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Abstract

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JEL Classification: G21, G24, G28

Keywords: Too Big To Fail, Dodd-Frank, bailout, implicit guarantee, moral hazard

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

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Abstract

Using unsecured bonds traded in the U.S. from 1990 to 2020, we examine the sensitivity of credit spreads to changes in firm risk. In the time period preceding the implementation of the Dodd-Frank Act, we find that credit spreads were less sensitive to risk for large financial firms compared to small financial firms and compared to large non-financial firms. This lack of spread-risk sensitivity is consistent with investors expecting government guarantees on unsecured debt of large financial firms. In the post-Dodd Frank period after 2012, we do not observe differences in this sensitivity by firm size. These results are consistent with a strengthening of market discipline in the aftermath of the policy reforms implemented following the financial crisis.

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1. Introduction

The financial sector received an unprecedented amount of government support during the global financial crisis of 2008. The nature and the magnitude of this support raised significant concerns about moral hazard arising from investor expectations of government bailouts of large financial firms. The financial crisis also highlighted the weaknesses in regulations that were in place to supervise and resolve large systemically important financial institutions. As a response to the crisis, the Dodd-Frank Wall Street Reform and Consumer Protection Act (Dodd-Frank) was created and passed into law on July 2010 with the goal of strengthening market discipline and limiting the economic damage posed by large financial institutions.

In this paper, we examine the risk sensitivity of spread on unsecured debt in the financial and non-financial sectors in the U.S. over the 1990 to 2020 time period. We find that in the time period preceding the implementation of the Dodd-Frank Act, the unsecured bond spreads were less sensitive to measures of risk for large financial institutions compared to smaller financial institutions, and large financial institutions compared to large non-financial firms. In the post-Dodd Frank period after 2012, we do not observe significant differences in this spread-risk sensitivity based on firm size. Overall, our results are consistent with a strengthening of market discipline in the aftermath of the policy reforms that were implemented following the financial crisis.

The differences in spread-risk sensitivity we observe in the pre-Dodd-Frank time period are consistent with investors expecting a government guarantee to support unsecured creditors of large financial institutions in times of distress. This expectation of support can result from the government following a too-big-to-fail (TBTF) policy of not allowing large financial institutions to fail because their failure would cause significant disruption to the financial system and economic activity. The expectation by the market that the government may provide a bailout is commonly referred to as an implicit guarantee; implicit because the government does not have any explicit, ex-ante commitment to intervene. In the absence of an implicit government guarantee, market participants would evaluate an institution's financial condition and incorporate those assessments into securities' prices, in particular demanding higher yields on uninsured debt in response to greater risk-taking by the financial institution.

However, for the market to discipline financial institutions in this manner, debtholders must believe that they will bear the cost of an institution becoming insolvent or financially distressed. An implicit government guarantee weakens market discipline by reducing investors' incentives to monitor and price the risk taking of potential TBTF candidates. In turn, anticipation of government support for major financial institutions could enable these institutions to borrow at costs that do not reflect the risks otherwise inherent in their operations compared to other industries. The implicit nature of the TBTF guarantee also implies that investors may not expect the government to always implement TBTF policies. The possibility of a bailout may exist in theory but not reliably in practice, and as a result, market participants may not price an implicit guarantee fully.[5]

In this paper, we explore these issues relating to investor expectations of TBTF implicit government guarantees by distinguishing between large and small financial institutions based on the size of their balance sheet assets. We define institutions that are in the 90th percentile in terms of assets in a given year as large financial institutions. To determine whether unsecured bondholders of major financial institutions expect government support, we estimate how the size of a financial institution affects the relationship between the firm's credit spread and its risk, which we refer to as the spread-risk sensitivity.

We position our empirical analyses within the structural credit risk models of Merton (1974) and Merton (1977). In the structural models, the credit spreads of firms increase with asset volatility and leverage. The structural models also provide a link between equity returns and bond returns through their exposures to the underlying firm value. In particular, the hedge ratio – the derivative of changes in debt value to changes in equity values – determine the sensitivity of bond returns to equity returns. As the risk of a firm increases, the correlation between its equity returns and its debt returns also increases (Schaefer and Strebulaev 2008). To motivate our analyses, we introduce analytically the possibility of a government guarantee to the Merton (1974) model. We assume that the government will intervene and cover loses of creditors in the event a financial institution fails. We show analytically that the existence of the government guarantee dampens the relationship between credits spreads and asset volatility and the relationship between credit

[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 announce their willingness to support institutions they consider too big to fail. Rather, they prefer to be ambiguous about which troubled institutions, if any, would receive support. Ever since the U.S. Comptroller of the Currency named 11 banks as "too big to fail" in 1984, authorities have walked a thin line between supporting large institutions and declaring that support was neither guaranteed nor to be expected, permitting institutions to fail when possible to emphasize the point. This has led authorities to take a seemingly random approach to intervention, for instance by saving AIG but not Lehman Brothers, in order to make it difficult for investors to rely on a government bailout.

spreads and leverage. Similarly, we show analytically that the existence of a government guarantee also reduces the sensitivity of bond returns to equity returns.

In the empirical analyses, we use asset volatility, leverage and the Merton's distance-to-default as our primary risk measures. As there are limitations to the structural models of credit risk when applied to financial firms, for robustness we also use the Nagel and Purnandam (2020) extension of the Merton model for financial institutions, the S&P credit rating, and an accounting-based measure of risk (z-score) as additional risk measures.

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

In the pre-Dodd-Frank time period from 1990 to 2011, we find that the spread-risk sensitivity is significantly weaker for the largest financial institutions. Importantly, we show that the relation between firm size and the risk sensitivity of bond credit spreads is not present in non-financial firms during this time period. We find similar results when we examine the sensitivity of bond returns to equity returns. We find that the positive correlation between bond and equity returns is significantly weaker for larger financial firms in the pre-Dodd-Frank period.

We also examine risk-shifting behavior of financial institutions based on the deposit insurance pricing model of Merton (1977). Such risk-shifting occurs when financial institutions are able to increase the value of the deposit insurance without fully internalizing the cost of increased insurance. Absent government guarantees uninsured creditors have incentives to discipline such bank risk-taking by limiting the amount they are willing to lend to these firms. As the risk of financial institutions increases, there is growing market pressure on these firms to reduce their leverage. In the empirical analyses, we examine the relative strength of these competing forces. In the pre-Dodd-Frank time period, we find that large financial institutions have a greater ability to shift risk than their smaller counterparts. We find similar results when we repeat the analyses using non-financial institutions as controls.

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

How are these results affected in the post-Dodd-Frank period? In the aftermath of the financial crisis, regulators adopted ending moral hazard and TBTF as one of their main policy objectives. The Dodd-Frank Act came into law on July 2010 and set-up a new macro-prudential framework to govern bank behavior. An important component of new regulations has been to develop rules and procedures to resolve large financial institutions while minimizing the destabilizing effect their resolution may have on the financial system.[6] With this goal in mind, the Federal Deposit Insurance Corporation (FDIC) has created a detailed plan to resolve large financial institutions using a 'single point of entry' (SPOE) approach. Under this approach, FDIC has the authority to create a new bridge company that can take over a failed institution at the bank holding company level. This allows business lines under the holding company (such as insurance and commercial banking arms) to continue operating independently. Under the new SPOE approach, supervisors can assign losses to specific claimants of a failed institution significantly weakening market expectations of a bailout.[7]

However, there have been some criticisms of these regulatory changes and resolution processes, with some critics suggesting that the reforms have not eliminated the potential for government bailouts of large financial institutions. First, by explicitly defining systemically important institutions, some argue that the regulatory authorities are reinforcing expectations of support to large financial institutions when they get into trouble.[8] Companies may be incentivized

[6] Other important changes include higher capital and liquidity requirements, additional capital surcharges for institutions deemed systemically important, and enhanced supervision of risk management and risk reporting processes at banks including periodic stress tests.

[7] As part of Dodd-Frank, large financial institutions are also required to submit resolution plans, so called "living wills," to the FDIC. These resolution plans describe the institution's strategy for orderly resolution and liquidation in the event of a failure of the institution.

[8] There is some evidence of positive stock price reactions to institutions being designated as systemically important (Dewenter and Riddick 2018). On the other hand, there have also been cases of firms trying to avoid the

to become large enough to qualify under the new resolution rules because the market would provide them cheaper cost of funding (Skeel 2011). Second, the new resolution policies may give too much discretion to the regulatory authorities, and critics suggest that a modified bankruptcy code may be a better approach to resolving large financial institutions (Jackson and Skeel 2012). Ultimately, the FDIC has discretion to potentially take politically motivated action that could result in creditors being treated differently than they anticipated and taxpayer funds to be at risk.

Given these conflicting views, it is important to evaluate the efficacy of the rules and regulations that have been put in place in the aftermath of the financial crisis. To this end, we repeat the spread-risk sensitivity analyses for the post-Dodd-Frank time period from 2012 to 2020. We use a longer window of years to take into account the fact that Dodd-Frank has gone through changes and was implemented in various stages over time. It is important to note that the capital and liquidity positions of financial institutions have improved as a result of these reforms and financial institutions are significantly more resilient than they were in 2007. However, we should note that while the risk of an average financial institution has declined, what we are interested in and what we examine is the sensitivity of credit spreads to risk. In other words, if credit spreads continue to incorporate the expectation of government support, then we would still observe differences in risk-sensitivity between large and small financial institutions even with lower risk levels and lower default probabilities.

We find that there has been a significant increase in spread-risk sensitivity of unsecured bonds of the largest financial institutions after the implementation of regulatory changes. In particular, we find that there are no significant differences between large financial firms and their small counterparts in the post-Dodd-Frank era. We find consistent results using different measures of risk described earlier. Our results are similar when we use non-financial firms as a control group and compare the spread-risk sensitivity of large financial firms to large non-financial firms.

When examine the sensitivity of bond returns to equity returns, we again find no significant differences between large financial and small financial firms in the post-Dodd-Frank period. We also find consistent results examining the risk-shifting behavior of financial institutions. Large financial institutions were able to shift risk onto tax-payers in the pre-Dodd-Frank era but are not able to do so in the post-Dodd-Frank time period. As before, we find results to be consistent also

systemically important designation. Met Life, for instance, successfully sued to avoid the systemically important classification and General Electric reorganized to become smaller in order to avoid the new resolution rules.

using non-financial firms as a control group.

Finally, we use the Covid-19 pandemic and the various interventions in the capital markets by the Treasury and the Federal Reserve as possible shocks to investor expectations and examine changes in spreads in response to these interventions using the event study approach described above. As the pandemic was largely unexpected and affected all financial institutions at the same time, it provides us with a plausibly exogenous shock to empirically assess the efficacy of the Dodd-Frank reforms that were implemented in response to the financial crisis. We examine changes in spreads around key policy announcements in March and April of 2020. In contrast to the shocks to investor expectations during the global financial crisis, we find no significant difference in changes in spreads between large and small financial institutions in response to these events.

As there were a number of policy interventions around the onset of the Covid-19 pandemic, we also use a longer time window to examine the risk-sensitivity of credit spreads for the March 1, 2020 to March 31, 2020 time period, and separately for the March 1, 2020 to June 31, 2020 time period. Again, we do not find significant differences in spread-risk sensitivity in either of the two time periods. Large financial institutions' credit spreads were not less sensitive to risk compared to smaller financial institution. Similarly, large financial institutions' credit spreads were not less sensitive to risk compared to large non-financial firms. These results are consistent with risk-sensitivity having increased for large financial firms' bonds returns, consistent with an effective dampening of TBTF expectations after Dodd-Frank.

Our paper contributes to a large literature on market discipline. One of the earlier studies, Gorton and Santomero (1990) uses an option pricing framework to derive an explicit pricing model for subordinated debt and show that there is weak relationship between accounting measures of risk and volatility of bank assets derived from the pricing model. Other studies (Flannery 1998; Calomiris 1999; Levonian 2000; DeYoung et al. 2001; Jagtiani, Kaufman, and Lemieux 2002; Morgan and Stiroh 2000) present evidence that subordinated debt spreads do reflect the issuing bank's financial condition. However, our primary thesis is that the existence of risk-sensitive pricing does not necessarily mean that investors are not also pricing an implicit guarantee.

More closely related to our study is a strand of this literature that focuses on how the spread-risk sensitivity changes as investor perceptions of implicit government support changes. Flannery and Sorescu (1996) examine yield spreads on the subordinated debt of U.S. banks over the 1983-1991 period. 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. 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. Morgan and Stiroh (2005) using 11 banks that were declared “too big to fail” by the Comptroller of the Currency in 1984 determine that the spread-risk sensitivity was lower for the named TBTF banks than it was for other banks. They find that this flat relation for the TBTF banks existed during the 1984 bailout of Continental Illinois and persisted into the 1990s, even after the passage of FDICIA in 1991, contrary to the findings of Flannery and Sorescu (1996). Similarly, Balasubramnian and Cyree (2011) suggest that the spread-risk sensitivity dampened for the TBTF banks following the rescue of Long-Term Capital Management in 1998. These studies analyze the risk sensitivity of debt without explicitly differentiating potential TBTF candidates based on size from other banks and without using large non-financial firms as controls.

Closer to our study, Santos (2014) using initial bond issues shows that credit spreads are lower for bonds issued by the largest banks compared to bonds issued by small banks, as well as bonds issued by the largest and nonfinancial firms, consistent with expectations of support for large financial institutions. Afonso, Santos and Traina (2015) using Fitch support ratings to proxy for expected government support show that TBTF banks take on more risk and have higher impaired loans and net charge-offs. While Santos (2014) examines *levels* of spreads, we examine *sensitivity* of spreads to risk.

Other studies in the literature have taken different approaches to measuring funding cost differentials. One approach uses focus on the rating “uplift” that a financial institution receives from a rating agency as a result of expectations of government support. (Rime 2005; Haldane 2010; Ueda and Mauro 2012). Another approach uses differential deposit rates in interest rates paid on uninsured deposits for banks of different sizes (Jacewitz and Pogach 2018; Baker and McArthur 2009).[9] Although most research on implicit government guarantees has examined debt prices, some papers investigate equity prices (O’Hara and Shaw 1990; Ghandi and Lustig

[9] Jacewitz and Pogach (2018) find that deposit risk premium paid by the largest banks was 35 bps lower than the risk premium at other banks between 2007 and 2008, which disappeared following a regulatory change in the deposit limit. Baker and McArthur (2009) quantify the relative cost of funds for TBTF banks and other banks, before and after the crisis using deposit rates from FDIC.

2015; Ghandi, Lustig and Plazzi 2020; Minton, Stulz and Taboada 2019).[10] Lambert et. al (2014) provide an overview of these different approaches.

A smaller set of papers examines changes in TBTF expectations in the aftermath of the global financial crisis. A strand of this literature examines equity valuation impact of being designated as globally systemically important (GSIB) by the Financial Stability Board with mixed evidence.[11] Atkeson, d'Avernas, Eisfeldt, and Weill (2018), examine TBTF expectations embedded in the market-to-book ratios of banks, and find that post-Dodd-Frank reduction in TBTF expectations resulted in significantly lower market-to-book ratios. Sarin and Summers (2016) and Chousakos and Gorton (2017), however, argue that the post-Dodd-Frank decline in bank market-to-book ratios is the result of lower franchise values and profitability emanating from greater regulatory burden. Gorton and Tallman (2016), argue that TBTF policies may in fact be an optimal response to vulnerability of short-term debt runs.

