a financial institution is in the top 90th percentile of financial institutions ranked by assets in a given year (*size90*), and a third is whether a financial institution is one of the ten largest institutions in terms of size in a given year (*size_top_10*).[8] These latter two measures are meant to capture very large institutions, which are likely to benefit most from TBTF policies. As mentioned earlier, although systemic importance and size are likely to be highly related, there could be areas of differences. Hence, for robustness, we also examine too-big-to-fail 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, Engle and Richardson (2012) and Acharya et al. (2010) systemic risk measure (*srisk*). The computation of these systemic importance measures is in Appendix A.

A number of different measures of credit risk have been used in the literature. We use Merton's distance-to-default (*mertondd*) as our primary risk measure (*risk*). 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

[8] For non-financial firms, we compute similar measures. Since financials 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.

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.[9] We follow Campbell, Hilscher and Szilagyi (2008) and Hillegeist et al. (2004) in calculating Merton's distance-to-default. The details of the calculation are in Appendix A. A higher distance-to-default number signals a lower probability of insolvency.

Implicit guarantees might affect equity values resulting in underestimation of risk using the Merton (1974) distance-to-default model. To address this concern, we verify our results using alternative measures of risk. 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, divided by the standard deviation of return on assets over four years (Roy 1952). The z-score measures the number of standard deviations that a financial institution's rate of return on assets can fall in a single period before it becomes insolvent. A higher z-score signals a lower probability of insolvency. A z-score is calculated only if we have accounting information for at least four years. We also compute an adjusted distance-to-default measure, by removing the effect of size on market leverage and standard deviation of equity returns. Each month, we run a cross-sectional regression of equity volatility and market leverage on *size*.[10] 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*).[11] 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.[12] Following Longerstaey et al. (1996), we use a weighting coefficient of 0.94. We use the exponential

[9] The Merton distance-to-default measure has been shown to be a good predictor of defaults, outperforming accounting-based models (Campbell, Hilscher and Szilagyi 2008; Hillegeist et al. 2004). Although the Merton distance-to-default measure is more commonly used in bankruptcy prediction in the corporate sector, Merton (1977) points out the applicability of the contingent claims approach to pricing deposit insurance in the banking context. Anginer and Demirguc-Kunt (2014), Bongini, Laeven, and Majnoni (2002), and others have used the Merton model to measure the default probabilities of commercial banks.

[10] Market leverage is computed as total liabilities divided by the sum of market equity and total liabilities.

[11] 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.

[12] Exponentially weighted moving average standard deviations are computed as: $\sigma_{i,t}^2 = \lambda\sigma_{i,t-1}^2 + (1-\lambda)\varepsilon_{i,t-1}^2$.

moving average method (EWMA) to compute standard deviations, which are then used to construct this alternative distance-to-default measure (*ewma-mertondd*). We also use equity return volatility (*volatility*), without imposing any structural form, as a risk measure.[13] Volatility is computed using daily data over the past 12 months. 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 value-weighted average distance-to-default of all other firms using 36 months of past data.[14]

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 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 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 in this set. 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. We also use a range-base 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. The *roll* measure captures transitory price movements induced by lack of liquidity and proxies for the bid-ask spread of a

[13] 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.
[14] 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.

bond, based on the work of Roll (1984). The *roll* measure is computed as the covariance of consecutive price changes. 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. We also 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*.

Second, a liquidity measure is computed 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). This measure, *liquidity*, is computed 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.

Following the empirical model in 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:

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

In equation (1), the subscripts *i*, *b*, and *t* indicate the firm, the bond, and the time (month), respectively, and *FE* denotes 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, as discussed above.

IV. Results

In this section, we examine whether bondholders of major financial institutions have an expectation of government support by investigating the relationship between an institution's systemic importance and its credit spreads, after controlling for risk and other variables. We also examine the impact of an institution's size on the credit spread-to-risk relationship. We then analyze the effectiveness of outside discipline on the risk-taking behavior of financial institutions. Finally, we quantify the value of the funding subsidy TBTF institutions received on a yearly basis over the 1990-2012 period.

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 appear in Table 2. The table shows a significant inverse relationship between credit spreads and systemic importance. First, we use asset size (*size*) to identify systemic importance. In column 1, we see that *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 spreads. In column 3, we define a systemically important institution as one of the ten largest institutions in terms of size in a given year (*size_top_10*). Results again show that TBTF status has a significant negative effect on spreads. In column 4, following Adrian and Brunnermeier (2011), we use an institution's contribution to systemic risk (*covar*) to identify systemically important financial institutions. Higher values of *covar* indicate greater systemic risk contribution. Results show a significant negative relationship between *covar* and spread. That is, the greater an institution's contribution to systemic risk, the lower its spread. The second systemic risk measure we use (*srisk*) is based on the expected capital shortfall framework developed by Acharya, Engle and Richardson (2012) and Acharya et al. (2010). Results in column 5 show a significant negative relationship between *srisk* and spread. The greater an institution's systemic risk, the lower its spread.

We also look at whether the size-spread relationship 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 spreads is most significant for the banks. Size does not reduce spreads as much when the financial institution is an insurance company or a broker-dealer.

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 differences in spreads of large and small financial institutions to differences in 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.[15] Therefore, for robustness, we include non-financial companies (column 7 of Table 2) 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*.[16] This interaction term captures the differential effect size has on 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 size on spreads is larger for financial firms than for non-financial firms.

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

Does a financial institution's size affect this relationship between credit spreads and risk? To answer that question, we interact the size and risk variables. The results are in Table 3 (Panel A). For brevity, we report only variables of interest in this table. There is a significant and

[15] If there is an expectation of 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.
[16] S*ize90* indicates a firm in the top 90th percentile of its size distribution.

positive coefficient on the term interacting *size90* and *mertondd* (column 1). This indicates that the spread-to-risk relationship diminishes with TBTF status. For institutions that achieve systemically-important status, spreads are less sensitive to risk. This result is consistent with investors pricing an implicit government guarantee for the largest financial institutions. In column 7, we add an additional dummy variable indicating an institution between the 60^{th} and 90^{th} percentiles (*size60*). We interact both size dummy variables with *mertondd.* The interaction coefficient on *size60* lack significance. These results indicate that the effect of size on the spread-to-risk relationship comes from the very large financial institutions. In economic terms, a one standard deviation increase in distance-to-default reduces spreads by 60 bps in the overall sample. But for financial institutions in the top 90th percentile in terms of size, a one standard deviation increase in distance-to-default reduces spreads by only 12 bps. In comparison, for institutions between the 60th and 90th percentiles, spreads are reduced by 51 bps.

Moreover, these results are robust to different measures of risk. In place of *mertondd,* we employ z-score (*zscore*) in column 2 and volatility (*volatility*) in column 3. In each specification, the coefficient on the interaction term is significant and offsets the coefficient on the risk variable, indicating that the spread-to-risk relationship diminishes for the largest institutions.

These relationships can be seen in Figure 1. The left panel of Figure 1 shows the relationship between the size of a financial institution and the credit spread on its bonds. It shows a negative relationship between size and spreads: larger institutions have lower spreads. Why do larger institutions have lower spreads? Are they less risky than smaller ones? The right panel of Figure 1 plots the size of a financial institution against its risk (distance-to-default). There does not appear to be any observable relationship between size and risk. That is, larger institutions do not offer lower risk of large losses than smaller institutions. Hence, Figure 1 provides evidence supporting the supposition that large institutions enjoy lower spreads because of implicit government support, not because of their underlying risk profiles.

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 III. 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 using the unadjusted distance-to-default measure, *mertondd*. 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, Engle and Richardson 2012; Acharya and Yorulmazer 2007) so as to increase the value of the implicit 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 do 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.

Finally, in results reported in column 7, we allow the risk variable to have a non-linear relationship with the bond spread. In particular, we include an interaction term of the squared *mertondd* variable with the *size_90* variable. 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.[17]

As before, we also compare financial institutions to non-financial institutions when examining the impact of risk on spreads. The results are reported in Panel B of Table 3. For brevity, we do not report coefficients on the control variables. We are interested in the $financial_{t-1} \times Risk_{t-1} \times size90_{t-1}$ 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-*

[17] 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.

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.

2. Time-series variation of Implicit Subsidy

As the above results show, major financial institutions enjoy a funding subsidy as a result of implicit government support. In this subsection, we provide an estimate of this 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 2. The implicit subsidy provided large financial institutions a funding cost advantage of approximately 30 basis points over the 1990-2012 period. The subsidy increased during the crisis years 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 2.[18] The subsidy amounts to on average $30 billion per year and rose above $100 billion during the financial crisis.

Despite the magnitude of the implicit subsidy, few studies have attempted to quantify it, although some have attempted to measure explicit government support (e.g., Laeven and Valencia 2010 and Veronesi and Zingales 2010). Direct costs of bailouts have always caught 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 2 shows that expectations of government support for large financial institutions persist over time. Expectations of support

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

exist not only in times of crisis, but also in times of relative tranquility, and vary with government policies and actions. In the post-crisis period after 2009, the implicit subsidy has remained at positive levels.

3. Market Discipline

In this section, we examine the effectiveness of outside discipline on the risk-taking behavior of financial institutions. We use two methods to examine outside discipline's effect on risk. The first method is based on the concept that capital should increase with risk. 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 relationship 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:

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

where D is the book value of debt, V is the market value of assets, and s_A is the volatility of market value of assets. V and s_A are computed using the structural model of Merton (1974) described in Appendix A. In equation (2), 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 to reduce their leverage. Similar to the sensitivity of 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 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 4. Consistent with Duan, Moreau and Sealey (1992), we find evidence of 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 outside 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 relationship 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). This approach compares the restraining effect of outside 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 relationship empirically, we follow Duan, Moreau and Sealey (1992) and use the following reduced-form specification:

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

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. To derive this relationship, we assume a linear approximation for the value of the liabilities put option, $IPP_{i,t} = \propto + \theta^1 D/V_{i,t} + \theta^2 s_{A_{i,t}}$, and plug in the value of $D/V_{i,t} = \delta + \beta^1 \Delta s_{A_{i,t}}$ from the relationship discussed above. 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 outside 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 4. 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 financials to be greater than those of large non-financials (column 8).

V. Robustness

In this section, we do a number of robustness checks around 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, which provide third-party measures of an institution's credit risk and an institution's likelihood of receiving external support in a crisis. Third, we perform an event study to examine shocks to investor expectations of support.

1. Impact of Liquidity

It is possible that our results might be affected by the liquidity of the bonds we study. In Panel B of Table 5, we show that our main results from Table 2 are robust to controls for liquidity. 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 III and in detail in Appendix A. We use the same specifications and controls used in Table 2. 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.

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. These liquidity variables are described in Section III and in detail in Appendix A. In columns 2 and 3, 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*.

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 if there are significant differences in the liquidity of bonds issued by financial and non-financial firms. We use the same specification and controls used 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). 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.

2. Stand-Alone and Support Ratings

To alleviate potential concerns about endogeneity, we use credit ratings and government-support ratings as alternative measures of credit risk and implicit support. We examine ratings issued by Fitch, which provide a third-party's estimate of credit risk and potential external support.

In rating financial institutions, Fitch assigns both an "issuer rating" and a "stand-alone rating." Fitch's issuer rating is a conventional credit rating. It measures a financial institution's ability to repay its debts after taking into account all possible external support. In contrast, Fitch's stand-alone rating measures a financial institution's ability to repay its debts without taking into consideration any external support. The stand-alone rating reflects an institution's independent financial strength, or in other words, the intrinsic capacity of the institution to repay its debts. The difference between these two ratings reflects Fitch's judgment about 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 spread regression specified in equation (1).[19]

Table 6 (Panel A) contains results of regressions similar to the spread regressions of Table 2, but with the addition of the rating variables. The stand-alone rating is employed in column 1. Column 2 employs the issuer rating. Although both ratings are significant in affecting spreads, the issuer rating has a greater economic impact on spreads. In column 3, both ratings are employed simultaneously. In that specification, the coefficient on the issuer rating

[19] 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.

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 have a similar effect. Investors significantly price implicit government support for the institution. 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.

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 support, and we see that larger institutions have significantly better issuer ratings. In contrast, the TBTF measures do not have a significant effect on the stand-alone rating. The stand-alone rating excludes potential government support, and we find that large institutions do not have significantly better stand-alone ratings.

3. Event Study

Next, we examine how credit spreads were 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 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.[20] This intervention likely reinforced expectations that the government would guarantee the obligations of large financial institutions. Similarly, the later decision to allow Lehman Brothers

[20] In connection with Bear Stearns' merger with JP Morgan Chase in 2008, the Federal Reserve provided JP Morgan 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 banks like Lehman, Merrill Lynch, and Goldman Sachs.

to fail, in contrast, served as a negative shock to those expectations. Although the Federal Reserve and the Treasury intervened the day after Lehman was allowed to collapse (including a rescue of AIG's creditors), the government adopted a series of unpredictable and confusing policies around Lehman's collapse, making future intervention increasingly uncertain. Hence, both the Bear Stearns event and the Lehman event provide contrasting shocks to investor expectations of government support. We also examine other events that may have affected investor expectations positively. In particular, we examine the events surrounding the passage of the Troubled Asset Relief Program (TARP), as well as other announcements of liquidity and financial support to the banking sector.[21]

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

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

We use *size90* as our measure of systemic importance. We use a dummy variable, *post*, which equals one on the event date and the five subsequent trading days. We use issue fixed effects (*Issue FE*) and the regression corresponds to a difference-in-differences estimation. We examine the change in the TBTF subsidy after the event, as well as the change in risk sensitivity. 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 with respect to those firms. Specifically, we run the following regression for a sample of firms that includes both financial institutions and non-financial institutions:

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

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

The coefficient on the $TBTF_{i,t} \times financial_{i,t} \times post$ variable captures the impact of the event on spreads for large financial institutions compared to large non-financials. 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 relationship for large financials compared to large non-financials.

The results are in Table 7. For brevity, we report only variables discussed above. We find that announcements of government financial and liquidity support have been associated with a decrease in credit spreads for larger financial institutions. In particular, the bailout of Bear Stearns and the revised TARP bill passing the House of Representatives led to decreases in spreads in excess of 100 bps (column 1). Large financial institutions also saw a decrease in the risk sensitivity of their debt to changes in risk (column 2). We find similar results when we use 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, namely the bankruptcy filing by Lehman Brothers on September 15, 2008. Again, our variable of interest is the term interacting *post* with *size90*. The coefficient on the interaction term is significant and positive for the Lehman event (column 1 in Table 7). The result indicates that larger institutions saw greater increases in their credit spreads after the government allowed Lehman to collapse.[22] 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 two regulatory reforms that have been proposed to address problems associated with TBTF institutions. The first is the adoption of the Dodd-Frank Wall Street

[22] 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.

Reform and Consumer Protection Act (Dodd-Frank). One of the main purposes of the legislation was to end investors' expectations of future government bailouts. Table 7 shows results for June 29, 2010, the date the House and Senate conference committees issued a report reconciling the bills of the two chambers, and July 21, 2010 when 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 Dodd-Frank actually lowered credit spreads for the very largest financial institutions relative to the others (although the 3 basis point effect is economically small). The coefficient on *size90*×*mertondd*×*post* is significant and positive, indicating that Dodd-Frank decreased the risk sensitivity of credit spreads for large institutions (although the effect again is economically very small). We find a small positive increase in spreads using the July 21, 2010 event date.