Finally, Lindstrom and Osborne (2020) examine changes in the risk-sensitivity of credit spreads for 37 European banks after the implementation of requirements to hold bail-in bonds. They find that the risk sensitivity of banks' credit spreads increased after the reforms, and that the level and risk sensitivity of spreads on senior bail-in bonds were higher than those of comparable non-bail-in bonds. Cetorelli and Traina (2018) show that cost-of-capital of banks measured using accounting variables and analyst forecasts have increased after the introduction of living will regulations. Berndt, Duffie and Zhu (2021) examine the information content of credit default swap spreads with respect to the likelihood of government bailout.[12] They find large post-Dodd-Frank reductions in market-implied probabilities of government bailout from a calibrated model. Afonso, Blank, and Santos (2018) examining bond spreads of bank parent companies and their

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[10] O'Hara and Shaw (1990) find positive wealth effects accrued to shareholders of the eleven banks named TBTF by the Comptroller in 1984. Ghandi and Lustig (2015) examine equity data in the U.S. and show that large banks have lower cost of equity. Gandhi, Lustig and Plazzi (2020), examining international equity markets, also provide empirical evidence consistent with the idea that implicit government guarantees are priced in equity markets in developed countries. Minton, Stulz and Taboada (2019), on the other hand, find no evidence that large banks are valued more highly than other firms.

[11] Dewenter and Riddick (2018) and Zanghieri (2017) find significant positive equity price reaction for insurance companies; however the price reaction for banks is found to be mixed (Abreu and Gulamhussen 2013; Bongini, Nieri, and Pelagatti 2015). Schich and Toader (2018) find that the systemically important designation has not significantly altered the value of implicit guarantees as measured by rating uplifts for the largest banks.

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

subsidiaries find that the difference between parent and subsidiary spreads have not changed since the announcement of the SPOE approach. They conclude that the investors remain skeptical about the effectiveness new regulations aimed at ending TBTF.

Overall, we contribute to this vast literature by examining how risk is priced in unsecured debt markets for large financial institutions. We conduct a more detailed analysis of the role TBTF status plays in the spread-risk sensitivity than prior studies have done by formulating our analyses within a structural model of credit risk with guarantees. In addition to comparing large financial institutions to small financial institutions, we also compare larger financial firms to large non-financial firms and conduct event studies to address endogeneity concerns, and examine the long-run impact of policy reforms that were implemented in the aftermath of the global financial crisis.

In the next section, we describe the data and methodology. Our main results are described in Section 3. We conclude in Section 4. The online appendices include analytical derivations and additional empirical tests.

2. Data and Methodology

2.1. Corporate Bond Sample

We collect data for financial firms and non-financial firms that have bonds traded during the 1990-2020 period. Financial firms are classified using the Standard Industrial Classification (SIC) code 6. We exclude debt issued by government agencies and government-sponsored enterprises. Firm-level accounting and stock price information are obtained from Compustat and CRSP. 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 2006-2020 period. We also use the Fixed Income Securities Database (FISD) for bond descriptions. Although the bond dataset starts in 1980, it has significantly greater coverage starting in 1990.

Our sample includes all unsecured bonds issued in the U.S. by firms in the above datasets that satisfy common selection criteria in the corporate bond literature (e.g., Anginer and Yildizhan 2018; Anginer and Warburton 2014). We exclude all bonds that are matrix-priced (rather than market-priced). In our main analyses, we focus on plain vanilla bonds. 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. For robustness, we also repeat our analyses including all bonds and using dummies for bond characteristics; in particular, we set respective dummies equal to one if the bond is *puttable*, *redeemable*, *exchangeable*, or if the bond has fixed-rate coupons (*fixrate*). There are a number of extreme observations for the variables constructed from the bond datasets. To ensure that the results are not heavily influenced by outliers, we set all observations higher than the 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 399 unique financial institutions with 195,307 observations, and about 1,778 non-financial firms with 676,864 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.

2.2. Measures of Firm Risk and Systemic Importance

We are interested in systemically important financial institutions, as they are the most likely 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 on average tend to be highly correlated with the size of a financial institution's balance sheet. Adrian and Brunnermeier (2016), for instance, show that the systemic risk contribution of a given financial institution is driven significantly by the relative size of its assets. The Dodd-Frank Act also emphasizes size in defining systemically important financial institutions. Large size, even without significant interconnectedness, may carry political influence (Johnson and Kwak 2010).[13] Hence, our main measure of systemic importance

[13] There is also evidence that investors benefit from mergers and acquisitions that result in a bank achieving TBTF status (e.g., Kane 2000). Brewer and Jagtiani (2007) and Molyneux, Schaeck, and Zhou (2010) find that greater

is a dummy variable that takes on a value of one for financial institutions that are in the top 90th percentile of financial institutions ranked by assets in a given year (*size90*).

To determine whether bondholders of major financial institutions expect government support, we estimate how the size of a financial institution affects the relationship between the firm's credit spread and its risk. We also examine how this relationship has changed since the implementation of Dodd-Frank Act. Our analyses are positioned within the structural model of Merton (1974) and Merton (1977), extended to allow for government guarantees. In particular, we conduct three sets of analyses that are based on these models.

Our first set of results follows naturally from the Merton (1974) model that incorporates a potential government guarantee. In the structural models, Equity and Debt values of a firm are modeled as call and put options on a firm's assets:

$$\begin{gathered} D = AN(-d_1) + Xe^{-rT}N(d_2) \\ E = AN(d_1) - Xe^{-rT}N(d_2) \\ d_1 = \left(\ln\left(\frac{A}{X}\right) + \left(r + \frac{\sigma_A^2}{2}\right)T\right)/\sigma_A\sqrt{T}\,;\, d_2 = d_1 - \sigma_A\sqrt{T} \end{gathered} \tag{1}$$

Above, A is the value of firm's assets, E is the value of equity, D is the value of debt, X is face value of debt, T is time-to-maturity, r is the risk-free rate, σ_A is the volatility of firm's assets and N is the cumulative normal function. By re-arranging, we can express debt values in terms of default probabilities and recovery rates:

$$\begin{aligned} D &= Xe^{-rT}\big(1 - N(-d_2)\big) + N(-d_2)A\frac{N(-d_1)}{N(-d_2)} \\ &= Xe^{-rT}(1 - P_D) + P_D R \end{aligned} \tag{2}$$

Here, P_D is the risk-neutral probability of default, which is equal to the probability of asset values falling below the face value of liabilities, given by $N(-d_2)$. The d_2 term can be interpreted as 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. It is commonly referred to as "distance-to-default", the number of standard deviations the firm is away from the default boundary. The recovery amount R is equal to the conditional asset value when it falls below face value of liabilities ($A < X$) in the event of default. The debt value is equal to the probability of default multiplied by the expected recovery amount plus one minus the probability of default multiplied by the discounted face value of risk-

premiums are paid in larger M&A transactions, reflecting safety net subsidies. Similarly, Penas and Unal (2004) show that bond spreads also tend to decline after a bank merger when the resulting entity attains TBTF status.

free debt.

The debt values in equation (2) are in notional amounts. In order to make comparison across different debt and across firms, they are typically expressed in terms of credits spreads. In particular, the debt values can be expressed as the face value of debt discounted back to today using the risk-free rate plus a credit risk spread, *s*: $D = Xe^{-(r+s)T}$. In the structural models, the spreads increase with leverage ($\frac{X}{A}$) and asset volatility (σ_A). That is the first derivative of the spreads with respect to asset volatility and leverage is positive: $\partial s/\partial \sigma_A > 0$ and $\partial s\ /\partial \frac{X}{A} > 0$.

To motivate our analyses, we introduce the possibility of a government guarantee to the Merton model described above. We assume that in the event of default, government will intervene with probability P_G to fully cover losses on debt and make creditors whole. We further assume that the government will not cover losses on equity and that σ_A is not affected by government guarantees. With the potential of a government intervention, the debt values are now determined as:

$$D = Xe^{-rT}(1 - P_D + P_D P_G) + P_D(1 - P_G)R \tag{3}$$

In the event of default, there is a P_G chance that the government will intervene and the creditors will not suffer any losses. The expected recovered amount then becomes the probability of default multiplied by one minus the probability of government intervention multiplied by the expected recovery. In Appendix C, we show analytically that the existence of the government guarantee dampens the relationship between spreads and asset volatility and the relationship between spreads and leverage. That is the sensitivity of spreads to asset volatility and leverage decline with the probability of government intervention (P_G) to cover losses. In particular, we show that $\partial^2 s/\partial \sigma_A \partial P_G < 0$ and $\partial^2 s\ /\partial \frac{X}{A} \partial P_G < 0$.

In the empirical analyses, we use Merton's distance-to-default (*dd*) and its components as our primary risk measures. We follow Hillegeist et al. (2004) and Campbell, Hilscher, and Szilagyi (2008) in calculating Merton's distance-to-default. The details of the calculation are in Appendix A. A higher distance-to-default number signals a lower probability of insolvency. In the analyses, we use the natural log of distance-to-default multiplied by minus one such that higher values indicate greater risk. The two main drivers of the distance-to-default are asset volatility and leverage. Higher leverage and higher volatility of a firm's assets reduce distance-to-default and lead to higher default risk. In the analyses, we use leverage (*leverage*) and asset volatility (*assetvol*) calculated from the Merton model as additional risk variables. Asset volatility is calculated using the option pricing formula provided in equation (2). As asset volatility is unobserved and calculated from a model, we also use equity volatility (*equityvol*) calculated from daily equity returns over the past 12 months.

There are limitations to using Merton's original distance-to-default model for financial institutions. Equity values may also be impacted by potential government guarantees. Inflated market values would then make large financial firms appear less risky than they truly are in structural models that rely on market values of equity to derive market values of assets. Potential government guarantees could also reduce equity volatility. While these measures are therefore likely to underestimate the risk, we also use S&P credit rating (*rating*) and an accounting-based measure of risk (z-score) as additional measures of risk that do not rely on market valuations. We convert ratings to numeric scores ranging from 1 to 21 corresponding to S&P credit ratings from AAA to C, with higher numbers corresponding to greater credit risk. Z-score is 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 five years, divided by the standard deviation of return on assets over five years (Roy 1952). A higher z-score signals a lower probability of insolvency. A z-score is calculated only if we have accounting information for at least five years. We take the negative of log of z-score *(-log(zscore)*) such that higher values indicate greater risk. It is important to note, however, that although these measures are less likely to be affected by potential government guarantees, credit ratings may also reflect government support of financial institutions. Potential government support can also inflate firm profitability and lead to lower z-score values.

Another limitation of the structural model is the assumption of constant volatility. Nagel and Purnandam (2020) argue that bank assets are similar to put options on borrower's assets and that bank volatility increases after borrower assets decline in value. Assumption of constant volatility in the structural models can thus lead to underestimating risk in good times. They derive a modified version of the Merton model that takes into account the limited upside of bank assets. We follow their approach and derive a modified Merton's distance-to-default measure on a monthly basis. We use the modified distance-to-default measure (*NPdd*), as an additional measure of risk. In the analyses, we use the natural log of modified distance-to-default multiplied by minus one (*-log(NPdd))* such that higher values indicate greater risk.

In our second analysis, we examine the sensitivity of stock returns to bond returns which are linked through the hedge-ratio (the first derivative of changes in debt values with respect to changes in equity values) in the Merton model. While structural models of credit risk do a poor job of explaining the level of spreads (see for instance Huang and Huang 2003), Schaefer and Strebulaev (2008) show that the Merton's structural model works much better in explaining the sensitivity of changes in debt to changes in equity for non-financial corporates. They use the important insight that corporate bonds and equities (D and E) are linked through their exposures to the underlying firm value (A). The relationship between bond returns and equity returns is provided by the "equity hedge ratio" – the first derivative of changes in debt values to changes in equity values in the Merton model. Using the same notation as in equations (1) and (2), the hedge ratio is the first derivative of a firm's changes in debt values to changes in its equity values: $\partial D/\partial E = 1 \;/\; (N(d_1) - 1) \times (A/D - 1)$. As firms' asset values fall, the correlation between equity returns and debt returns increases. When the firm is near default, its debt trades like equity.

This, however, need not be the case for financial firms. If there's an expectation by market participants for the government to intervene and support its creditors when a large financial institution fails or is near default, then such an expectation of support will dampen the relationship between a financial institution's equity returns and its bond returns. At the extreme if the market expects a full guarantee on a financial institution's debt, then equity returns of the institution would have no correlation with the firm's bond returns. In Appendix C, we show that the existence of a government guarantee reduces the sensitivity of bond returns to equity returns. In particular we show that $\partial^2 s \Big/ \frac{\partial E}{E} \partial P_G < 0$; the sensitivity of spreads to equity returns declines with government guarantees. Empirically, we therefore examine the sensitivity of bond returns to equity returns. We calculate bond returns (*Dreturn*) on a monthly basis using end-of-month bond prices and coupon payments made during the month.

Our final analysis is that of the risk-shifting behavior of financial institutions based on the deposit insurance pricing model of Merton (1977). Merton (1977) models explicit and implicit deposit guarantees as a put option issued by the bank's deposit guarantor, and 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. This concept of financial institutions increasing the value of the option without internalizing the costs is called "risk-shifting" (Jensen and Meckling 1976). Following Duan, Moreau, and Sealey (1992), we assume a linear approximation to the value of the put option (*IPP*):

$$IPP = \gamma_0 + \gamma_1 \sigma_A + \gamma_2 \frac{D}{A} \tag{4}$$

IPP is the fair insurance premium per dollar of liabilities calculated using the Merton (1977) model and is described in Appendix A. The σ_A is the volatility of asset values and D and A are respectively the market values of debt and assets of a given firm. γ_1 represents the derivative of IPP with respect to asset volatility. Similarly, γ_2 represents the derivative of IPP with respect to leverage, D/A. Merton (1977) shows that $\gamma_1 > 0$ and $\gamma_2 > 0$.

Uninsured creditors and bondholders (as well as regulators) can impose discipline on banks by limiting the amount leverage banks can take on if they observe an increase in risk in banks assets and activities. To incorporate this disciplinary action Duan, Moreau, and Sealey (1992) use a linear equilibrium relationship between bank leverage and bank risk measured by asset volatility:

$$\frac{D}{A} = \beta_0 + \beta_1 \sigma_A \tag{5}$$

In equilibrium, as risk increases, financial institutions are pressured by the market to reduce their leverage with $\beta_1 < 0$. To incorporate this moderating effect, we plug in leverage specified in equation (5) into leverage in equation (4):

$$IPP = \theta_0 + \theta_1 \sigma_A \tag{6}$$

After substitution, $\theta_1 = \gamma_1 + \gamma_2 \beta_1$ in equation (6). Since, γ_1 and γ_2 represent the derivatives of IPP with respect to asset volatility and leverage, $\theta_1 = \frac{\partial IPP}{\partial \sigma_A} + \frac{\partial IPP}{\partial (D/A)} \beta_1$. The first term captures the incentives of financial institutions to increase risk, while the second term captures the offsetting effect of market discipline (given $\beta_1 < 0$) in moderating risk-taking. A positive θ_1 is consistent with the ability of financial institutions to risk-shift, since the disciplining effect does not completely neutralize incentives to increase risk. If uninsured creditors expect a government intervention when large financial institution fails, their incentives to monitor and discipline risk-taking would be substantially curtailed. In the empirical analysis, we estimate equation (6) in changes and test whether $\theta_1 > 0$, indicating risk-shifting by financial institutions.