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

V. Impact of Dodd Frank

The results from the previous section suggest that the adoption of Dodd-Frank has not significantly altered investors' perceptions of implicit government support. In this section, we examine the impact of Dodd-Frank 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). Results using this longer window are shown in Table BI of Appendix B. The relevant coefficients are largely insignificant statistically and economically. In all, these results 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 Federal Deposit Insurance Corporation's (FDIC) Temporary Liquidity Guarantee 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 FDIC's Temporary Liquidity Guarantee Program (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 that opted to participate in the program.[23]

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.[24] 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. Figure 3 shows the difference in spreads for each of the top six financial institutions. Control variables are not used in Figure 3.

We introduce controls by regressing spreads on a dummy variable (*guarantee*) that takes a value of one if the bond is backed by the FDIC guarantee:

$$Spread_{i,b,t} = \propto + \beta^1 Bond\ Controls_{i,b,t} + \beta^2 guarantee_{i,t-1} + \ Firm \times Trading\ Day\ FE + \varepsilon_{i,b,t} \qquad (6)$$

To maximize sample size, we include all bonds issued by the firms covered under the TLG Program. We control for the age of the bond since issuance in years (*age*) and the time to

[23] Not all the debt of these institutions was eligible to be guaranteed under the TLG Program. 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 the October 31, 2009. The FDIC charged issuers a fee for the guarantee, and institutions could opt out of the program.

[24] 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, JP Morgan Chase, Morgan Stanley, Sovereign Bancorp, State Street, Suntrust, US Bancorp, Wells Fargo, PNC Bank, HSBC USA, Keycorp, Metlife, John Deere Capital, and GE Capital.

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).[25]

Figure 4 displays the coefficient on the *guarantee* variable obtained by running the regression specified in (6) on a daily basis. In the middle of the time period (June 2010), Dodd-Frank was adopted. We do see a slight increase in the value of the FDIC guarantee in the months preceding Dodd-Frank's adoption. At that time, it was unclear what the final language of the legislation would be. After Dodd-Frank was finalized, however, the value of the FDIC guarantee resumed its downward trend. Dodd-Frank does not appear to have changed investors' expectations of 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 (6) above, but with an additional variable, *post*. *Post* is a dummy equal to one during the 5 trading days (or 132 trading days) following the adoption of Dodd-Frank. *post* is interacted with an indicator variable (*guarantee*) that equals one if a bond is guaranteed under the FDIC's 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. The results appear 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 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.

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

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

(*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 (see, e.g., Skeel 2010; Wilmarth 2011; Standard & Poor's 2011). And although Dodd-Frank grants new authority to resolve large institutions, those decisions will involve political considerations.[26]

VI. Conclusion

We find that expectations of government support are embedded in the credit spreads of bonds issued by large U.S. financial institutions. Using bonds traded between 1990 and 2012, we find that credit spreads are risk sensitive for most financial institutions, while credit spreads lack risk sensitivity for the largest financial institutions. In other words, we find that bondholders of large financial institutions have an expectation that the government will shield them from losses 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 relationship between firm size and risk-sensitivity of bond spreads is not seen 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 have not had a significant impact in eliminating expectations of government support. In the post-crisis period after 2009, the implicit subsidy has

[26] 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."

remained at positive levels. We find that the passage of Dodd-Frank in the summer of 2010 did not significantly alter investors' expectations of government support.

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Figure 1: Size, Spreads and Risk

The figure on the left shows the relationship between the size of a financial institution and the credit spread on its bonds. Size (x-axis) is the relative size of a financial institution, computed as size (log of assets) in a 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. The figure on the right shows the relationship between the size of a financial institution and its risk. Size (x-axis) is the relative size of a financial institution, computed as its size (log of assets) in a year divided by the average size of all financial institutions in that year. Risk (y-axis) is the average distance-to-default of a financial institution in a given year, computed as described in Appendix A.

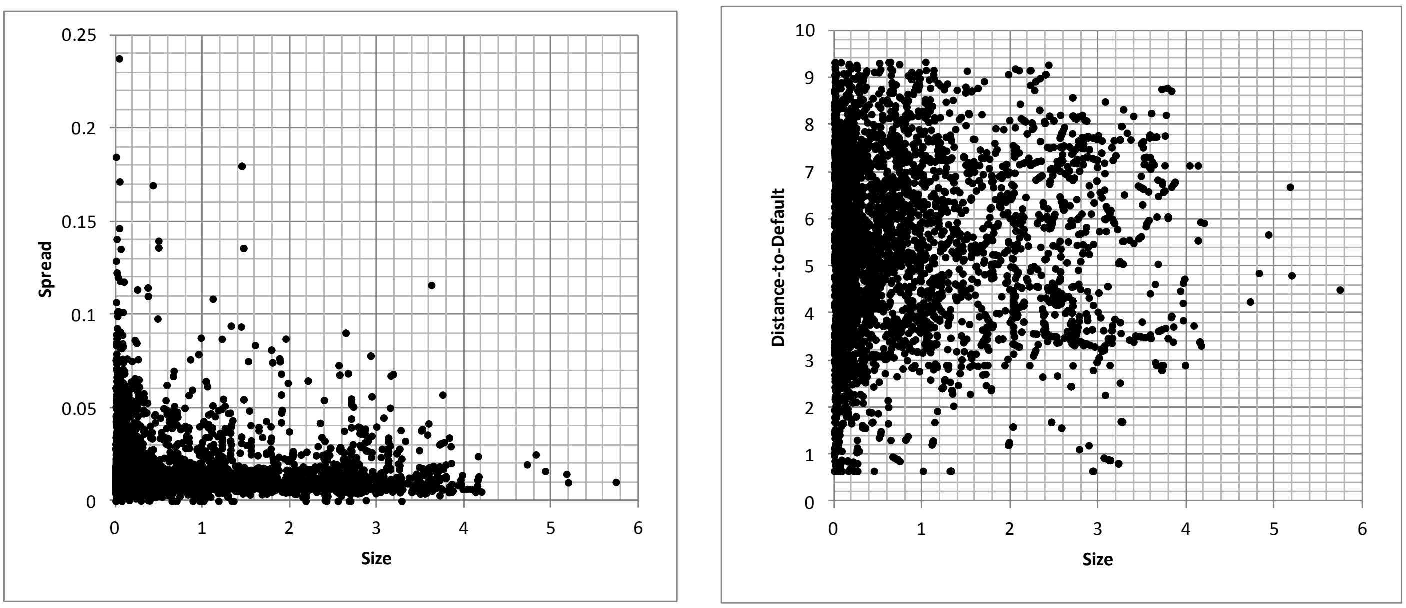

Figure 2: Value of the Implicit Subsidy over Time

This figure shows the annual subsidy to large financial institutions due to the implicit government guarantee. To compute the annual subsidy, we run the following regression 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.

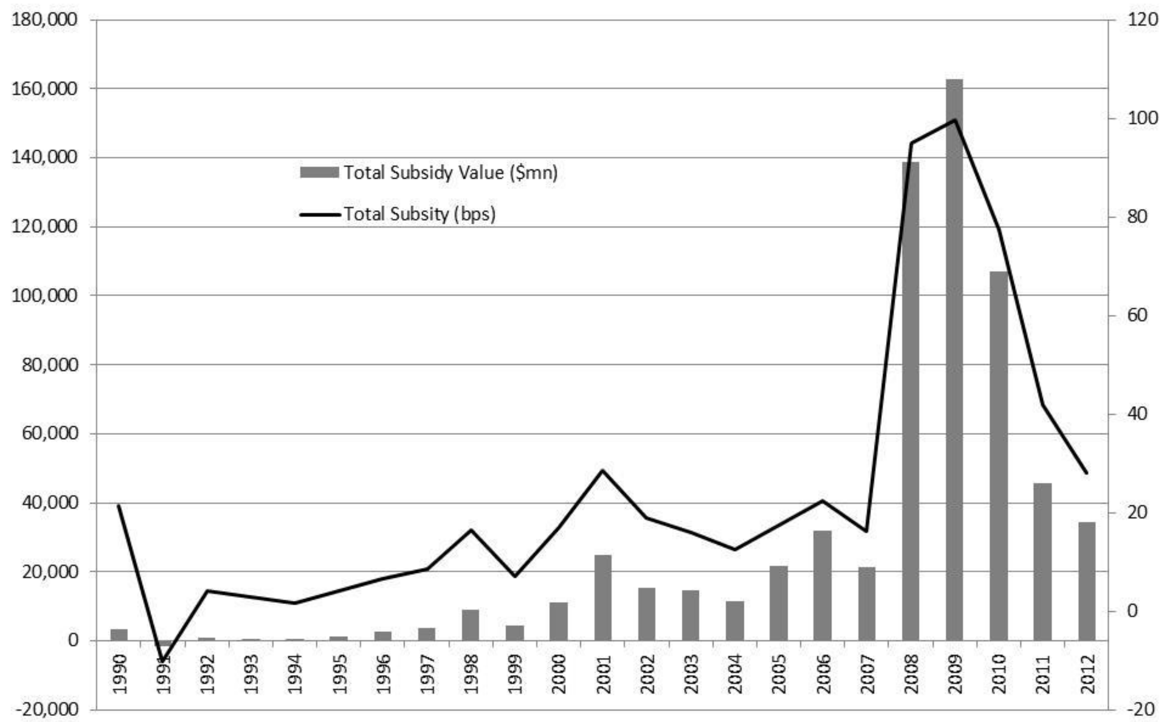

Figure 3: Explicit and Implicit Guarantee Spread Difference
This figure shows the difference in spreads between FDIC guaranteed and non-guaranteed bonds for six financial institutions. *BAC* is Bank of America, *C* is Citibank, *MS* is Morgan Stanley, *WFC* is Wells Fargo, *GS* is Goldman Sachs, and *JPM* is JP Morgan Chase. We plot averages for each month for each company if there are more than 10 daily trading observations.

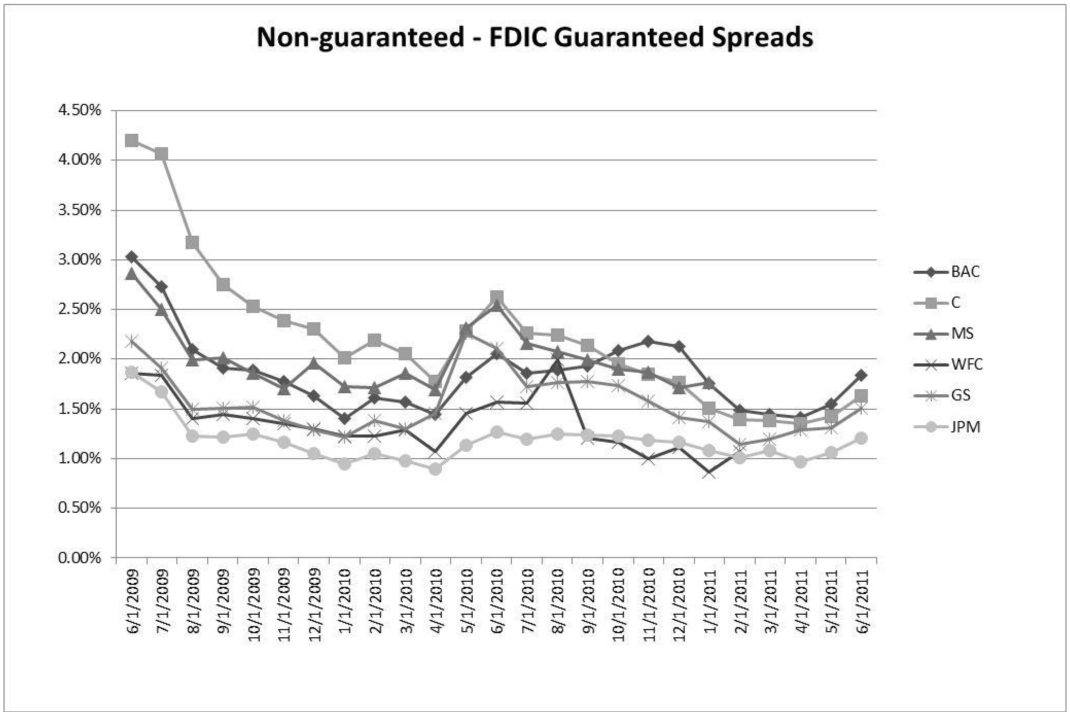

Figure 4: Explicit Guarantee Premium

This figure shows the estimated FDIC guarantee premium. To compute the premium, we run the following regression each day: $Spread_{i,b,t} = \propto + \beta^1 seniority_{i,b,t} + \beta^2 ttm_{i,b,t} + \beta^3 fixed\ rate_{i,b,t}$
$+\beta^4 puttable_{i,b,t} + \beta^5 exchangeable_{i,b,t} + \beta^6 redeemable_{i,b,t} + \beta^7 guarantee_{i,b,t} + Firm\ FE + \varepsilon_{i,b,t}$
The sample includes financial institutions that issued bonds under the FDIC's Temporary Liquidity Guarantee Program. *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. *age* is the age of the bond since issuance in years. *ttm* is time to maturity of the bond 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. Regression includes firm fixed effects (Firm FE). 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.

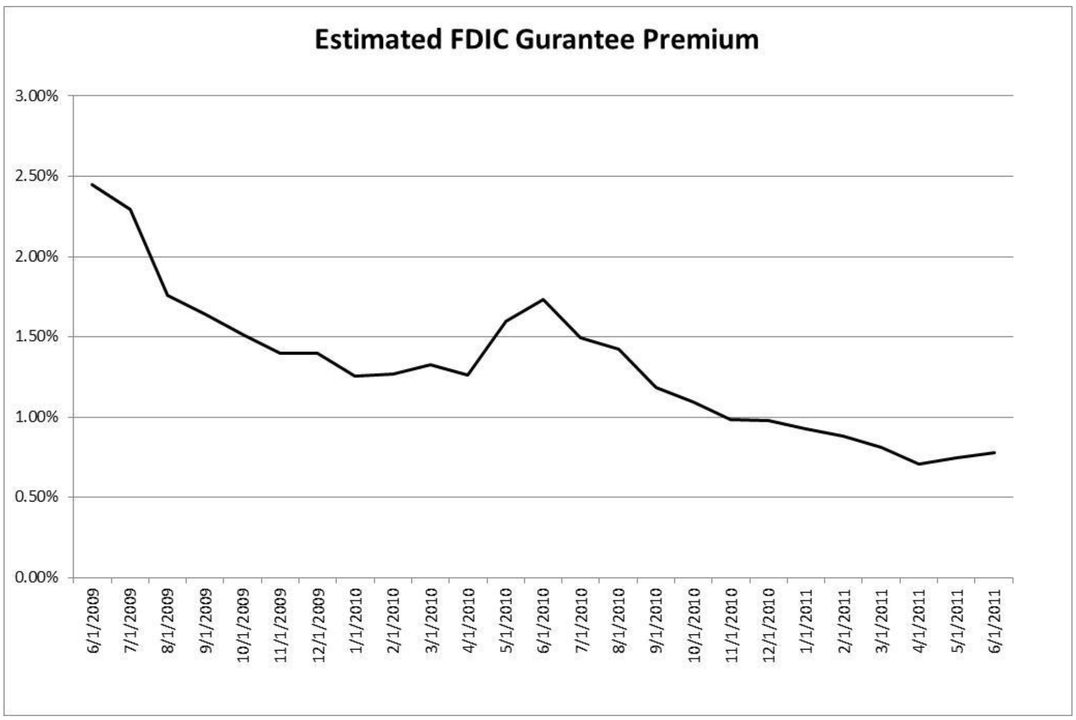

Table 1: Summary Statistics

This table presents summary statistics for the variables; Panel A for financial firms and Panel B for non-financial firms. *ttm* is years 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