2.3. Control variables

Our firm-level controls include return on assets, market-to-book ratio, and maturity mismatch. Our bond-level controls include time-to-maturity and seniority of the bonds. 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 compute two corporate bond liquidity measures based on transaction data availability. First liquidity measure is computed for the time period starting in 2003, after the introduction of TRACE. Instead of relying on a single measure, following Dick-Nielsen, Feldhutter, and Lando (2012), we calculate and combine four liquidity measures. We use all bond transactions to compute these four 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. The second measure is based on range of prices (*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 third measure, *roll,* captures transitory price movements induced by lack of liquidity and proxies for the bid-ask spread of a bond, based on the work of Roll (1984). The *roll* measure is computed as the covariance of consecutive price changes. 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 standardize the liquidity measures for each bond each month and then aggregate these standardized measures to compute *illiquidity high freq* measure.

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

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

3. Results

3.1. Implicit and Explicit Guarantees

We begin our analyses by examining differences in credit spreads of implicitly and explicitly guaranteed bonds, a test facilitated by the policy response to the global financial crisis. To help restore confidence in financial institutions, following the collapse of Lehman Brothers in September 2008, FDIC implemented Temporary Liquidity Guarantee Program (TLG Program) issuing a temporary explicit guarantee for certain new debt that financial institutions issued during the financial crisis. The TLG Program provided a guarantee for senior unsecured debt issued after October 14, 2008 and before June 30, 2009 (later extended to October 31, 2009). The guarantee remained in effect until June 30, 2012 (or the date the debt matured, if earlier). The TLG Program was available to insured depository institutions and financial holding companies participating in the program; however, not all of their debt was eligible to be guaranteed. To be eligible, the debt had to be senior unsecured debt issued from October 2008 to October 2009. In addition, an institution could only issue new debt under the TLG Program in an amount up to 125% of its senior unsecured debt that was outstanding on September 30, 2008 and scheduled to mature on or before October 31, 2009. The FDIC charged issuers a fee for the guarantee, and institutions could opt out of the program.

We examine the institutions in our data set that issued bonds under the TLG Program and also had similar bonds outstanding outside of the Program. The following sixteen companies in the TRACE/FISD databases issued bonds under the FDIC guarantee as well as non-guaranteed bonds: Bank of America, Citigroup, Goldman Sachs, JPMorgan Chase, Morgan Stanley, Sovereign Bancorp, State Street, SunTrust, U.S. Bancorp, Wells Fargo, PNC Bank, HSBC USA, Keycorp, MetLife, John Deere Capital, and GE Capital. For a given firm, we look at the difference between spreads on bonds backed by the FDIC guarantee and spreads on bonds without the FDIC guarantee. This approach allows us examine *within-firm variation* and compare *implicitly* guaranteed bonds to *explicitly* guaranteed bonds issued by the same firm.

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

$$\log(spread)_{i,b,t} = \propto + \beta_1 Bond\ Controls_{i,b,t} + \beta_2 guarantee_i + \gamma_{it} + \varepsilon_{i,b,t}. \qquad (7)$$

In equation (7), the subscripts i, b, and t indicate the firm, the bond, and the time (day), respectively. The dependent variable log (*spread*) is the credit spread. We control for the age of the bond since issuance in years (*age*) and the time to maturity in years (*ttm*), and include dummies set to one if the bond is *puttable*, *redeemable*, *exchangeable*, *enhanced* or if the bond has fixed-rate coupons (*fixrate*). We also include firm-trading day fixed effects (γ_{it}) to examine within-company variation on a given trading day.

Panel A of Figure 1 shows the raw difference (without controlling for bond characteristics) in spreads between bonds backed by the FDIC guarantee and the spreads on bonds without the FDIC guarantee for each of the top six financial institutions. Panel B displays the coefficient on the *guarantee* variable obtained by running the regression specified in (7) on a daily basis. We see a significant difference between implicitly and explicitly guaranteed bonds. There is also significant variation over time. Table 2 shows the regression results using data on all sixteen financial firms. In the first column, the coefficient on the *guarantee* dummy is significant and negative. Spreads of explicitly guaranteed bonds are 90% lower than the bonds that are not guaranteed by the FDIC for the same firm. In the second column, we include an interaction of our risk measure (*dd*) with the guarantee dummy. The positive coefficient indicates that explicitly guaranteed bonds are less sensitive to risk for the large financial institutions included in the sample.

This initial analysis shows that there is indeed a difference between explicit and implicit guarantees even within the largest financial institutions and that this difference varies over time. It is therefore not a priori clear to what extent investors expect potential government support for large financial institutions in the absence of explicit guarantees. In the next section, we examine how credit spread sensitivity to risk changes in a broader sample of financial firms with our size-based proxy for TBTF status and how this risk sensitivity has changed after the implementation of the Dodd-Frank Act.

3.2. Expectations of Government Support and Risk Sensitivity

To determine whether bondholders of major financial institutions expect government support, we estimate how the size of a financial institution affects the relationship between credit spreads and the firms' risk. The primary empirical model we estimate is based on Campbell and Taksler (2003) and Gopalan, Song, and Yerramilli (2014). We estimate the following regression using a panel with one observation for each bond-month pair:

$$
\begin{aligned}
\log(spread_{i,b,t}) = \\
&\propto +\beta_1 size90_{i,t-1} + \beta_2 Risk_{i,t-1} + \beta_3 size90_{i,t-1} \times Risk_{i,t-1} \qquad (8)\\
&+ \beta_4 Bond\ Controls_{i,b,t} + \beta_5 Firm\ Controls_{i,t-1} + \gamma_t + \varepsilon_{i,b,t}
\end{aligned}
$$

In equation (8), the subscripts i, b, and t indicate the firm, the bond, and the time (month), respectively, and γ_t denotes year-month fixed effects. The dependent variable log (*spread*) is the credit spread. To measure the systemic importance of an institution we focus on *size90*, which is a dummy variable that takes on a value of one for financial institutions that are in the top 90th percentile of financial institutions ranked by assets in a given year. Bond-level controls include time-to-maturity (*ttm*) in years and a dummy variable indicating whether the bond is senior (*senior*). Firm-level controls are *leverage*, return-on-assets (*roa*), market-to-book ratio (*mb*), and maturity mismatch (*mimatch*). The variable of interest is the term interacting risk with systemic importance - $size90_{i,t-1} \times Risk_{i,t-1}$. An implicit government guarantee weakens market discipline by reducing investors' incentives to monitor and price the risk taking of TBTF institutions. As spreads increase with risk, a negative coefficient ($\beta_3 < 0$) would indicate a reduction in risk-sensitivity for large financial institutions.

There may be advantages associated with size that are not fully captured by the control variables. Larger firms may have lower funding costs due to greater diversification, larger economies of scale, or better access to capital markets and liquidity in times of financial turmoil. We control for such general size advantages in estimating investor expectations of government support by using non-financial firms as controls. We use a difference-in-differences approach and compare the differences in the credit spreads of large and small financial institutions to differences in the credit spreads of large and small companies in non-financial sectors. If investors expect government support only for financial firms, then the estimate of the large-small difference in the financial sector compared to the large-small difference in non-financial sectors (without an expectation of government support of large firms) would provide a measure of the advantage large financial firms have from expectations of government support.[14]

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

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

$$
\begin{aligned}
\log(spread)_{i,b,t} = \\
&\propto +\beta_1 size90_{i,t-1} + \beta_2 Risk_{i,t-1} + \beta_3 size90_{i,t-1} \times Risk_{i,t-1} + \beta_4 financial_{i,} \\
&+ \beta_5 financial_i \times size90_{i,t-1} + \beta_6 financial_i \times Risk_{i,t-1} \qquad (9) \\
&+ \beta_7 financial_i \times Risk_{i,t-1} \times size90_{i,t-1} + \beta_8 Bond\ Controls_{i,b,t} \\
&+ \beta_9 Firm\ Controls_{i,t-1} + \gamma_t + \varepsilon_{i,b,t}
\end{aligned}
$$

Above, $financial_i$ is a dummy variable that takes on a value of one if firm i is in the financial sector. is in the financial sector. If investors expect government support only for large financial firms, then we expect the TBTF effect on the risk-spread relationship to be significantly weaker for non-financial firms. We are interested in the $financial_i \times Risk_{i,t-1} \times size90_{i,t-1}$ variable. This triple interaction term captures the risk sensitivity of the credit spreads of large financial institutions compared to that of large non-financials. A negative coefficient $(\beta_7 < 0)$ would indicate that the risk sensitivity is lower for large financial institutions than for large non-financial institutions.

Finally, as we are interested in the long-term impact of the Dodd-Frank Act, we estimate the two regression models by splitting our sample into two periods, before and after the implementation of Dodd-Frank.[15] Using a longer window of years, allows us to take into account the fact that Dodd-Frank has gone through changes and was implemented in various stages over time. We run the regression separately in the pre-Dodd Frank (1990 to 2011) and post-Dodd Frank (2012-2020) time-periods.

The results for the regression model (8) are reported in Table 3. Panel A reports results for the pre-Dodd-Frank period and Panel B reports results for the post-Dodd-Frank period. The dependent variable is the natural logarithm of spreads. Our main measure of risk is the natural logarithm of Merton's distance-to-default. We multiply the distance-to-default measure by -1 so that higher values indicate greater risk. As alternative risk measures, we use components of distance-to-default, namely asset volatility, leverage, as well as, equity volatility, rating, natural logarithm of the z-score and the modified distance-to-default measure of Nagel and Purnandam (2020). Since the modified distance-to-default measure is not applicable for non-financial

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

institutions given their balance sheet structure, we use the modified distance-to-default measure for financial firms and the regular distance-to-default measure for non-financial firms in estimating regression specified in equation (9).[16] These risk measures are listed in column headers in the Table. To control for potential omitted variables, we also include a specification where we include firm fixed effects in the regressions specified above. Results including firm fixed effects are reported in column 8. Finally, for the time period starting in 2003 after the introduction of TRACE (for which we have all bond transactions), we use our high frequency measure of illiquidity described above as a control variable when examining the relationship between spreads and distance-to-default in column 9.

Overall, we find that in the pre-Dodd-Frank period, the relation between size and risk sensitivity to be weaker for the largest financial institutions. This indicates that the spread-to-risk relation diminishes with TBTF status. This result is consistent with investors pricing an implicit government bailout guarantee for the largest financial institutions. Based on the coefficients reported in column 1, we find that a 10% increase in risk as measured by distance-to-default, increases spreads on average by 4.6% for financial institutions. However, the corresponding increase for the largest financial institutions is only 0.85%. We find consistent results across different risk measures.

However, in the post-Dodd-Frank period, we do not find larger financial institutions credit spreads to be less sensitive to risk. The results from the regression specified in equation (8) are reported in Panel B of Table 3. Across, all risk measures, the coefficients are either insignificant or slightly positive indicating an increase in risk-sensitivity for larger financial institutions for the post-Dodd-Frank period.

Next, we compare financial institutions to non-financial institutions when examining the impact of risk on credit spreads. We use the regression specified in equation (9). The results are reported in Table 4 in Panel A for the pre-Dodd-Frank period and in Panel B for the post-Dodd-Frank period. of Table 4. For brevity, we do not report coefficients on the control variables. We use the same set of risk variables we used in Table 3: *-log(dd)*, *leverage*, *assetvol*, *equityvol*, *rating* *-log(zscore)* and *-log(NPdd)*. Based on the coefficient on the triple interaction term, $financial_{t-1} \times Risk_{t-1} \times size90_{t-1}$, 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

[16] We find qualitatively similar results if we use the modified distance-to-default measure for non-financial firms.

find the same qualitative reduction in risk sensitivity for large financials that we found in Panel A of Table 3.

What about the post-Dodd-Frank time period? In Panel B of Table 4, we find that the triple interaction term is insignificant suggesting that the there is no difference in risk-sensitivity between large financial and large non-financial firms, suggesting that there has been a marked increase in risk-sensitivity for large financial institutions in the aftermath of Dodd-Frank implemented after the financial crisis. While these results are consistent with a reduction in investor expectation of government support for large financial firms, there may be confounding effects emanating from changes in business structure after the Dodd-Frank Act. In particular, new regulations may have resulted in lower reduced earnings for larger financial firms.

We do two robustness checks around our main findings. While it is standard in the literature to examine only plain vanilla bonds (as the option values can be driven by factors not related to credit risk), we estimate the regressions specified in equations (8) and (9) using all bonds. To control for various bond characteristics and embedded optionality, we include dummy variables in the regression and set these dummy variables to one if a given bond is *puttable*, *redeemable*, *exchangeable*, *enhanced* or if the bond has fixed-rate coupons (*fixrate*). The results are reported in Table 1 in Appendix B. The coefficients on the variables of interest ($size90 \times Risk$ and $financial \times size90 \times Risk$) are overall similar to those we report in Tables 3 and 4.

While the choice of cut-off for systemic importance is somewhat arbitrary, we show that our risk-sensitivity results are mostly contained to the very largest firms. We create a dummy variable *size80_90*, that takes on a value of one for firms that are in the 80^{th} to 90^{th} percentile in terms of size in a given year. We include this dummy variable and in its double and triple interaction with distance-to-default variable and the financial dummy variable in regressions specified in (8) and (9). We repeat the same analyses by also examining firms that are in the top 10 of firms in terms of size in a given year. We create dummy variables, *sizetop10* and *sizetop11_20*, that take on a value of one of if a firm is ranked top 10 or ranked 11 to 20, respectively, in terms of size in a given year. The results are reported in Table 2 in Appendix B. Panel A reports results using size percentiles and Panel B reports results using size ranks. The results for the pre-Dodd-Frank time period are reported in columns 1 and 2 and regression results for the post-Dodd-Frank time period are reported in columns 3 and 4.

We find that interaction terms of the both the *size90* and *sizetop10* variables with our risk measure are negative and significant in the pre-Dodd-Frank time period suggesting a reduction in risk-sensitivity. The interaction of the *size80* and *sizetop11_20* variables are not significant during this time period. These results suggest that the reduction in risk-sensitivity in the pre-Dodd-Frank period is contained within the largest firms. Consistent with our earlier results, we do not find a significant difference in risk-sensitivity for the largest firms after the implementation of the Dodd-Frank Act.