Regression results for the model $Spread_{i,b,t} = \propto + \beta^1 TBTF_{i,t-1} + \beta^2 Financial_{i,t-1} + \beta^3 Risk_{i,t-1} + \beta^4 TBTF_{i,t-1} \times Financial_{i,t-1} + \beta^5 Bond\ Controls_{i,b,t} + \beta^6 Firm\ Controls_{i,t-1} + \beta^7 Macro\ Controls_t + Year\ FE + \varepsilon_{i,b,t}$ are reported in this table. We measure the systemic importance (*TBTF*) of an institution using a number of different proxies. s*ize* is log value of total assets of a financial institution. s*ize90* is a dummy variable equal to one if a given financial institution's size is in the top 90^{th} 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. (2012) and Acharya et al. (2010). *bank, insurance* and *broker* dummies are variables set to one if the firm belongs to the corresponding industry based on its SIC code. *financial* is a dummy variable set to one if the firm is a financial firm (SIC code starting with 6). *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 Appendix A. Standard errors are reported in parentheses below their coefficient estimates and are adjusted for both heteroscedasticity and within correlation clustered at the issuer level. ***, **, and * indicate significance at the 1%, 5%, and 10% two-tailed levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	spread	spread	spread	spread	spread	spread	spread
ttm	0.018**	0.020***	0.020***	0.019**	0.103**	0.020***	0.014***
	(0.007)	(0.008)	(0.008)	(0.008)	(0.046)	(0.008)	(0.003)
seniority	-0.128	-0.121	-0.123	-0.044	0.020***	-0.154	-0.034
	(0.127)	(0.132)	(0.132)	(0.133)	(0.007)	(0.154)	(0.105)
$leverage_{t-1}$	-0.230	-2.138***	-2.137***	-2.009***	-0.083	-2.114***	0.855
	(0.870)	(0.687)	(0.686)	(0.673)	(0.127)	(0.667)	(0.597)
roa_{t-1}	-5.839	-6.350	-6.362	-4.075	-2.596***	-6.370	-3.404***
	(4.037)	(4.256)	(4.264)	(3.006)	(0.682)	(4.243)	(0.811)
mb_{t-1}	-0.176**	-0.140*	-0.139*	-0.226**	-5.992	-0.148*	0.000
	(0.082)	(0.083)	(0.083)	(0.095)	(4.149)	(0.087)	(0.001)
$mismatch_{t-1}$	0.076	0.035	0.031	0.305	-0.150*	-0.087	-0.723***
	(0.319)	(0.318)	(0.319)	(0.340)	(0.087)	(0.313)	(0.238)
def	1.560***	1.540***	1.540***	1.622***	0.193	1.542***	1.292***
	(0.200)	(0.197)	(0.198)	(0.186)	(0.314)	(0.195)	(0.116)
term	0.057	0.055	0.056	0.079	1.681***	0.054	0.012
	(0.047)	(0.046)	(0.047)	(0.050)	(0.210)	(0.045)	(0.023)
mkt	-0.653	-0.639	-0.645	-0.581	0.058	-0.640	-0.440**
	(0.516)	(0.513)	(0.516)	(0.519)	(0.041)	(0.513)	(0.222)
$mertondd_{t-1}$	-0.291***	-0.310***	-0.311***	-0.263***	-0.375	-0.308***	-0.254***
	(0.050)	(0.054)	(0.055)	(0.059)	(0.500)	(0.056)	(0.030)
$size_{t-1}$	-0.246***						
	(0.065)						
$size90_{t-1}$		-0.320**					0.019
		(0.148)					(0.120)
$size\_top\_10_{t-1}$			-0.331**				
			(0.148)				
$srisk_{t-1}$				-0.011**			
				(0.005)			
$covar_{t-1}$					-9.316**		
					(3.625)		
$size_{t-1}$ × bank dummy						-0.382**	
						(0.183)	
$size_{t-1}$ × insurance dummy						-0.296	
						(0.334)	
$size_{t-1}$ × broker dummy						-0.196	
						(0.209)	
$financial_{t-1}$							-0.284**

							(0.181)
size90 $_{t-1}$ × financial $_{t-1}$							-0.241**
							(0.128)
constant	4.827***	4.075***	4.121***	3.112***		4.116***	0.192
	(1.038)	(1.032)	(1.033)	(0.854)		(1.043)	(0.619)
Year FE	Y	Y	Y	Y	Y	Y	Y
Rating Dummies	Y	Y	Y	Y	Y	Y	Y
Observations	39,164	39,164	39,164	36,219	36,504	39,164	104,127
R^2	0.432	0.423	0.423	0.444	0.422	0.423	0.439

Table 3: TBTF and Risk Interactions

Regression results for the model $Spread_{i,b,t} = \propto + \beta^1 TBTF_{i,t-1} + \beta^2 Risk_{i,t-1} + \beta^3 TBTF_{i,t-1} \times Risk_{i,t-1} + \beta^4 Bond\ Controls_{i,b,t} + \beta^5 Firm\ Controls_{i,t-1} + \beta^6 Macro\ Controls_t + Firm\ FE + Year\ FE + \varepsilon_{i,b,t}$ are reported in Panel A. 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. In column 7, we also include interactions for two other size dummy variables: *size60* is a dummy variable equal to one if a given financial institution's size is between the 60th and 90th percentiles. *size30* is a dummy variable equal to one if a given financial institution's size is between the 30th and 60th percentiles. *Risk* of a financial institution is measured by distance-to-default (*mertondd*) in columns 1 and 7, 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 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. In column 8, we include interactions with the squared term of the risk variable. For brevity, we do not report coefficients on the control variables in Panel A. Panel B reports regression results for the model $Spread_{i,b,t} = \propto + \beta^1 TBTF_{i,t-1} + \beta^2 Risk_{i,t-1} + \beta^3 TBTF_{i,t-1} \times Risk_{i,t-1} + \beta^4 Financial_{i,} + \beta^5 Financial_i \times TBTF_{i,t-1} + \beta^6 Financial_i \times Risk_{i,t-1} + \beta^7 Financial_i \times Risk_{i,t-1} \times TBTF_{i,t-1} + \beta^8 Bond\ Controls_{i,b,t} + \beta^9 Firm\ Controls_{i,t-1} + \beta^{10} Macro\ Controls_t + Firm\ FE + Year\ FE + \varepsilon_{i,b,t}$. *Risk* and *TBTF* variables are the same as in Panel A. *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 in Panel B. Standard errors are reported in parentheses below their coefficient estimates and are adjusted for both heteroscedasticity and within correlation clustered at the issuer level. ***, **, and * indicate significance at the 1%, 5%, and 10% two-tailed levels, respectively.

PANEL A

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	mertondd	zscore	volatility	adj-mertondd	ewma-mertondd	dd-beta	mertondd	mertondd
$size90_{t-1}$	-2.022***	-1.305***	0.876***	-1.819**	-1.211***	-0.172*	-2.846***	-3.519***
	(0.568)	(0.401)	(0.256)	(0.896)	(0.384)	(0.091)	(0.629)	(0.959)
$risk\_measure_{t-1}$	-0.446***	-0.336***	4.885***	-0.467***	-0.097***	0.142*	-0.524***	-1.521***
	(0.082)	(0.082)	(1.106)	(0.112)	(0.021)	(0.076)	(0.092)	(0.376)
$size90_{t-1} \times risk\_measure_{t-1}$	0.332***	0.266**	-3.342***	0.399**	0.104***	-0.295**	0.418***	1.121***
	(0.091)	(0.115)	(0.824)	(0.187)	(0.034)	(0.131)	(0.096)	(0.348)
$size60_{t-1}$							-1.186	
							(0.926)	
$size60_{t-1} \times risk\_measure_{t-1}$							0.078	
							(0.109)	
$(risk\_measure_{t-1})^2$								0.113***
								(0.032)
$size90_{t-1} \times (risk\_measure_{t-1})^2$								-0.087***
								(0.031)
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Rating Dummies	Y	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Observations	39,125	37,856	39,125	39,125	39,125	38,344	39,125	39,125
R^2	0.457	0.429	0.492	0.326	0.425	0.438	0.465	0.484

PANEL B

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)
$financial_{t-1}$	0.482	0.162	0.558^{*}	0.268	0.011	-0.540^{**}
	(0.598)	(0.407)	(0.313)	(0.586)	(0.391)	(0.228)
$financial_{t-1} \times size90_{t-1}$	-1.554^{**}	-1.445^{**}	0.721^{*}	-1.225^{*}	-0.739	0.092
	(0.746)	(0.579)	(0.377)	(0.725)	(0.476)	(0.241)
$risk\_measure_{t-1}$	-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)
$financial_{t-1} \times risk\_measure_{t-1}$	-0.149	-0.134	-2.740^{***}	-0.130	-0.040	0.284^{**}
	(0.091)	(0.101)	(1.057)	(0.091)	(0.032)	(0.114)
$financial_{t-1} \times risk\_measure_{t-1} \times size90_{t-1}$	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 4: TBTF and Risk-Shifting

Columns 1-4 report regressions results for the model $\Delta D/V_{i,t} = \propto + \beta^1 \Delta s_{A_{i,t}} + \beta^2 TBTF_{i,t} + \beta^3 TBTF_{i,t} \times \Delta s_{A_{i,t}} + Year\ FE + \varepsilon_{i,t}$. 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 90th 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, $\Delta IPP_{i,t} = \propto + \beta^1 \Delta s_{A_{i,t}} + \beta^2 TBTF_{i,t} + \beta^3 TBTF_{i,t} \times \Delta s_{A_{i,t}} + Year\ FE + \varepsilon_{i,t}$. *ΔIPP* is the fair insurance premium per dollar of liabilities computed following Merton (1977). The estimation is described in Appendix A. Standard errors are reported in parentheses below their coefficient estimates and are adjusted for both heteroscedasticity and within correlation clustered at the issuer level. ***, **, and * indicate significance at the 1%, 5%, and 10% two-tailed levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Δ D/V	Δ D/V	Δ D/V	Δ D/V	Δ IPP	Δ IPP	Δ IPP	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)		
Δ asset vol × size $_{t-1}$		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)
Δ asset vol × size90 $_{t-1}$			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

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 reported in parentheses below their coefficient estimates and are adjusted for both heteroscedasticity and within correlation clustered at the issuer level. ***, **, and * indicate significance at the 1%, 5%, and 10% two-tailed levels, respectively.

Panel A

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

Panel B

VARIABLES	(1) issuer rating	(2) issuer rating	(3) stand-alone	(4) stand-alone
leverage $_{t-1}$	-19.374**	-25.011***	-2.654	-3.474
	(8.490)	(6.312)	(5.209)	(4.786)
roa $_{t-1}$	-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 $Spread_{i,b,t} = \propto + \beta^1 post + \beta^2 TBTF_{i,t} \times post + \beta^3 Financial_{i,t} \times post + \beta^4\ Risk_{i,t} \times post + \beta^5 TBTF_{i,t} \times Financial_{i,t} \times post + \beta^6 TBTF_{i,t} \times Risk_{i,t} \times post + \beta^7 Financial_{i,t} \times Risk_{i,t} \times post + \beta^8 TBTF_{i,t} \times Financial_{i,t} \times Risk_{i,t} \times post + \beta^9 Macro\ Controls_t + Issue\ FE + \varepsilon_{i,b,t}$ 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 5 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 reported in parentheses below their coefficient estimates and are adjusted for both heteroscedasticity and within correlation clustered at the issuer level. ***, **, and * indicate 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) $size90_{t-1} \times mertondd_{t-1} \times financial_{t-1} \times post$
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)
09/15/08	Lehman Brothers files for bankruptcy	1.005***	-1.464***	1.086***	-1.437***
		(0.329)	(0.293)	(0.436)	(0.184)
06/29/10	The House and the Senate conference committees	-0.034*	0.039*	-0.003	0.033
	reconcile the Dodd-Frank bill	(0.019)	(0.021)	(0.022)	(0.023)
07/21/10	President Obama signs Dodd-Frank into law	0.027*	-0.019	0.017	-0.016
		(0.016)	(0.014)	(0.019)	(0.015)
12/10/12	The FDIC and the Bank of England release a white paper	0.037***	-0.028**	0.030**	-0.029**
	and press release describing SPOE	(0.012)	(0.014)	(0.014)	(0.014)

Table 8: Impact of Dodd-Frank

Regression results for the model $Spread_{i,b,t} = \propto + \beta^1 \times Bond\ controls_{i,b,t} + \beta^2 \times guarantee_{i,b,t} + \beta^3 \times guarantee_{i,b,t} \times post + \beta^4 \times mertondd_{i,t-1} + \beta^5 mertondd_{i,t-1} \times post + \beta^6 \times guarantee_{i,b,t} \times mertondd_{i,t-1} + \beta^7 \times guarantee_{i,b,t} \times mertondd_{i,t-1} \times post + Issuer \times Trading\ day\ FE + \varepsilon_{i,b,t}$ 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 (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 reported in parentheses below their coefficient estimates and are adjusted for both heteroscedasticity and within correlation clustered at the issuer level. ***, **, and * indicate significance at the 1%, 5%, and 10% two-tailed levels, respectively.

	(1)	(2)	(3)	(4)
VARIABLES	spread	spread	spread	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 10: 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 reported in Panel A of this table. 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 $Spread_{i,b,t} = \propto + \beta^1 TBTF_{i,t-1} + \beta^2 Risk_{i,t-1} + \beta^3 Bond\ Controls_{i,b,t} + \beta^4 Firm\ Controls_{i,t-1} + \beta^5 Macro\ Controls_t + \beta^6 Bond\ Liquidity_{i,b,t} + Year\ FE + \varepsilon_{i,b,t}$ are reported in Panel B of this table. 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 reported in parentheses below their coefficient estimates and are adjusted for both heteroscedasticity and within correlation clustered at the issuer level. ***, **, and * indicate significance at the 1%, 5%, and 10% two-tailed levels, respectively

PANEL A:

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:

VARIABLES	(1) spread	(2) spread	(3) spread
mertondd $_{t-1}$	-0.263***	-0.364***	-0.591***
	(0.019)	(0.038)	(0.145)
size90 $_{t-1}$	-0.168**	-0.353***	-2.743***
	(0.067)	(0.143)	(1.005)
liquidity $_{t-1}$	-0.100***		
	(0.027)		
lambda$_{t-1}$		0.076***	0.068**
		(0.015)	(0.026)
size90$_{t-1}$× mertondd $_{t-1}$			0.457***
			(0.164)
Constant	-0.665**	3.876***	4.473***
	(0.289)	(0.920)	(1.573)
Year FE	Y	Y	Y
Rating FE	Y	Y	Y
Controls	Y	Y	Y
Observations	39,125	13,638	13,638
R^2	0.521	0.555	0.601