3.3. Expectations of Government Support and Equity and Bond Return Sensitivity

As the default risk of a firm increases, the correlation between equity returns and debt returns also increases. The equity hedge ratio of Schaefer and Strebulaev (2008), as explained section 3, is increasing in both asset volatility and leverage as higher asset volatility and leverage are associated with a greater likelihood of default. However, if the market expects a government intervention when a large financial institution fails, then the correlation between equity and debt returns will be lower. If there is a full guarantee provided on debt the correlation would in fact be zero. Therefore, we examine whether the relationship between bond and equity returns is different for larger financial institutions. We follow Schaefer and Strebulaev (2008) and examine the relationship between bond returns and equity returns multiplied by the hedge ratio. In particular, we estimate the following regression model:

$$\begin{aligned} Dreturn_{i,b,t} = \propto &+ \beta_1 (Ereturn_{i,t} \times hedgeratio_{i,t}) + \beta_2 size90_{i,t-1} \\ &+ \beta_3 (Ereturn_{i,t} \times hedgeratio_{i,t}) \times size90_{i,t-1} + \beta_4 Bond\ Controls_{i,b,t} \\ &+ \beta_5 Firm\ Controls_{i,t-1} + \gamma_t + \varepsilon_{i,b,t} \end{aligned} \tag{10}$$

Here, $Dreturn_{i,b,t}$ is the one month return of firm i's bond b in month t. The bond returns are calculated as in Schaefer and Strebulaev (2008). We use the bond price at the end of the month to calculate returns. Requiring bonds to have end-of-month prices results in a substantial loss of data. For robustness, we also repeat the analyses using prices traded in the last 5 days in a given month. These results are reported in Table C3 in the Appendix. As bond returns are lower in magnitude, we multiply the bond returns by 100 so that the regression coefficients reported on the control variables are easier to read in the tables. $Ereturn_{i,t}$ is firm i's equity return in month t. $hedgeratio_{i,t}$ is the equity hedge ratio, calculated as $1 \,/\, (N(d_1) - 1) \times (A/D - 1)$ using the parameters from the Merton model described in the Appendix A. Bond level controls include time-to-maturity (*ttm*) in years and a dummy variable indicating whether the bond is senior

(*senior*). Firm-level controls are *leverage*, return-on-assets (*roa*), market-to-book ratio (*mb*), and maturity mismatch (*mimatch*). γ_t are year-month fixed effects. By including time fixed effects, we control, for instance, for the overall level of interest rates. The variable of interest is the interaction term $Ereturn_{i,t} \times hedgeratio_{i,t} \times size90_{i,t-1}$. The coefficient on this variable (β_3) captures the differences in the bond-equity return sensitivity of large financial institutions compared to their smaller counterparts.

We also use non-financial firms as a control group and examine if the bond-equity return relationship is different for large non-financial firms. In particular, we estimate the following regression:

$$\begin{aligned} Dreturn_{i,b,t} = \propto &+ \beta_1(Ereturn_{i,t} \times hedgeratio_{i,t}) + \beta_2 size90_{i,t-1} \\ &+ \beta_3(Ereturn_{i,t} \times hedgeratio_{i,t}) \times size90_{i,t-1} \\ &+ \beta_4(Ereturn_{i,t} \times hedgeratio_{i,t}) \times financial_{i,t-1} \\ &+ \beta_5(Ereturn_{i,t} \times hedgeratio_{i,t}) \times size90_{i,t-1} \times financial_{i,t-1} \\ &+ \beta_6 Bond\ Controls_{i,b,t} + \beta_7 Firm\ Controls_{i,t-1} + \gamma_t + \varepsilon_{i,b,t} \end{aligned} \quad (11)$$

As before, $financial$ is a dummy variable that takes on a value of one for financial firms. We are interested in the triple interaction term $Ereturn_{i,t} \times financial_{i,t-1} \times size90_{i,t-1}$. The coefficient β_5 captures the differential in the bond-equity return sensitivity of large financial firms compared to their non-financial counterparts.

The results for regressions specified in equations (10) and (11) are reported in Table 5. The left panel reports results for the pre-Dodd-Frank period, and the right panel for the post-Dodd-Frank time period. Consistent with the Merton model, we find a significant positive relationship between equity and bond returns. We should note that the coefficient on the $Ereturn_{i,t} \times hedgeratio_{i,t}$ variable is less than 100 for financial firms in aggregate, possibly reflecting a potential guarantee on the whole financial system and possibly due limitations of the hedge-ratio for financial firms which tend to have significantly higher leverage compared to non-financial firms. For the for non-financials in aggregate we find that the coefficient is 106 consistent with findings in Schaefer and Strebulaev (2008). In columns (1) and (3) we report results for financial firms only. We find that the positive correlation between bond and equity returns is weaker for larger financial firms in the pre-Dodd-Frank period (column 1), but we find no size effect in the bond-equity return relationship in the post-Dodd-Frank period (column 3).

Finally, we report results of the triple interaction regression in columns 2 and 4. The triple interaction term in the pre-Dodd-Frank time period is negative and statistically significant. For the post-Dodd-Frank time period, however, the coefficient is positive suggesting that equity-bond return relationship was stronger for larger financial firms compared to larger non-financial firms after Dodd-Frank. Overall, bond-return sensitivity results are consistent with the risk-sensitivity results we reported in the previous section and imply a TBTF expectation of large financial firms in the pre-Dodd-Frank era.

3.4. Expectations of Government Support and Risk Shifting

The presence of guarantees should weaken the market discipline of large financial institutions by outside investors. In this section, we examine whether larger financial institutions are able to take on more leverage and shift risk onto debtholders and taxpayers. We use the deposit insurance pricing model of Merton (1977) described in section 3 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 tax-payers by increasing asset risk or leverage.

Uninsured creditors and bondholders would have incentives to reign in excessive risk-taking by financial institutions by limiting institution's leverage. As risk increases, financial institutions are pressured by the market to reduce their leverage. However, if there is an expectation of government support to large financial institutions if they fail, then incentives of uninsured creditors to monitor and discipline financial institutions will be significantly weakened. We compare the restraining effect of market discipline to the strength of financial institutions' incentives to take on risk. To examine these two countervailing factors empirically, we follow Duan, Moreau, and Sealey (1992), Hovakimian and Kane (2000) and Bushman and Williams (2012) and estimate the reduced form model specified in (6) in section 3:

$$\Delta IPP_{i,t} = \beta_0 + \beta_1 \Delta\sigma_{A_{i,t}} + \beta_2 \Delta\sigma_{A_{i,t}} size90_{i,t} + \gamma_t + \varepsilon_{i,t} \tag{12}$$

Here, *IPP* is the fair insurance premium per dollar of liabilities. As discussed earlier, the coefficient β_1 captures two offsetting effects: the risk-shifting incentives of financial institutions and outside discipline. A positive β_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 with the prior analyses, we interact asset volatility with our *size90* measure, and use large non-financial institutions as controls.

The results are reported in Table 6. In columns 1 to 3 we report results for the pre-Dodd-Frank time period and in columns 4 to 6 we report results for the post-Dodd-Frank period. On average, financial institutions are able to engage in risk-shifting, as evidenced by the positive coefficient on asset volatility (columns 1 and 4). This risk-shifting effect is stronger for larger financial institutions (column 2) in the pre-Dodd-Frank period but becomes insignificant after Dodd-Frank is implemented. When we use large non-financial institutions as controls, we find the risk-shifting incentives of large financial institutions to be greater than those of large non-financial institutions (column 3) in the pre-Dodd-Frank period and the difference becomes insignificant in the post-Dodd-Frank period.

3.5. Event Studies

Next, we examine how credit spreads are impacted around specific events that might have changed investor expectations of government support. The events and their corresponding dates are in Table 8. These events offer natural experiments to assess changes in TBTF expectations within-firm over time. For instance, prior to the global 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.[17] This intervention on March 13, 2008 likely reinforced expectations that the government would guarantee the obligations of large financial institutions.

Conversely, the latter decision to allow Lehman Brothers to fail served as a negative shock to those expectations. While the Federal Reserve and the Treasury intervened the day after the Lehman collapse on September 15, 2008 (including a rescue of AIG's creditors), the government

[17] In connection with Bear Stearns' merger with JPMorgan Chase in 2008, the Federal Reserve provided JPMorgan Chase with regulatory relief and nearly $30 billion in asset guarantees, and Bear Stearns with lending support under section 13(3) of the Federal Reserve Act of 1913, the first time since the Great Depression that the Federal Reserve directly supported a non-bank with taxpayer funds. The Fed also announced the Primary Dealer Credit Facility, which opened the discount window to primary dealers in government securities, some of which are investment banks, bringing into the financial safety net investment institutions like Lehman, Merrill Lynch, and Goldman Sachs.

and regulators adopted a series of unpredictable and confusing policies before and around Lehman's collapse, making future intervention increasingly uncertain. Hence, both the Bear Stearns and Lehman events are contrasting shocks to investor expectations of government support. We also examine two other policy events that may have affected investor expectations positively. We examine the events surrounding the passage of the Troubled Asset Relief Program (TARP) on October 3, 2008 and the Treasury's announcement of capital injection on October 14, 2008.[18]

For the post-Dodd-Frank period, we examine the introduction of the Economic Growth, Regulatory Relief, and Consumer Protection Act[19], which increased the size threshold for enhanced supervision by the Federal Reserve Board[20], as well as, various policy interventions during the onset of the Covid-19 pandemic. Given that the pandemic was unexpected and given its systemic nature, it provides an us with an excellent exogenous shock to assess the efficacy of the Dodd-Frank reforms implemented in 2010. The liquidity and financial support provided by the Treasury and the Federal Reserve in response to the Covid-19 pandemic were much greater in magnitude, speed and scope compared to the support provided during the financial crisis. We examine changes in spreads around key policy announcements in March and April of 2020. In particular, we examine i) March 17, 2020 announcement by the FED, FDIC and OCC to set up various funding facilities to provide liquidity to the financial system;[21] ii) March 23, 2020 announcement by the FED to introduce extensive measures to support the economy;[22] iii) April 1, 2020 announcement by the FED to reduce leverage ratios to ease strains in the Treasury market;[23] and finally, iv) April 9, 2020 announcement to provide up to \$2.3 trillion in loans to

We examine a window of ± 3 trading days around the event. We run the following regression for financial firms:

$$\log(spread)_{i,b,t} = \propto + \beta_1 post_t + \beta_2 size90_{i,t} \times post_t + \theta_b + \gamma_t + \varepsilon_{i,b,t}. \quad (13)$$

The dummy variable, $post$, equals one on the event date and the five subsequent trading days. γ_t are trading day fixed effects to control for changes in the market environment that affects all bonds. The regression also includes issue (θ_b) fixed effects and the regression corresponds to a difference-

[18] https://www.treasury.gov/press-center/press-releases/Pages/hp1207.aspx
[19] https://www.congress.gov/bill/115th-congress/senate-bill/2155
[20] Asset threshold was increased from \$50 billion to \$250 billion for enhanced supervision, from \$10 billion to \$250 billion for stress tests, and from \$10 billion to \$50 billion for mandatory risk committees.
[21] https://www.federalreserve.gov/newsevents/pressreleases/monetary20200317a.htm
[22] https://www.federalreserve.gov/newsevents/pressreleases/monetary20200323b.htm
[23] https://www.federalreserve.gov/newsevents/pressreleases/bcreg20200401a.htm

in-differences estimation. As before, we use non-financial institutions as controls and examine changes in spreads for large financial firms compared to large non-financial firms and estimate the following regression by including the interaction of the *financial* dummy variable:

$$\log(spread)_{i,b,t} = \propto + \beta_1 post_t + \beta_2 size90_{i,t} \times post_t + \beta_3 financial_{i,t} \times post + \beta_4 financial_{i,t} \times post \times size90_{i,t} + \theta_b + \gamma_t + \varepsilon_{i,b,t}. \quad (14)$$

The results are reported in Table 7. We find that announcements of government financial and liquidity support are associated with a decrease in credit spreads for larger financial institutions. In particular, the bailout of Bear Stearns and the passage of the revised TARP bill by the House of Representatives led to statistically an economically significant decrease in spreads. We find similar results when we use non-financial institutions as controls. These triple-difference results are provided in the second column. For a negative shock to investor expectations of government support, namely the bankruptcy filing by Lehman Brothers on September 15, 2008, the coefficient on the interaction term is significant and positive for the Lehman event. The result indicates that larger institutions saw greater increases in their credit spreads after the Lehman collapse.[24] The increase is also economically significant at over 100 bps. The results are similar when we use non-financials as controls.

The results for the post-Dodd-Frank Act events are provided in the lower panel of Table 8. We observe significant differences in changes in spreads between large and small financial institutions for the March 23, 2020 Federal Reserve announcement of support events. However, when we use large non-financial firms as a control the differences become insignificant. Similarly, for the introduction of the Economic Growth, Regulatory Relief, and Consumer Protection Act Bill, we do not find significant differences.[25] These results are therefore consistent with lower investor expectations of government support after Dodd-Frank.

As there were a number of policy interventions around the onset of the Covid-19 pandemic,

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[24] 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 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). Our results do not change if we include this dummy variable.

[25] Since the Economic Growth, Regulatory Relief, and Consumer Protection Act affected financial institutions with assets greater than \$100 billion those with assets greater than \$250 billion differently, we also ran regressions using size dummies set to one for institutions with assets between \$50 billion and \$100 billion and another size enhanced we have also used as size dummies institutions with assets \$50 billion to \$100 billion and set to one for financial institutions with assets between \$100 billion and \$250 billion. We obtained similar results as those reported in Table 8.

we also use a longer time window to examine risk-sensitivity of credit spreads. In particular, we use daily data and examine risk-sensitivity using regression models specified in equations (8) and (9) above for the March 1, 2020 to March 31, 2020 time period, as well as, the March 1, 2020 to June 31, 2020 time period. The results from these regressions are reported in Table 9. In columns 1 and 3, we report risk-sensitivity results for financial institutions, and in columns 2 and 4 we report triple interaction results using non-financial firms as controls. For both time periods and for both specifications, we do not find significant differences in risk-sensitivity. Large financial institutions' credit spreads were not less sensitive to risk compared to smaller financial institution. Similarly, large financial institutions' credit spreads were not less sensitive to risk compared to large non-financial firms. These results are consistent with risk-sensitivity increasing for large financial firms' bonds returns, consistent with an effective dampening of TBTF expectations after Dodd-Frank.

4. Conclusion

In this paper, we examine if expectations of implicit government support are embedded in the credit spreads of unsecured bonds issued by large U.S. financial institutions. We find that in the pre-Dodd Frank time period bond spreads were less sensitive to risk for large financial firms compared to smaller financial institutions. Comparing large financial firms to large non-financial firms, we also find lower spread-risk sensitivity for large financial institutions, consistent with investors expecting large financial firms to benefit from implicit government guarantees. In the post-Dodd Frank period after 2012, there are no differences in the spread-risk sensitivity of large financial firms compared to small financial firms as well as their large industrial counterparts. These results are consistent with a strengthening of market discipline in the aftermath of the policy reforms implemented following the financial crisis. We confirm the robustness of our results by conducting an event study examining shocks to investor expectations during the global financial crisis and the Covid-19 pandemic.

It is important to emphasize that the real economic costs of government interventions to rescue financial institutions go beyond the pricing distortions we document in this paper. There are indirect economic costs such as distortions to incentives for risk-taking, a weakening of monitoring of financial institutions, uncertainty created by ad-hoc bail-out policies (e.g. rescuing some institutions and not others), and real economic distortions resulting from these channels.

These indirect economic costs are difficult to quantify but they can have long lasting effects. It is also difficult to quantify the economic trade-off associated with moral hazard on one hand and excessive regulations and restrictions potentially slowing credit creation on the other.