Appendix A: Variable Descriptions

Variable	Description
Bond characteristics	
spread	The difference between the yield on a firm's bond and the yield on a maturity-matched Treasury bond. Spread is in percentages.
ttm	Year to maturity.
seniority	Dummy variable indicating whether the bond is senior.
age	Age of the bond since issuance in years.
puttable	Dummy variable set equal to 1 if the bond is puttable.
redeemable	Dummy variable set equal to 1 if the bond is redeemable.
exchangeable	Dummy variable set equal to 1 if the bond is exchangeable.
fixrate	Dummy variable set equal to 1 if the bond has fixed rate coupons.
guarantee	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."
liquidity	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. The maximum liquidity value assigned to a bond is four and the minimum liquidity value is zero. The estimation is described in detail below.
amihud	Liquidity measure based on Amihud (2002). It is computed as the monthly average absolute value of daily returns divided by total daily dollar volume. This variable is computed using the TRACE database and is available only after 2003. The estimation is described in detail below.
roll	Liquidity measure based on Roll (1984). It is computed as two times the square root of the negative covariance between two consecutive price changes. This variable is computed using the TRACE database and is available only after 2003. The estimation is described in detail below.
range	Range-based liquidity measure. It is computed as the monthly average of the difference of the high and low price of a given bond scaled by square root of volume in a given trading day. This variable is computed using the TRACE database and is available only after 2003. The estimation is described in detail below.
zeros	Liquidity measure based on trading activity. It is computed as the percentage of days during a month in which the bond did not trade. This variable is computed using the TRACE database and is available only after 2003.
lambda	Liquidity measure computed by aggregating the *amihud*, *roll*, *range* and *zeros* measures. The four liquidity measures are standardized for each bond each month by subtracting the mean and standard deviation of the liquidity measures computed for the full sample. The four standardized liquidity measures are then aggregated for each bond. This variable is computed using the TRACE database and is available only after 2003.
Firm characteristics	
size	Size of a financial institution defined as the log value of total assets.
size90	Dummy variable that equals 1 if an issuer's size is greater than the 90th percentile of its distribution in that fiscal year and 0 otherwise.
size60	Dummy variable that equals 1 if an issuer's size is greater than the 60th percentile of its distribution in that fiscal year but less than or equal to the 90th percentile and 0 otherwise.

size30	Dummy variable that equals 1 if an issuer's size is greater than the 30th percentile of its distribution in that fiscal year but less than or equal to the 60th percentile and 0 otherwise.
size_top_10	Dummy variable that equals 1 if an issuer ranks in the top ten in terms of size in that fiscal year and 0 otherwise.
financial	Dummy variable that equals 1 if the company is a financial firm defined as having an SIC code starting with 6.
bank dummy	Dummy variable that takes on a value of one for firms with SIC codes that start with 60 and 61 and firms with SIC code 6712.
insurance dummy	Dummy variable that takes on a value of one for firms with SIC codes that start with 63 and 64.
broker dummy	Dummy variable that takes on a value of one for firms with SIC codes that start with 62.
stand-alone rating	Fitch individual rating, which is a number between 1 and 9, with 1 indicating the highest issue quality.
issuer rating	Fitch long term issuer rating, which is a number between 1 and 9, with 1 indicating the highest issue quality.
covar	Covar measure of systemic fragility, as described below.
srisk	Systemic risk based on expected capital shortfall, as described below.
leverage	Total liabilities divided by total assets.
roa	Return on assets, measured as net income divided by total assets.
std roa	Standard deviation of *roa* computed over 5 years.
mb	Market value of total equity divided by book value of total equity.
mismatch	Short-term debt minus cash divided by total liabilities.
mertondd	Merton's distance-to-default measure, as described below.
adj-mertondd	Merton's distance-to-default measure, calculated using scaled standard deviations for firms in the 90th percentile in terms of size to match the average standard deviations of all other firms in a given month.
ewma-mertondd	Merton's distance-to-default measure, calculated using standard deviations computed using the exponentially weighted moving average method with weight factor of 0.94.
dd-beta	Merton's distance-to-default beta, obtained by 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 past 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.
zscore	Z-score, calculated as the sum of *roa* and equity ratio (ratio of book equity to total assets), averaged over four years, divided by the standard deviation of *roa* over four years.
volatility	Stock return volatility computed using returns over the past 12 months.
D/V	Book value of debt divided by the market value of assets. Market value of assets is computed using the Merton model.
IPP	IPP is the fair insurance premium per dollar of liabilities computed following Merton (1977). The estimation is described in detail below.
asset vol	Volatility of market value of assets computed using the Merton model.
Macro controls	
mkt	Market risk premium, computed as the CRSP value weighted stock return minus the risk free-rate.
term	Term structure premium, measured by the yield spread between long-term (10-year)

	Treasury bonds and short-term (three-month) Treasuries.
def	Default risk premium, measured by the yield spread between BAA-rated and AAA-rated corporate bonds.

Merton Measure of Credit Risk

We follow Campbell, Hilscher and Szilagyi (2008) and Hillegeist et al. (2004) in calculating Merton's (1974) distance-to-default. The market equity value of a company is modeled as a call option on the company's assets:

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

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

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

We simultaneously solve equations (A1) and (A2) to find the values of V_A and s_A. We use the market value of equity for V_E and total liabilities to proxy for the face value of debt, X.[27] Since the accounting information is on an annual basis, we linearly interpolate the values for all dates over the period, using end of year values for accounting items. The interpolation method has the advantage of producing a smooth implied asset value process and avoids jumps in the implied default probabilities at year end. s_E is the standard deviation of daily equity returns over the past 12 months. In calculating standard deviation, we require the company to have at least 90 non-zero and non-missing returns over the previous 12 months. T equals one year, and r is the one-year Treasury bill rate, which we take to be the risk-free rate. The dividend rate, d, is the sum of the prior year's common and preferred dividends divided by assets. We use the Newton method

[27] For financial firms, we have found similar results using short-term debt plus the currently due portion of long-term liabilities plus demand deposits as the default barrier.

to simultaneously solve the two equations above. For starting values for the unknown variables, we use $V_A = V_E + X$ and $s_A = s_E V_E/(V_E+X)$. After we determine asset values V_A, we follow Campbell, Hilscher and Szilagyi (2008) and assign asset return *m* to be equal to the equity premium (6%).[28] Merton's (1974) distance-to-default (*dd*) is finally computed as:

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

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

Covar Measure of Systemic Fragility

Following Adrian and Brunnermeier (2011), we compute a conditional value-at-risk measure (*covar*) for each of the financial institutions in our sample using quantile regression. *Covar* is the value-at-risk (Var) of the financial system conditional on institutions being under distress. A financial institution's contribution to systemic risk is the difference between *covar* conditional on the institution being under distress and the *covar* in the normal state of the institution. Following Adrian and Brunnermeier (2011), we compute a time-series of *Covar* measures for each bank using quantile regressions and a set of macro state variables. We run the following quantile regressions over the sample period:

$$\Delta BankDD_{i,t} = \propto_i + \gamma_i M_{t-1} + \varepsilon_{i,t}$$
$$\Delta SystemDD_t = \propto_{system|i} + \beta_{system|i}\,\Delta BankDD_{i,t} + \gamma_{system|i} M_{t-1} + \varepsilon_{system|i,t} \tag{A4}$$

where $\Delta BankDD_{i,t}$ is the change in the Merton (1974) distance-to-default variable for bank *i* in week *t* and $\Delta SystemDD_t$ is similarly the change in the value-weighted Merton distance-to-default variable for all financial firms in the sample. M_{t-1} are lagged state variables and include the change in the term spread (*term*), the change in the default spread (*def*), the CBOE implied volatility index (*vix*), the S&P 500 return (*spret*), and the change in the 3-month T-bill rate