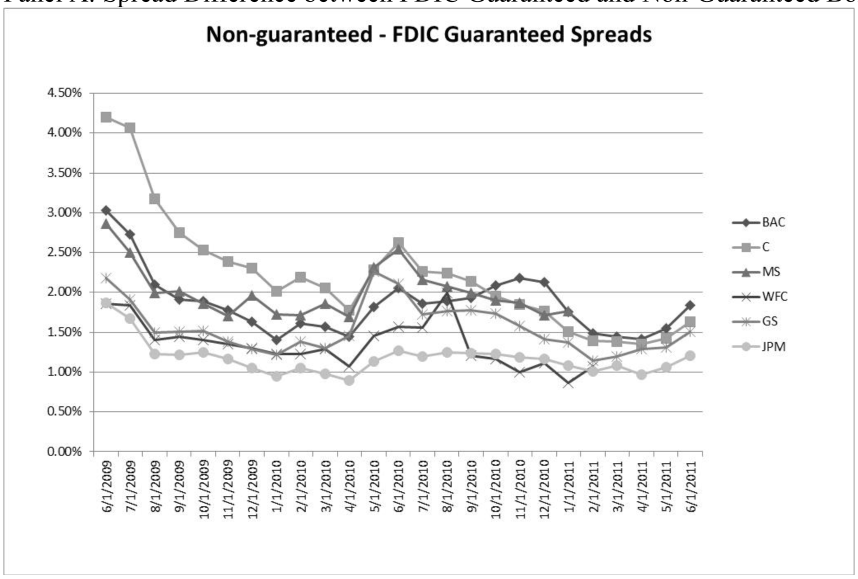
Policy discussions of optimal state interventions from a global perspective are further complicated by the fact that states must have monetary and fiscal resources in the first place to bail-out large financial institutions (see Martinez-Peria and Schmukler 2001, Acharya, Dreschsler and Schnabl 2014, and Taneli, Sarno and Zina 2020), as a result there could be significant variation in the credibility of sovereign guarantees across countries.

While quantifying these trade-offs is difficult, our paper highlights the important role incentives play in market discipline. Market participants must have "skin in the game" in order to effectively monitor and influence risk-taking. This requires failed large financial firms to be orderly liquidated or re-organized and for their investors to share in the losses. The Dodd-Frank Act appears to have succeeded on this front by significantly improving the risk-sensitivity of unsecured bond spreads of large financial firms. While some key policy issues remain open, reforms requiring large financial firms to hold more bail-in debt and continuing to streamline rules for efficient resolution and orderly liquidation can have the effect of better aligning unsecured creditor incentives and strengthening market discipline.

Figure 1: Explicit and Implicit Guarantee Spread Difference

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

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



Panel B: Estimated FDIC Gurantee Premium

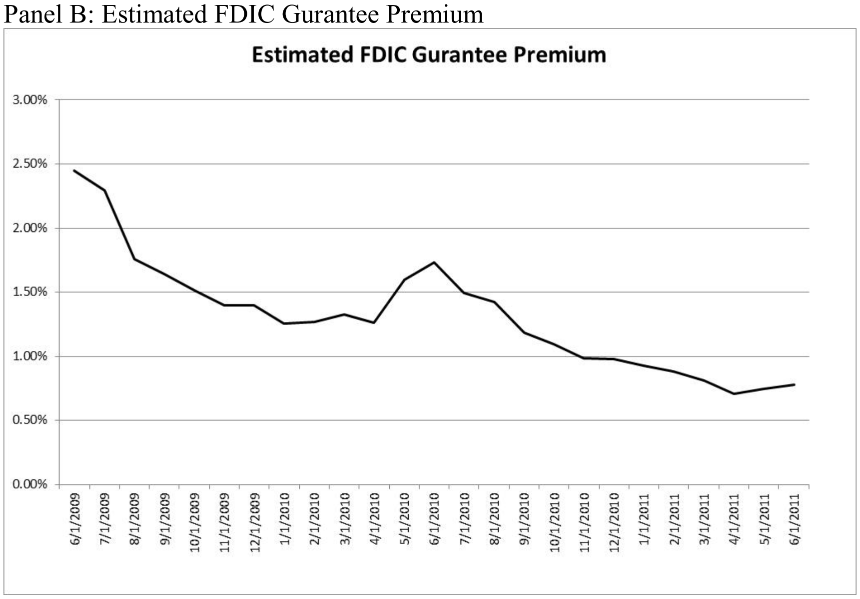


Table 1: Summary Statistics

This table presents summary statistics for the variables; Panel A for financial firms and Panel B for non-financial firms. *ttm* is the time-to-maturity for a bond. *senior* 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. *Size90* is a dummy variable equal to one if a given financial institution's size is in the top 90th percentile. *financial* is a dummy variable set to one if the firm is a financial firm (SIC code starting with 6). *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. *dd* is Merton's (1974) distance-to-default measure. *leverage* is total liabilities divided by market value of assets. *mb* is the market-to-book ratio computed as the value of total equity divided by book value of total equity. *assetvol* is asset volatility computed from the Merton model. e*quityvol* is equity volatility calculated using daily equity returns over the past 12 months. *rating* is a number ranging from 1 to 21 corresponding to S&P credit ratings from AAA to C, with higher numbers corresponding to greater credit risk. *Ndd* is the distance-to-default measure calculated using the method in Nagel and Purnandam (2020). *IPP* is the fair insurance premium per dollar of liabilities computed following Merton (1977) multiplied by 1000. *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 five years, divided by the standard deviation of roa over five years. *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. *illiquidity (highfreq)* is the aggregate illiquidity measure described in the text calculated using trade date reported in TRACE. Variables are defined in Appendix A.

Panel A: Financial Firms						
Variables	Obs	Mean	Std. Dev.	P25	P50	P75
log(spread)	89,913	-4.352	0.914	-4.899	-4.434	-3.917
ttm	89,913	6.628	6.061	2.581	4.658	8.369
senior	89,913	0.728	0.445	0.000	1.000	1.000
size	89,913	12.422	1.696	11.146	12.708	13.795
roa	89,913	0.010	0.016	0.006	0.009	0.013
mb	89,913	1.511	0.842	0.976	1.336	1.830
mismatch	89,913	0.028	0.160	-0.059	0.021	0.104
liquidity	89,913	1.623	0.894	1.000	2.000	2.000
rating	89,913	7.767	2.296	6.000	7.000	9.000
assetvol	89,913	0.043	0.039	0.022	0.029	0.047
equityvol	89,913	0.340	0.238	0.206	0.266	0.378
leverage	89,913	0.923	0.541	0.858	0.908	0.945
-log(dd)	89,913	-1.699	0.664	-2.081	-1.848	-1.523
-log(Ndd)	89,913	-1.699	0.664	-2.081	-1.848	-1.523
-log(zscore)	87,607	-3.195	0.850	-3.746	-3.279	-2.792
IPP	89,913	14.652	96.992	0.000	0.007	0.362

Panel B: Non-Financial Firms						
Variables	*N*	Mean	Std. Dev.	P25	P50	P75
log(spread)	137,384	-4.351	0.889	-4.927	-4.424	-3.821
ttm	137,384	9.955	10.785	3.169	6.590	13.394
senior	137,384	0.954	0.209	1.000	1.000	1.000
size	137,384	10.020	1.598	8.866	9.988	11.003
roa	137,384	0.040	0.060	0.017	0.039	0.069
mb	137,384	2.941	6.206	1.164	1.818	2.883
mismatch	137,384	-0.008	0.172	-0.056	0.008	0.079
liquidity	137,384	1.228	0.975	0.000	1.000	2.000
rating	137,384	8.427	3.380	6.000	8.000	10.000
assetvol	137,384	0.143	0.078	0.090	0.130	0.182
equityvol	137,384	0.309	0.156	0.211	0.269	0.360
leverage	137,384	0.521	0.248	0.350	0.516	0.654
-log(dd)	137,384	-1.734	0.498	-2.064	-1.781	-1.468
-log(Ndd)	137,384	-1.734	0.498	-2.064	-1.781	-1.468
-log(zscore)	135,312	-2.888	0.957	-3.491	-2.930	-2.335
IPP	137,384	2.145	30.789	0.000	0.000	0.010

Table 2: Implicit and Explicit Guarantees

This table reports regression results where the dependent variable is log(spread). *dd* 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 regression includes issuer-trading day fixed effects (*Issuer×Trading Day FE*). Other control variables are described in Table 1 and in Appendix A. Standard errors are in parentheses below their coefficient estimates and are adjusted for both heteroscedasticity and within correlation clustering at the issuer level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% two-tailed levels, respectively.

VARIABLES	(1)	(2)
ttm	0.015***	0.016***
	(0.002)	(0.002)
age	-0.003	-0.004
	(0.003)	(0.003)
senior	-0.234***	-0.237***
	(0.031)	(0.032)
callable	0.014	0.014
	(0.048)	(0.049)
fixrate	0.105***	0.114***
	(0.040)	(0.041)
redeemable	-0.020	-0.016
	(0.034)	(0.035)
enhanced	0.045	0.046
	(0.053)	(0.054)
puttable	0.288***	0.361***
	(0.077)	(0.065)
guarantee	-2.252***	-2.183***
	(0.083)	(0.083)
guarantee × -log(dd)		0.059*
		(0.032)
Constant	-3.954***	-3.996***
	(0.056)	(0.057)
Issuer ×Trading Day FE	Y	Y
Observations	391,017	373,254
R^2	0.641	0.621

Table 3A: Spread-Risk sensitivity

This table presents regression results where the dependent variable is the natural logarithm of spreads. *ttm* is the time-to-maturity for a bond. *senior* 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. *Size90* is a dummy variable equal to one if a given financial institution's size is in the top 90th percentile. *financial* is a dummy variable set to one if the firm is a financial firm (SIC code starting with 6). *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. *dd* is Merton's (1974) distance-to-default measure. *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. *assetvol* is asset volatility computed from the Merton model. e*quityvol* is equity volatility calculated using daily equity returns over the past 12 months. *rating* is a number ranging from 1 to 21 corresponding to S&P credit ratings from AAA to C, with higher numbers corresponding to greater credit risk. *Mdd* is the distance-to-default measure calculated using the method in Nagel and Purnandam (2020). *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 five years, divided by the standard deviation of roa over five years. *illiquidity* 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. *illiquidity (highfreq)* is the aggregate illiquidity measure described in the text calculated using trade date reported in TRACE. Pre-Dodd-Frank is the time period before 2012. All regression models include month/year fixed effects. Standard errors are in parentheses below their coefficient estimates and are adjusted for both heteroscedasticity and within correlation clustering at issue and month/year. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% two-tailed levels, respectively.

Panel A: pre-Dodd-Frank period

VARIABLES	(1) -log(dd)	(2) leverage	(3) assetvol	(4) equityvol	(5) rating	(6) -log(zscore)	(7) -log(NPdd)	(8) -log(dd)	(9) -log(dd)
ttm	0.016***	0.016***	0.015***	0.016***	0.017***	0.015***	0.020***	0.017***	0.021***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)
senior	0.073***	0.078***	0.056**	0.052**	0.122***	0.054**	0.040	0.044	-0.020
	(0.025)	(0.026)	(0.026)	(0.024)	(0.021)	(0.025)	(0.028)	(0.046)	(0.028)
roa	-1.629*	-1.259	-4.788***	-0.189	-1.453*	-4.455***	-0.344	-4.299***	-2.180*
	(0.912)	(0.923)	(1.129)	(0.688)	(0.837)	(1.010)	(0.808)	(0.787)	(1.193)
mb	-0.112***	-0.083**	-0.120***	-0.096***	-0.067***	-0.119***	-0.113***	-0.042*	-0.157***
	(0.037)	(0.035)	(0.043)	(0.028)	(0.023)	(0.019)	(0.026)	(0.023)	(0.026)
mismatch	-0.120*	-0.167**	-0.044	-0.245***	-0.104*	-0.123	-0.277***	-0.646***	0.180
	(0.071)	(0.076)	(0.079)	(0.064)	(0.063)	(0.079)	(0.068)	(0.164)	(0.139)
liquidity	-0.110***	-0.114***	-0.111***	-0.110***	-0.090***	-0.114***	-0.120***	-0.085***	
	(0.012)	(0.012)	(0.012)	(0.011)	(0.011)	(0.012)	(0.011)	(0.010)	
size90	-0.472***	0.077	0.047	0.115**	0.555***	-0.328***	-0.054*	-0.373***	-0.371***
	(0.074)	(0.093)	(0.038)	(0.048)	(0.085)	(0.093)	(0.028)	(0.070)	(0.071)
risk measure	0.384***	0.370***	2.634***	1.790***	0.128***	0.123***	0.146***	0.324***	0.366***
	(0.036)	(0.096)	(0.579)	(0.119)	(0.007)	(0.016)	(0.013)	(0.037)	(0.040)
risk measure × size90	-0.220***	-0.238**	-3.703***	-0.649***	-0.074***	-0.060**	-0.073***	-0.188***	-0.142***
	(0.041)	(0.094)	(0.579)	(0.107)	(0.011)	(0.028)	(0.024)	(0.037)	(0.034)
liquidity (highfreq)									0.037***
									(0.005)
Constant	-3.409***	-4.403***	-4.112***	-4.707***	-5.221***	-3.561***	-4.204***	-3.618***	-3.334***
	(0.095)	(0.127)	(0.072)	(0.080)	(0.080)	(0.079)	(0.059)	(0.073)	(0.087)
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	No	No	No	Yes	No
Observations	62,491	62,491	62,491	62,491	62,491	60,241	50,896	62,485	23,672
R-squared	0.453	0.449	0.452	0.472	0.483	0.453	0.369	0.511	0.688

Panel B: post-Dodd-Frank period

VARIABLES	(1) -log(dd)	(2) leverage	(3) assetvol	(4) equityvol	(5) rating	(6) -log(zscore)	(7) -log(NPdd)	(8) -log(dd)	(9) -log(dd)
ttm	0.026***	0.025***	0.026***	0.025***	0.027***	0.025***	0.025***	0.025***	0.032***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
senior	-0.187***	-0.214***	-0.218***	-0.191***	-0.069**	-0.243***	-0.232***	-0.301***	-0.209***
	(0.034)	(0.036)	(0.033)	(0.034)	(0.029)	(0.032)	(0.032)	(0.025)	(0.039)
roa	-1.632	-4.283***	-2.911***	-2.472	0.555	-0.580	-3.432*	-2.637***	-4.783***
	(1.765)	(1.129)	(1.076)	(1.744)	(0.934)	(1.238)	(1.775)	(0.434)	(0.995)
mb	-0.169***	-0.294***	-0.318***	-0.166***	-0.136***	-0.159***	-0.165***	0.004	-0.220***
	(0.035)	(0.040)	(0.035)	(0.035)	(0.021)	(0.025)	(0.031)	(0.032)	(0.032)
mismatch	1.075***	1.227***	1.260***	1.071***	0.276**	1.131***	0.943***	-0.325	1.175***
	(0.149)	(0.131)	(0.116)	(0.144)	(0.108)	(0.125)	(0.159)	(0.234)	(0.163)
liquidity	-0.217***	-0.199***	-0.197***	-0.224***	-0.208***	-0.206***	-0.199***	-0.163***	
	(0.017)	(0.016)	(0.015)	(0.016)	(0.012)	(0.014)	(0.016)	(0.014)	
size90	-0.079	-0.951	-0.169*	-0.228***	0.227	-0.361***	-0.144***	-0.004	0.200
	(0.174)	(0.685)	(0.095)	(0.043)	(0.170)	(0.133)	(0.043)	(0.104)	(0.199)
risk measure	0.638***	-1.521***	8.411***	28.453***	0.181***	0.258***	0.196***	0.333***	0.760***
	(0.106)	(0.293)	(1.019)	(8.309)	(0.013)	(0.032)	(0.027)	(0.081)	(0.118)
risk measure × size90	0.072	0.850	0.995	-2.547	-0.024	-0.056	-0.012	-0.070	0.195*
	(0.094)	(0.763)	(3.133)	(1.723)	(0.019)	(0.039)	(0.038)	(0.052)	(0.105)
liquidity (highfreq)									0.060***
									(0.005)
Constant	-2.478***	-2.176***	-3.793***	-3.731***	-5.647***	-2.838***	-3.701***	-3.553***	-2.239***
	(0.195)	(0.276)	(0.074)	(0.076)	(0.159)	(0.103)	(0.062)	(0.170)	(0.213)
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	No	No	No	Yes	No
Observations	27,422	27,422	27,422	27,422	27,422	27,366	25,598	27,420	18,075
R-squared	0.486	0.480	0.476	0.472	0.614	0.526	0.492	0.663	0.580

Table 4: Spread-Risk Sensitivity (Financial vs. Non-financial Sector)

This table presents regression results where the dependent variable is the natural logarithm of spreads. *ttm* is the time-to-maturity for a bond. *seniority* is a dummy variable indicating whether the bond is senior. *spread* is the difference between the yield on a given firm's bond and the yield on a maturity-matched Treasury bond. *Size90* is a dummy variable equal to one if a given financial institution's size is in the top 90th percentile. *financial* is a dummy variable set to one if the firm is a financial firm (SIC code starting with 6). *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. *dd* is Merton's (1974) distance-to-default measure. *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. *assetvol* is asset volatility computed from the Merton model. e*quityvol* is equity volatility calculated using daily equity returns over the past 12 months. *rating* is a number ranging from 1 to 21 corresponding to S&P credit ratings from AAA to C, with higher numbers corresponding to greater credit risk. *Mdd* is the distance-to-default measure calculated using the method in Nagel and Purnandam (2020). *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 five years, divided by the standard deviation of roa over five years. *illiquidity* 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. *illiquidity (highfreq)* is the aggregate illiquidity measure described in the text calculated using trade date reported in TRACE. Pre-Dodd-Frank is the time period before 2012. All regression models include month/year fixed effects. Standard errors are in parentheses below their coefficient estimates and are adjusted for both heteroscedasticity and within correlation clustering at issue and month/year. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% two-tailed levels, respectively.

Panel A: pre-Dodd-Frank period

VARIABLES	(1) -log(dd)	(2) leverage	(3) assetvol	(4) equityvol	(5) rating	(6) -log(zscore)	(7) -log(NPdd)	(8) -log(dd)	(9) -log(dd)
liquidity	-0.137***	-0.142***	-0.148***	-0.138***	-0.080***	-0.130***	-0.138***	-0.099***	
	(0.010)	(0.010)	(0.011)	(0.009)	(0.009)	(0.011)	(0.010)	(0.008)	
size90	-0.273***	-0.462***	0.132***	-0.192***	0.231***	0.124	-0.263***	-0.016	-0.248**
	(0.061)	(0.046)	(0.049)	(0.032)	(0.042)	(0.079)	(0.061)	(0.057)	(0.112)
financial	-0.597***	0.043	-0.318***	0.107***	0.286***	-0.168**	-1.648***	0.232*	-0.468***
	(0.063)	(0.086)	(0.044)	(0.032)	(0.067)	(0.072)	(0.052)	(0.140)	(0.093)
size90 × financial	-0.199**	0.984***	-0.077	0.259***	0.258***	-0.431***	0.185***	-0.393***	-0.143
	(0.096)	(0.101)	(0.066)	(0.060)	(0.098)	(0.120)	(0.066)	(0.086)	(0.145)
risk measure	0.833***	1.658***	-1.075***	2.792***	0.157***	0.188***	0.846***	0.472***	0.726***
	(0.029)	(0.068)	(0.149)	(0.092)	(0.004)	(0.012)	(0.028)	(0.031)	(0.046)
risk measure × size90	-0.084***	0.366***	-2.452***	0.157	-0.021***	0.096***	-0.084***	-0.052**	-0.045
	(0.030)	(0.094)	(0.283)	(0.105)	(0.005)	(0.022)	(0.030)	(0.026)	(0.047)
risk measure × financial	-0.283***	-0.814***	1.266***	-0.819***	-0.023***	-0.018	-0.636***	-0.046	-0.149***
	(0.035)	(0.111)	(0.431)	(0.087)	(0.008)	(0.020)	(0.031)	(0.031)	(0.047)
risk measure × size90 × financial	-0.141***	-1.044***	-1.165	-0.776***	-0.044***	-0.147***	0.043	-0.152***	-0.145**
	(0.053)	(0.133)	(0.815)	(0.147)	(0.012)	(0.034)	(0.040)	(0.044)	(0.067)
liquidity (high freq)									0.034***
									(0.004)
Constant	-2.658***	-4.990***	-3.820***	-4.915***	-5.691***	-3.391***	-2.617***	-3.603***	-2.836***
	(0.060)	(0.045)	(0.044)	(0.041)	(0.043)	(0.053)	(0.058)	(0.074)	(0.091)
Year-Month FE / Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	No	No	No	Yes	No
Observations	170,755	170,755	170,755	170,755	170,755	166,458	159,160	170,737	44,688
R-squared	0.497	0.516	0.435	0.528	0.577	0.468	0.487	0.629	0.629

Panel A: post-Dodd-Frank period

VARIABLES	(1) -log(dd)	(2) leverage	(3) assetvol	(4) equityvol	(5) rating	(6) -log(zscore)	(7) -log(NPdd)	(8) -log(dd)	(9) -log(dd)
liquidity	-0.357***	-0.385***	-0.370***	-0.350***	-0.298***	-0.366***	-0.352***	-0.243***	
	(0.016)	(0.017)	(0.017)	(0.017)	(0.014)	(0.017)	(0.017)	(0.014)	
size90	-0.942***	-0.895***	-0.029	-0.122	0.278***	-0.301***	-0.951***	0.043	-1.443***
	(0.170)	(0.113)	(0.088)	(0.094)	(0.105)	(0.109)	(0.168)	(0.102)	(0.236)
financial	-0.690***	-0.104	-0.179**	0.069	-0.256*	-0.000	-1.905***	0.000	-1.149***
	(0.195)	(0.228)	(0.079)	(0.083)	(0.136)	(0.134)	(0.123)	(0.000)	(0.289)
size90 × financial	1.017***	-0.274	0.106	0.225**	0.149	0.084	0.985***	-0.094	1.816***
	(0.280)	(0.730)	(0.119)	(0.111)	(0.185)	(0.184)	(0.178)	(0.146)	(0.369)
risk measure	1.013***	0.604***	0.228***	3.045***	0.168***	0.221***	0.992***	0.457***	1.238***
	(0.061)	(0.159)	(0.054)	(0.198)	(0.009)	(0.033)	(0.062)	(0.047)	(0.094)
risk measure × size90	-0.375***	0.980***	-3.022***	-0.235	-0.029**	0.016	-0.380***	0.023	-0.555***
	(0.089)	(0.209)	(0.638)	(0.300)	(0.011)	(0.037)	(0.088)	(0.047)	(0.130)
risk measure × financial	-0.369***	-0.218	1.097*	-0.198	0.024*	0.025	-0.769***	-0.030	-0.520***
	(0.106)	(0.316)	(0.633)	(0.230)	(0.013)	(0.040)	(0.065)	(0.076)	(0.163)
risk measure × size90 × financial	0.430***	0.217	-1.064	-0.491	-0.004	-0.079	0.415***	-0.109	0.761***
	(0.146)	(0.836)	(3.092)	(0.357)	(0.022)	(0.055)	(0.098)	(0.070)	(0.199)
liquidity (high freq)									0.085***
									(0.005)
Constant	-1.890***	-3.991***	-3.639***	-4.565***	-5.520***	-2.923***	-1.889***	-3.201***	-1.539***
	(0.114)	(0.109)	(0.066)	(0.084)	(0.094)	(0.110)	(0.117)	(0.098)	(0.157)
Year-Month FE / Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	No	No	No	Yes	No
Observations	56,542	56,542	56,542	56,542	56,542	56,461	54,718	56,535	36,330
R-squared	0.555	0.535	0.502	0.562	0.680	0.546	0.562	0.756	0.568

Table 5: Equity Return sensitivity of Bond Returns

This table presents regression results where the dependent variable is the change in spread. *ttm* is the time-to-maturity for a bond. *seniority* is a dummy variable indicating whether the bond is senior. *spread* is the difference between the yield on a given firm's bond and the yield on a maturity-matched Treasury bond. *Size90* is a dummy variable equal to one if a given financial institution's size is in the top 90th percentile. *financial* is a dummy variable set to one if the firm is a financial firm (SIC code starting with 6). *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. *assetvol* is asset volatility computed from the Merton model. *illiquidity* 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. *Ereturn return* is the monthly equity return. *Dreturn* is the monthly bond return multiplied by 100. *hedgeratio* is the equity hedge ratio from the Merton (1974) model described in the Appendix. Pre-Dodd-Frank is the time period before 2012. All regression models include month/year fixed effects. Standard errors are in parentheses below their coefficient estimates and are adjusted for both heteroscedasticity and within correlation clustering at issue and month/year. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% two-tailed levels, respectively.

	Pre-Dodd-Frank		Post-Dodd-Frank	
	(1)	(2)	(3)	(4)
VARIABLES	Dreturn	Dreturn	Dreturn	Dreturn
ttm	0.010	0.015	0.011	0.008
	(0.015)	(0.010)	(0.009)	(0.008)
senior	0.059	0.022	0.020	0.001
	(0.082)	(0.069)	(0.035)	(0.039)
roa	-1.869	-0.863	-6.081**	-1.911**
	(5.563)	(1.725)	(2.554)	(0.770)
mb	0.053	0.010	-0.025	0.007
	(0.071)	(0.009)	(0.034)	(0.008)
mismatch	0.379	-0.022	0.347*	0.017
	(0.529)	(0.358)	(0.207)	(0.091)
liquidity	-0.112*	-0.053*	-0.120***	-0.096***
	(0.063)	(0.032)	(0.031)	(0.031)
size90	-0.079	0.027	0.054	-0.031
	(0.172)	(0.147)	(0.066)	(0.056)
Ereturn x hedgeratio	57.043***	92.017***	82.090***	107.594***
	(10.551)	(20.796)	(21.787)	(16.128)
Ereturn x hedgeratio x size90	-44.961***	19.321	8.929	0.648
	(12.119)	(23.749)	(37.345)	(53.938)
Ereturn x financial		-35.421		-24.327
		(24.741)		(26.908)
financial x size90		-0.124		0.151***
		(0.162)		(0.057)
Ereturn x hedgeratio x size90 x financial		-66.325**		41.252
		(29.972)		(67.960)
Constant	0.469*	0.477***	0.690***	0.523***
	(0.249)	(0.126)	(0.127)	(0.113)
Year-Month FE	Yes	Yes	Yes	Yes
Observations	19,242	35,270	16,163	29,177
R-squared	0.283	0.210	0.227	0.246

Table 6: Risk-Shifting

This table presents regression results where the dependent variable is the change in the fair insurance premium. *IPP* is the fair insurance premium per dollar of liabilities computed following Merton (1977). *assetvol* is asset volatility computed from the Merton model. *Size90* is a dummy variable equal to one if a given financial institution's size is in the top 90th percentile. *financial* is a dummy variable set to one if the firm is a financial firm (SIC code starting with 6).. All regression models include month/year fixed effects. Standard errors are in parentheses below their coefficient estimates and are adjusted for both heteroscedasticity and within correlation clustering at issue and month/year. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% two-tailed levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Pre-DoddFrank	Pre-DoddFrank	Pre-DoddFrank	Post-DoddFrank	Post-DoddFrank	Post-DoddFrank
VARIABLES	Δ IPP	Δ IPP	Δ IPP	Δ IPP	Δ IPP	Δ IPP
Δ asset vol	55.333***	52.790***	35.532***	27.273**	27.263**	37.917***
	(8.056)	(8.213)	(3.348)	(13.241)	(13.247)	(5.925)
size90		-0.036	-0.024		-0.010	-0.062***
		(0.057)	(0.029)		(0.012)	(0.019)
size90 × Δasset vol		51.012***	-15.827*		-2.496	-27.400***
		(18.397)	(8.429)		(6.406)	(9.060)
financial			-0.013			-0.058***
			(0.032)			(0.022)
financial × size90			-0.014			0.049**
			(0.071)			(0.022)
financial × Δasset vol			19.414**			-14.815
			(7.818)			(12.525)
financial × size90 × Δasset vol			70.424***			13.506
			(22.022)			(13.756)
Constant	0.005**	0.012	0.032***	0.014	0.015	0.074***
	(0.002)	(0.007)	(0.005)	(0.010)	(0.011)	(0.007)
Year/Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	22,832	22,832	135,321	12,860	12,860	74,426
R-squared	0.247	0.251	0.159	0.113	0.113	0.139

Table 7: Event Study Analyses

This table presents event regression results where the dependent variable is the natural logarithm of spreads. 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 three trading days prior to the event date. The events and the event dates are specified in the first two columns. We use the same set of controls used in regression reported in Table 2. *ttm* is the time-to-maturity for a bond. *senior* 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. *Size90* is a dummy variable equal to one if a given financial institution's size is in the top 90th percentile. *financial* is a dummy variable set to one if the firm is a financial firm (SIC code starting with 6). *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. *dd* is Merton's (1974) distance-to-default measure. *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. *illiquidity* 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. For brevity, we only report the coefficients of interest on the interaction terms which are specified in columns 3 to 6. All regression models include issue fixed effects. Standard errors are in parentheses below their coefficient estimates and are adjusted for both heteroscedasticity and within correlation clustering at issue level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% two-tailed levels, respectively.