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

(*rate*). The *covar* variable is then computed as the change in the Var of the system when the institution is at the q^{th} percentile (or when the institution is in distress) minus the Var of the system when the institution is at the 50% percentile:

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

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

SRISK Measure of Systemic Expected Shortfall

The second systemic risk measure we use is based on the expected capital shortfall framework developed by Acharya, Engle and Richardson (2012) and Acharya at al. (2010). The systemic expected shortfall of an institution describes the capital shortage a financial firm would experience in case of a systemic event. The capital short fall depends on the firm's leverage and equity loss conditional on an aggregate market decline:

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

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

Measure of Risk-Shifting

We follow Bushman and Williams (2012) and Hovakimian and Kane (2000) and use the Merton (1974) contingent claim framework to calculate asset return volatility (s_A) and the fair value of the insurance put-option per dollar of liabilities (*IPP*). IPP is computed as:

$$IPP = N\left(\frac{log\left(\frac{X}{V_A}\right)+\frac{s_A^2}{2}T}{s_A\sqrt{T}}\right)-\left(\frac{V_A}{X}\right)N\left(\frac{log\left(\frac{X}{V_A}\right)-\frac{s_A^2}{2}T}{s_A\sqrt{T}}\right) \tag{A7}$$

where V_A is the value of the bank's assets, X is the face value of debt maturing at time T, and s_A is the volatility of the market value of bank assets. V_A and s_A are computed using Merton's (1974) model.

Liquidity Measures

We compute two sets of 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 described in the next paragraph. Second, a liquidity measure is computed for the full time period, including years prior to 2003. We compute a liquidity measure (*liquidity*) based on bond characteristics following Longstaff, Mithal and Neis (2005). In particular, a dummy variable is set each month to a value of one or zero depending on the characteristics of the underlying bond. We then add up the dummy variables to compute an overall liquidity score. The first dummy variable captures the general availability of the bond issue in the market. If the outstanding market value of a bond is larger than the median value of all bonds, then the dummy variable is assigned a value of one. The second variable is the age of the bond and parallels the notion of on-the-run and off-the-run bonds in Treasury markets, with on-the-run bonds being more liquid. If the age of a bond is less than the median age of all bonds then the dummy variable is assigned a value of one. The third variable is the time-to-maturity of the bond. It has been shown that there exist maturity clienteles for corporate bonds and that shorter-maturity corporate bonds tend to be more liquid than longer-maturity bonds. If the time to maturity of a bond is less than seven years, then the dummy variable is assigned a value of one. The fourth proxy that we use is a dummy variable for bonds rated AAA/AA. As Longstaff, Mithal and Neis (2005) show, highly rated bonds tend to be more marketable and liquid in times of distress when there is a "flight to quality." The maximum liquidity value assigned to a bond is four and the minimum liquidity value is zero.

For the time period starting in 2003, we create four different measures of liquidity using transaction data, as well as an aggregate measure computed from the four individual liquidity measures. 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:

$$Amihud_{i,t} = \frac{1}{N_{i,t}} \sum_{k=1}^{N} \frac{|r_{i,k}|}{volume_{i,k}} \tag{A8}$$

Above, *k* is the number of days with valid returns in month *t* for bond *i*. $r_{i,k}$ is the return observed for the bond *i* on day *k*, and $volume_{i,k}$ is the total volume traded on day *k*. $N_{i,t}$ is the number of return observations in month *t*. Following Crotty (2013), we require returns to be computed from bond prices observed at most 5 days apart. We also require minimum of 5 returns in a given month to compute the *amihud* measure.

The second measure we use is the Roll proxy of bid-ask spreads, based on the work of Roll (1984). The *roll* measure is designed to capture transitory price movements induced by lack of liquidity for a bond. Following Bao, Pan, and Wang (2011) and Dick-Nielsen, Feldhutter and Lando (2012), we compute the *roll* measure as the covariance of consecutive price changes:

$$Roll_{i,t} = 2\sqrt{-Cov\left(\Delta P_{i,k}, \Delta P_{i,k-1}\right)} \tag{A9}$$

$P_{i,k}$ is the price of transaction *k* for bond *i* in month *t*. We require a minimum of 5 price changes in a month to compute the *roll* measure.

The third measure we use is based on daily price range proposed by Jirnyi (2010). The *range* measure is similar to *amihud* and is meant to capture the price impact of a trade. *Range* is computed as:

$$Range_{i,t} = \frac{1}{N_{i,t}} \sum_{k=1}^{N} \frac{P_{i,k}^{High} - P_{i,k}^{Low}}{volume_{i,k}} \tag{A10}$$

$P_{i,k}^{High}$ is the high price and $P_{i,k}^{Low}$ the low price for bond *i* on day *k*. $volume_{i,k}$ is the total volume traded on day *k*. $N_{i,t}$ is the number of price observations in month *t*. We include only days in which the high and low prices differ in computing the *range* measure.

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 a liquidity measure, *lambda*, that aggregates the four liquidity measures described above. Following Dick-Nielsen, Feldhutter and Lando (2012), we standardize each liquidity measure for each bond each month by subtracting the mean and standard deviation of the liquidity measure computed over the full sample. We then aggregate the four standardized liquidity measures for each bond to compute *lambda*.

Appendix B. Additional Results

Table BI: Impact of Dodd-Frank

Regression results for the model $spread = \propto + \beta^1 post + \beta^2 TBTF_{i,t} \times post + \beta^3 mertondd_{i,t} \times post + \beta^4 TBTF_{i,t} \times mertondd_{i,t} \times post + \beta^5 Macro\ Controls_t + Issuer\ FE + \varepsilon_{i,b,t}$ are reported in this table. 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. *mertondd* is Merton's (1974) distance-to-default measure, calculated using firm-level financial and stock return data, as described in Appendix A. The event date is June 29, 2010 (Dodd-Frank). The variable *post* equals 1 if the transaction date is the event date or one of the 132 trading days following the event date, and 0 if the transaction date is one of the 132 trading days prior to the event date. The control variables are described in Table 1 and in Appendix A. Standard errors are reported in parentheses below their coefficient estimates and are adjusted for both heteroscedasticity and within correlation clustered at the issuer level. ***, **, and * indicate significance at the 1%, 5%, and 10% two-tailed levels, respectively.

VARIABLES	(1) spread	(2) spread
ttm	0.031*	0.031*
	(0.018)	(0.018)
seniority	-0.213	-0.212
	(0.203)	(0.204)
leverage $_{t-1}$	4.951***	4.425***
	(1.568)	(1.343)
roa $_{t-1}$	-2.395	-2.738
	(4.138)	(3.517)
mb $_{t-1}$	0.059	0.244
	(0.145)	(0.173)
mismatch $_{t-1}$	-1.705***	-0.993
	(0.592)	(0.842)
def	0.512*	0.547*
	(0.277)	(0.280)
term	-0.130	-0.124
	(0.102)	(0.102)
mkt	2.377	2.481
	(3.406)	(3.427)
mertondd $_{t-1}$	-0.012	-0.266
	(0.111)	(0.179)
size90 $_{t-1}$	-0.722***	-0.499**
	(0.130)	(0.191)
post	-0.225**	-0.591***
	(0.102)	(0.217)
size90 $_{t-1}$* post	0.077	0.550*
	(0.094)	(0.276)
mertondd $_{t-1}$* post		0.237*
		(0.123)
size90 $_{t-1}$* mertondd $_{t-1}$ *post		-0.370*
		(0.187)
Constant	1.939**	2.130***
	(0.755)	(0.701)
Firm FE	Y	Y
Year FE	Y	Y
Rating Dummies	Y	Y
Observations	1,810	1,810
R^2	0.547	0.548