Date	Event	size90 ×post	size90 ×financial ×post
09/15/08	Lehman Brothers files for bankruptcy	0.400***	0.340***
		(0.052)	(0.057)
03/13/08	Bear Stearns bailout	-0.061***	-0.088***
		(0.019)	(0.026)
09/20/08	Paulson submits TARP proposal	-0.170***	-0.195***
		(0.032)	(0.040)
10/14/08	Treasury announces $250 billion capital injections	-0.096***	-0.014
		(0.034)	(0.044)
11/16/2017	Bill S2155 introduced to change asset size threshold	0.005	-0.011
	for enhanced supervision	(0.023)	(0.040)
3/17/2020	FED, FDIC, OCC announce coordinated actions (establish	-0.027	-0.096
	CP, MM, PD funding facility)	(0.025)	(0.068)
3/23/2020	Fed Announces extensive new measures to support the	-0.091*	0.050
	economy	(0.048)	(0.077)
4/1/2020	FED announces temporary change to Leverage Ratio Rule	0.013	0.038
		(0.036)	(0.047)
4/9/2020	FED announces up to $2.3 trillion in loans to support the	-0.042	0.003
	economy	(0.029)	(0.051)

Table 8: Spread-Risk sensitivity during the initial Covid-time period

This table presents regression results where the dependent variable is the natural logarithm of spreads. We examine the time period at onset of the pandemic. The left panel presents regression results for the time period from 3/1/2020 to 6/31/2020 and the right panel presents results for the 3/1/2020 to 3/31/2020 time period. *ttm* is the time-to-maturity for a bond. *senior* 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. *Size90* is a dummy variable equal to one if a given financial institution's size is in the top 90th percentile. *financial* is a dummy variable set to one if the firm is a financial firm (SIC code starting with 6). *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. *dd* is Merton's (1974) distance-to-default measure. *illiquidity* 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. All regression models include month/year fixed effects. Standard errors are in parentheses below their coefficient estimates and are adjusted for both heteroscedasticity and within correlation clustering at issue and month/year. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% two-tailed levels, respectively.

	3/1/2020- 6/31/2020		3/1/2020- 3/31/2020	
	(1)	(2)	(3)	(4)
VARIABLES	log(spread)	log(spread)	log(spread)	log(spread)
ttm	0.023***	0.016***	0.005***	0.007***
	(0.006)	(0.004)	(0.002)	(0.002)
senior	-0.244***	-0.219***	-0.132***	-0.114***
	(0.050)	(0.059)	(0.026)	(0.033)
roa	-17.632***	-8.022***	-20.769***	-5.978***
	(4.495)	(1.352)	(2.385)	(0.865)
mb	-0.070	0.003	0.069*	0.003
	(0.063)	(0.007)	(0.037)	(0.006)
mismatch	2.787***	-0.410	1.836***	0.165
	(0.376)	(0.330)	(0.248)	(0.217)
liquidity	-0.284***	-0.389***	-0.093***	-0.147***
	(0.065)	(0.090)	(0.021)	(0.035)
risk measure	0.312	0.744***	0.533	0.802***
	(0.196)	(0.119)	(0.619)	(0.155)
size90	-0.444*	-0.823**	-0.241	-1.888***
	(0.184)	(0.298)	(1.123)	(0.397)
risk measure × size90	-0.081	-0.421**	-0.054	-0.835***
	(0.105)	(0.171)	(0.596)	(0.210)
financial		-1.166**		-1.929
		(0.346)		(1.326)
risk measure × financial		-0.487*		-0.813
		(0.218)		(0.699)
financial × size90		0.682		2.223*
		(0.404)		(1.342)
risk measure × size90 × financial		0.418		
		(0.245)		(0.708)
Constant	-2.728***	-2.061***	-2.130*	-1.405***
	(0.267)	(0.182)	(1.162)	(0.264)
Year-Month FE	Yes	Yes	Yes	Yes
Observations	17,558	36,761	2,794	5,966
R-squared	0.669	0.579	0.23	0.305

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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	Time-to-maturity in years.
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.
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.
liquidity(high freq)	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	
size90	Dummy variable that equals 1 if an issuer's size is greater than the 90^{th} percentile of its distribution 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.
leverage	Total liabilities divided by total market value of assets.
roa	Return on assets, measured as net income divided by total assets.
mb	Market value of total equity divided by book value of total equity.
mismatch	Short-term debt minus cash divided by total liabilities.
rating	Number ranging from 1 to 21 corresponding to S&P credit ratings from AAA to C, with higher numbers corresponding to greater credit risk.
dd	Merton's distance-to-default measure, as described below.

NPdd	Modified distance-to-default measure calculated following Nagel and Purnandam (2020).
IPP	IPP is the fair insurance premium per dollar of liabilities computed following Merton (1977). The estimation is described in detail below.
equityvol	Stock return volatility computed using returns over the past 12 months.
assetvol	Volatility of market value of assets computed using the Merton model.
Dreturn	Monthly bond return
Ereturn	Monthly equity return
hedgeratio	Equity hedge ratio from the Merton (1974) model described below
rf	1 month t-bill rate

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 measure. The market equity value of a company is modeled as a call option on the company's assets:

$$E = Ae^{-dT}N(d_1) - Xe^{-rT}N(d_2) + (1 - e^{-dT})A$$
$$d_1 = \frac{\log\left(\frac{A}{X}\right)+\left(r-d+\frac{\sigma_A^2}{2}\right)T}{\sigma_A\sqrt{T}}; d_2 = d_1 - \sigma_A\sqrt{T}, \tag{A.1}$$

where *E* is the market value of a bank, *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 *A*. σ_A is the volatility of the value of assets, which is related to equity volatility through the following equation:

$$\sigma_E = \frac{A\, N(d_1)\sigma_A}{E}\ . \tag{A.2}$$

We simultaneously solve equations (1) and (2) to find the values of *A* and σ_A. We use the market value of equity for *E* and total liabilities to proxy for the face value of debt, *X*.[1] σ_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. We use the Newton method to simultaneously solve the two equations above. For starting values for the unknown variables, we use $A = E + X$ and $\sigma_A = \sigma_E E/(E+X)$. After we determine asset values *A*, we follow Campbell, Hilscher, and Szilagyi (2008) and assign asset return *m* to be equal to the equity premium of 6%. Merton's (1974) distance-to-default (*dd*) measure is finally computed as:

[1] 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.

$$dd = \frac{log\left(\frac{A}{X}\right)+\left(m-d-\frac{\sigma_A^2}{2}\right)T}{\sigma_A\sqrt{T}}. \tag{A.3}$$

Equity Hedge Ratio

The equity hedge ratio is the first derivative of the changes in debt values to changes in equity values in the Merton model described in equation (1) above:

$$\frac{\partial D}{\partial E} = (\frac{1}{N(d_1) - 1} - 1))(\frac{A}{D} - 1) \tag{A.4}$$

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 (σ_A) and the fair value of the insurance put-option per dollar of liabilities (*IPP*). IPP is computed as:

$$IPP = N\left(\frac{log\left(\frac{X}{A}\right)+\frac{\sigma_A^2}{2}T}{\sigma_A\sqrt{T}}\right) - \left(\frac{A}{X}\right)N\left(\frac{log\left(\frac{X}{V_A}\right)-\frac{\sigma_A^2}{2}T}{\sigma_A\sqrt{T}}\right), \tag{A.5}$$

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

Liquidity Measures

We compute the following corporate bond liquidity measures based on transaction data availability. The first liquidity measure is computed for the time period starting in 2003, after the introduction of TRACE. Following Dick-Nielsen, Feldhutter, and Lando (2012), we calculate and combine four liquidity measures. We use all bond transactions to compute these four liquidity measures. The first liquidity measure, *amihud*, is based on Amihud (2002). It measures the price impact of trading a bond. It is the average absolute value of daily returns divided by total daily dollar volume:

$$Amihud_{i,t} = \frac{1}{N_{i,t}}\sum_{k=1}^{N}\frac{|r_{i,k}|}{volume_{i,k}}. \tag{A.6}$$

In equation (5), k is the number of days with valid returns in month *t* for bond i. $r_{i,k}$ is bond's return 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 five days apart. We also require minimum of five returns in a given month to compute the *amihud* measure.

The second liquidity measure, *roll*, is the Roll proxy of bid-ask spreads, based on the work of Roll (1984). It is designed to capture transitory price movements induced by the 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:

$$Roll_{i,t} = 2\sqrt{-Cov\left(\Delta P_{i,k}, \Delta P_{i,k-1}\right)}, \tag{A.7}$$

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

The third liquidity measure, *range*, is based on daily price range proposed by Jirnyi (2010). It is similar to *amihud* and is designed to capture the price impact of a trade as follows:

$$Range_{i,t} = \frac{1}{N_{i,t}} \sum_{k=1}^{N} \frac{P_{i,k}^{High} - P_{i,k}^{Low}}{volume_{i,k}}, \tag{A.8}$$

where $P_{i,k}^{High}$ 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 liquidity measure, *zeros*, is based on trading activity. It computed as the percentage of days during a month in which the bond did not trade. We standardize the liquidity measures for each bond each month and then aggregate these standardized measures and multiply by -1 to compute *liquidity high freq*.

For the full time period (including years prior to 2003), we compute another liquidity measure based on bond characteristics following Longstaff, Mithal, and Neis (2005). We compute this *liquidity* measure based on four bond characteristics: amount outstanding, age, time-to-maturity, and rating. The maximum liquidity value assigned to a bond is four and the minimum liquidity value is zero. 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. 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 o is less than seven years, then the dummy variable is assigned a value of one. The fourth proxy 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.

Appendix B: Merton Model with Guarantees

In this Appendix section we analytically examine the impact of an exogenous government guarantee on the relationship between spreads and leverage and spreads and asset volatility in the Merton model. Bond spreads in the Merton model are a function of leverage, asset volatility and time-to-maturity. Spreads increase with asset volatility and leverage. We show that the government guarantees blunt the relationship between spreads and these two measures of credit risk.

I. Structural Model

In the Merton (1975) model, the equity values of firm are calculated as call and put options on the firm's assets:

$$E = AN(d_1) - Xe^{-rT}N(d_2) \tag{B.1}$$

$$d_1 = \frac{\ln\left(\frac{A}{X}\right) + \left(r + \frac{\sigma_A^2}{2}\right)T}{\sigma_A\sqrt{T}};\, d_2 = d_1 - \sigma_A\sqrt{T} \tag{B.2}$$

E is the market value of a firm, *A* is the value of the firm's assets, *X* is the face value of debt maturing at time *T*, *r* is the risk-free rate, and *N* is the cumulative normal function. σ_A is the volatility of the value of assets. Since the value of assets is equal to the sum of equity and debt values. The market value of debt of the firm is:

$$\begin{aligned} D &= A - E && \text{(B.3)} \\ &= A - AN(d_1) + Xe^{-rT}N(d_2) \\ &= A\big(1 - N(d_1)\big) + Xe^{-rT}N(d_2) \\ &= AN(-d_1) + Xe^{-rT}N(d_2) && \text{(B.4)} \end{aligned}$$

The debt value can also be expressed as the face value discounted back to today at the risk free rate plus a premium spread (*s*):

$$D = Xe^{-(r+s)T} \tag{B.5}$$
$$AN(-d_1) + Xe^{-rT}N(d_2) = Xe^{-(r+s)T} \tag{B.6}$$

We can then solve for the spread:

$$AN(-d_1) + Xe^{-rT}N(d_2) = Xe^{-(r+s)T} \tag{B.7}$$
$$s = -\frac{1}{T}\ln\left(\frac{A}{X}N(-d_1) + e^{-rT}N(d_2)\right) - r$$

$$
\begin{aligned}
&= -\frac{1}{T}\ln\left(e^{-rT}\left(\frac{A}{X}N(-d_1)e^{rT} + N(d_2)\right)\right) - r \\
&= -\frac{1}{T}\ln(e^{-rT}) - r - \frac{1}{T}\ln\left(\frac{A}{X}N(-d_1)e^{rT} + N(d_2)\right) \qquad \text{(B.8)} \\
&= -\frac{1}{T}\ln\left(\frac{A}{X}N(-d_1)e^{rT} + N(d_2)\right)
\end{aligned}
$$

We can write the debt value in terms of probability of default and expected recovery. Starting with equation (4) we have:

$$
\begin{aligned}
D &= AN(-d_1) + Xe^{-rT}N(d_2) \\
&= Xe^{-rT}\big(1 - N(-d_2)\big) + N(-d_2)A\frac{N(-d_1)}{N(-d_2)} \\
&= Xe^{-rT}(1 - P_D) + P_D R \qquad \text{(B.9)}
\end{aligned}
$$

In equation (8), P_D is the probability of default, which is equal to the probability of asset values falling below the face value of liabilities: $P_D = N(-d_2)$. The recovery amount R is equal to the the conditional asset value when asset values fall below face value of liabilities ($A < X$), which is equal to: $R = AN(-d_1)/N(-d_2)$.

In the Merton model, the spreads increase with leverage and asset volatility. That is the first derivative of the spreads with respect to asset volatility and leverage is positive: $\partial s/\partial\sigma_A > 0$ and $\partial s\ /\partial(\frac{X}{A}) > 0$.

II. Government Guarantees

To this setup, we now add the assumption that the government will intervene with probability P_G, to cover all losses on debt. We further assume that the government will not cover losses on equity and that σ_A is not affected by government guarantees. With a potential government intervention the debt values are given by:

$$
D = Xe^{-rT}(1 - P_D + P_D P_G) + P_D(1 - P_G)R \qquad \text{(B.10)}
$$

The existence of the government guarantee dampens the relationship between spreads and asset volatility and the relationship between spreads and leverage. That is the sensitivity of spreads to leverage and asset volatility decline with the probability of government intervention (P_G) to cover losses: $\partial^2 s/\partial\sigma_A\partial P_G < 0$ and $\partial^2 s\ /\partial\frac{X}{A}\partial P_G < 0$. To show this relationship we start with the following definitions and inequalities. Below, we use $N_a = N(-d_a)$, $N'_a = N'(-d_a)$, $\partial_a = \partial(-d_a)/\ \partial\sigma_A$ and $Y = X/A$.

$$
N(\mathrm{z}) = \frac{1}{\sqrt{2\pi}}\int_{-\infty}^{z} e^{\frac{-x^2}{2}}dx > 0 \qquad \text{(B.11)}
$$

$$
N'(\mathrm{z}) = \frac{1}{\sqrt{2\pi}}e^{\frac{-z^2}{2}} > 0 \qquad \text{(B.12)}
$$

$$\frac{\partial(-d_2)}{\partial \sigma_A} = -\frac{\partial}{\partial \sigma_A}\left(d_1 - \sigma_A\sqrt{T}\right) = \frac{\partial(-d_1)}{\partial \sigma_A} + \sqrt{T}$$

$$\Rightarrow \frac{\partial(-d_1)}{\partial \sigma_A} = -\frac{\partial}{\partial \sigma_A}\left[\frac{1}{\sigma_A}\frac{\ln\left(\frac{A}{X}\right) + rT}{\sqrt{T}} + \frac{1}{2}\sigma_A\sqrt{T}\right]$$

$$= \frac{1}{\sigma_A^2}\frac{\ln\left(\frac{A}{X}\right) + rT}{\sqrt{T}} - \frac{1}{2}\sqrt{T} = \frac{1}{\sigma_A} d_1 - \sqrt{T}$$

$$\Rightarrow \frac{\partial(-d_2)}{\partial \sigma_A} = \frac{1}{\sigma_A^2}\frac{\ln\left(\frac{A}{X}\right) + rT}{\sqrt{T}} - \frac{1}{2}\sqrt{T} + \sqrt{T} = \frac{1}{\sigma_A} d_1 \tag{B.13}$$

$$\frac{\partial(-d_2)}{\partial Y} = -\frac{\partial}{\partial Y}\left(d_1 - \sigma_A\sqrt{T}\right) = \frac{\partial(-d_1)}{\partial Y} \tag{B.14}$$

$$\frac{\partial(-d_1)}{\partial Y} = -\frac{\partial}{\partial Y}\frac{\ln Y^{-1} + \left(r + \frac{\sigma_A^2}{2}\right)T}{\sigma_A\sqrt{T}}$$

$$= \frac{1}{\sigma_A\sqrt{T}}\,\frac{1}{Y}$$

$$\Rightarrow \frac{\partial(-d_2)}{\partial Y} > 0 \tag{B.15}$$

$$N(-d_2) > N(-d_1) \tag{B.16}$$

$$\frac{\partial(-d_2)}{\partial \sigma_A} > \frac{\partial(-d_1)}{\partial \sigma_A} \tag{B.17}$$

Case $d_1 < 0$

$$\frac{\partial(-d_1)}{\partial \sigma_A} < 0 \tag{B.18}$$

$$\frac{\partial(-d_2)}{\partial \sigma_A} < 0 \tag{B.19}$$

$$N'(-d_1) > N'(-d_2) \tag{B.20}$$

Case $d_1 > 0$

$$\frac{\partial(-d_1)}{\partial \sigma_A} \text{ can be } > \text{ or } < \text{ than } 0 \tag{B.21}$$

$$\frac{\partial(-d_2)}{\partial \sigma_A} > 0 \tag{B.22}$$

$$N'(-d_2) > N'(-d_1) \tag{B.23}$$

$$N'(-d_2)e^{-rT} = \frac{1}{2\pi}\exp\left[-\frac{1}{2}\left(d_1 - \sigma_A\sqrt{T}\right)^2 - rT\right]$$

$$= \frac{1}{2\pi}\exp\left[-\frac{1}{2}{d_1}^2 + d_1\sigma_A\sqrt{T} - \frac{1}{2}{\sigma_A}^2 - rT\right]$$

$$= \frac{1}{2\pi}\exp\left[-\frac{1}{2}{d_1}^2 + \ln\left(\frac{1}{Y}\right) + rT + \frac{1}{2}{\sigma_A}^2 T - \frac{1}{2}{\sigma_A}^2 T - rT\right]$$

$$= \frac{1}{2\pi}\exp\left[-\frac{1}{2}{d_1}^2 + \ln\left(\frac{1}{Y}\right)\right]$$

$$= N'(-d_1)e^{\ln\left(\frac{1}{Y}\right)}$$

$$= \left(\frac{1}{Y}\right)N'(-d_1) \tag{B.24}$$

We want to show that $\frac{\partial^2 s}{\partial \sigma_A \, \partial P_G} < 0$. We start by writing the spread *s* in terms of *D* using equation (5):

$$
\begin{aligned}
D &= Xe^{-(r+s)T} \\
\Rightarrow \ln\left(\frac{D}{X}\right) &= \ln\left(e^{-(r+s)T}\right) \\
&= -(r+s)T \\
\Rightarrow s &= -\frac{1}{T}\ln\left(\frac{D}{X}\right) - r
\end{aligned}
\tag{B.25}
$$

Defining $I = D/X$ as

$$
I \equiv e^{-rT}(1 - P_D + P_D P_G) + P_D(1 - P_G)\frac{R}{X} \tag{B.26}
$$

$$
= e^{-rT}(1 - P_D + P_D P_G) + \frac{A}{X}(1 - P_G)N(-d_1) \tag{B.27}
$$

Inserting equation (9) into equation (24), we have:

$$
\begin{aligned}
s &= -\frac{1}{T}\ln(I) - r \\
&= -\frac{1}{T}\ln\left(\frac{Xe^{-rT}(1 - P_D + P_D P_G) + P_D(1 - P_G)R}{X}\right) - r
\end{aligned}
\tag{B.28}
$$

The derivative with respect to P_G is:

$$
\frac{\partial s}{\partial P_G} = -\frac{1}{T}\frac{1}{I}\frac{\partial I}{\partial P_G} \tag{B.29}
$$

We then take the derivative with respect to σ_A:

$$
\begin{aligned}
\frac{\partial^2 s}{\partial P_G \, \partial \sigma_A} &= -\frac{1}{T}\left[-\frac{1}{I^2}\frac{\partial I}{\partial \sigma_A}\frac{\partial I}{\partial P_G} + \frac{1}{I}\frac{\partial^2 I}{\partial P_G \partial \sigma_A}\right] \\
&= -\frac{1}{T}\frac{\left(I\frac{\partial^2 I}{\partial \sigma_A \, \partial P_G} - \frac{\partial I}{\partial \sigma_A}\frac{\partial I}{\partial P_G}\right)}{I^2} \\
&= -\frac{1}{T}\frac{e^{-2rT}\sqrt{T}N'(-d_2)}{I^2}
\end{aligned}
\tag{B.30}
$$

from which we can see that

$$
\frac{\partial^2 s}{\partial P_G \, \partial \sigma_A} < 0 \tag{B.31}
$$

since both the numerator and denominator are positive. Equation (29) is obtained as follows:

$$
I = e^{-rT} - e^{-rT}N_2 + e^{-rT}N_2 P_G + \frac{1}{Y}N_1 - \frac{1}{Y}N_1 P_G \tag{B.32}
$$

$$
\frac{\partial I}{\partial P_G} = e^{-rT}N_2 - \frac{1}{Y}N_1 \tag{B.33}
$$

$$\frac{\partial I}{\partial \sigma_A} = e^{-rT}(P_G - 1)N'_2\,\partial_2 - \frac{1}{Y}(P_G - 1)N'_1\,\partial_1 \tag{B.34}$$

$$\frac{\partial^2 I}{\partial P_G\,\partial \sigma_A} = e^{-rT}N'_2\,\partial_2 - \frac{1}{Y}N'_1\,\partial_1 \tag{B.35}$$

we then have:

$$\begin{aligned}
&\left(I\frac{\partial^2 I}{\partial\sigma_A\,\partial P_G} - \frac{\partial I}{\partial\sigma_A}\frac{\partial I}{\partial P_G}\right)\\
&= e^{-2rT}N'_2\,\partial_2 - e^{-2rT}N'_2N_2\,\partial_2 + e^{-2rT}N'_2N_2P_G\,\partial_2\\
&\quad - \frac{1}{Y}e^{-rT}N_1N'_2\,\partial_2 - \frac{1}{Y}e^{-rT}N_1N'_2P_G\,\partial_2 - \frac{1}{Y}e^{-rT}N'_1\,\partial_1\\
&\quad + \frac{1}{Y}e^{-rT}N'_1N_2\,\partial_1 - \frac{1}{Y}e^{-rT}N'_1N_2P_G\,\partial_1 - \frac{1}{Y^2}N_1N'_1\,\partial_1\\
&\quad + \frac{1}{Y^2}N_1N'_1P_G\,\partial_1 - e^{-2rT}N'_2N_2P_G\,\partial_2 + e^{-2rT}N'_2N_2\,\partial_2\\
&\quad + \frac{1}{Y}e^{-rT}N'_1N_2P_G\,\partial_1 - \frac{1}{Y}e^{-rT}N'_1N_2\,\partial_1 - \frac{1}{Y^2}N_1N'_1P_G\,\partial_1\\
&\quad + \frac{1}{Y^2}e^{-rT}N'_1N_2\,\partial_1 + \frac{1}{Y}e^{-rT}N_1N'_2P_G\,\partial_2 + \frac{1}{Y}e^{-rT}N_1N'_2\,\partial_2
\end{aligned} \tag{B.36}$$

$$\begin{aligned}
&= e^{-2rT}N'_2\,\partial_2 - e^{-rT}\frac{1}{Y}N'_1\,\partial_1\\
&= e^{-2rT}N'_2\left(\partial_1 + \sqrt{T}\right) - e^{-rT}\frac{1}{Y}N'_1\,\partial_1
\end{aligned} \tag{B.37}$$

$$= e^{-rT}[e^{-rT}N'_2\,\partial_1 + e^{-rT}N'_2\sqrt{T} - \frac{1}{Y}N'_1\,\partial_1] \tag{B.38}$$

$$= e^{-rT}\left[\partial_1\left(\underbrace{e^{-rT}N'_2 - \frac{1}{Y}N'_1}_{=0}\right) + e^{-rT}N'_2\sqrt{T}\right] \tag{B.39}$$

$$= e^{-2rT}N'_2\sqrt{T} \tag{B.40}$$

We also have:

$$\begin{aligned}
\frac{\partial I}{\partial P_G} &= e^{-rT}N(-d_2) - N(-d_2)\frac{R}{X}\\
&= e^{-rT}N(-d_2) - \frac{A}{X}N(-d_1)\\
&= \underbrace{\frac{1}{X}}_{>0}\underbrace{N(-d_2)}_{>0}\underbrace{[Xe^{-rT} - R]}_{>0}\\
&> 0
\end{aligned} \tag{B.41}$$

where it is assumed that the recovery amount is less than the present value of the debt.

Next, we show that We want to show that $\frac{\partial^2 s}{\partial\sigma_A\,\partial\frac{X}{A}} < 0$.

Setting

$$Y = \frac{X}{A} \tag{B.42}$$

We have:

$$I = e^{-rT} - e^{-rT}N_2 + e^{-rT}N_2P_G + \frac{1}{Y}N_1 - \frac{1}{Y}N_1P_G \tag{B.43}$$

$$\begin{aligned}
\frac{\partial I}{\partial Y} &= -e^{-rT}N'_2\,\partial_2 + e^{-rT}N'_2\partial_2P_G + \frac{1}{Y}N'_1\partial_1 - \frac{1}{Y^2}N_1 - \frac{1}{Y}N'_1P_G\partial_1 + \frac{1}{Y^2}N_1P_G \\
&= (P_G - 1)\partial_1\underbrace{\left[e^{-rT}N'_2 - \frac{1}{Y}N'_1\right]}_{=0} + (P_G - 1)\frac{N_1}{Y^2} \\
&= (P_G - 1)\frac{N_1}{Y^2} \qquad \text{(B.44)}
\end{aligned}$$

$$\frac{\partial I}{\partial P_G} = e^{-rT}N_2 - \frac{1}{Y}N_1 \tag{B.45}$$

$$\frac{\partial^2 I}{\partial P_G \partial Y} = \frac{N_1}{Y^2} \tag{B.46}$$

where equations (23) and (13) are used. We then have:

$$\begin{aligned}
\frac{\partial^2 s}{\partial P_G \partial Y} &= -\frac{1}{T}\frac{1}{I^2}\left[I\frac{\partial^2 I}{\partial P_G \partial Y} - \frac{\partial I}{\partial P_G}\frac{\partial I}{\partial Y}\right] \\
&= -\frac{1}{T}\frac{1}{I^2}[e^{-rT}\frac{N_1}{Y^2} - e^{-rT}\frac{N_1N_2}{Y^2} + e^{-rT}\frac{N_1N_2P_G}{Y^2} \\
&\quad + \frac{{N_1}^2}{Y^3} - \frac{{N_1}^2P_G}{Y^3} - e^{-rT}\frac{N_1N_2P_G}{Y^2} + e^{-rT}\frac{N_1N_2}{Y^2} \\
&\quad + \frac{{N_1}^2P_G}{Y^3} - \frac{{N_1}^2}{Y^3}] \\
&= -\frac{1}{T}\frac{1}{I^2}\left[e^{-rT}\frac{N(-d_1)}{Y^2}\right] \qquad \text{(B.47)} \\
&< 0 \qquad \text{(B.48)}
\end{aligned}$$

which is less than zero because the term in the brackets is positive. From this result we can see that:

$$\frac{\partial s}{\partial Y} > 0 \tag{B.49}$$

since:

$$\frac{\partial s}{\partial Y} = \underbrace{-\frac{1}{T}}_{<0}\ \underbrace{\frac{1}{I}}_{>0}\ \underbrace{\frac{\partial I|_{P_G=0}}{\partial Y}}_{<0} > 0 \tag{B.50}$$

Finally, we want to show that the hedge ratio – the sensitivity of changes in equity values to changes in debt values also decline with government guarantees. As in Schaefer and Strebulaev (2008), the hedge ratio is given by:

$$\begin{aligned}
\frac{\partial D}{\partial E}\frac{E}{D} &= \frac{\partial \ln(D)}{\partial \ln(E)} = \left(\frac{\frac{\partial D}{\partial A}}{\frac{\partial E}{\partial A}}\right)\frac{E}{D} = \left(\frac{\frac{\partial(A-E)}{\partial A}}{\frac{\partial E}{\partial A}}\right)\frac{E}{D} \\
&= \left(\frac{1 - \frac{\partial E}{\partial A}}{\frac{\partial E}{\partial A}}\right)\frac{E}{D} = \left(\frac{1}{\frac{\partial E}{\partial A}} - 1\right)\frac{E}{D}
\end{aligned}$$

$$= \underbrace{\left(\frac{1}{N(d_1)}\right)}_{<0}\underbrace{\left(\frac{A}{D}-1\right)}_{>0} \tag{B.51}$$

We can also write this sensitivity with respect to spreads.

$$D = Xe^{-(r+s)T} \tag{B.52}$$

$$s = -\frac{1}{T}\ln(\mathrm{D}) + \frac{1}{\mathrm{T}}\ln(X) - r \tag{B.53}$$

$$\frac{\partial s}{\left(\frac{\partial E}{E}\right)} = -\frac{1}{T}\frac{\partial \ln(D)}{\partial \ln(E)} = -\frac{1}{T}\underbrace{\left(\frac{1}{N(d_1)}-1\right)}_{<0}\underbrace{\left(\frac{A}{D}-1\right)}_{=E/D>0} > 0 \tag{B.54}$$

We want to show that government guarantees dull the relationship between spreads and changes in equity values: $\partial^2 s \,/\partial\left(\frac{\partial E}{E}\right)\partial P_G < 0$. Taking the second derivative, we have:

$$\begin{aligned}\frac{\partial^2 s}{\left(\frac{\partial E}{E}\right)\partial P_G} &= \frac{\partial}{\partial P_G}\left[-\frac{1}{T}\left(\frac{1}{N(d_1)}-1\right)\left(\frac{A}{D}-1\right)\right] \\ &= -\frac{A}{T}\underbrace{\left(\frac{1}{N(d_1)}-1\right)}_{<0}\underbrace{\frac{\partial}{\partial P_G}\frac{1}{D}}_{<0} \\ &< \;0\end{aligned} \tag{B.55}$$

where

$$\begin{aligned}\frac{\partial}{\partial P_G}\frac{1}{D} &= -\frac{1}{D^2}\frac{\partial}{\partial P_G}D \\ &= -\frac{1}{D^2}\frac{\partial}{\partial P_G}[Xe^{-rT}(1-P_D+P_DP_G)+P_D(1-P_G)R] \\ &= -\frac{1}{D^2}[Xe^{-rT}P_D - P_DR] \\ &= -\frac{1}{D^2}P_D[Xe^{-rT}-R] \\ &< \;0\end{aligned} \tag{B.56}$$

again assuming that the recovery is less than the present value of the debt.

Appendix C: Robustness Checks

Table C1: Spread-Risk sensitivity including all bonds with embedded optionality

This table presents regression results where the dependent variable is the natural logarithm of spreads. Panel A reports regression results using the interaction of the top two decile seize dummies. Panel B reports results using firm fixed effects. Panel C reports results using a sample of all bonds including non-plain-vanilla bonds. *ttm* is the time-to-maturity for a bond. *seniority* is a dummy variable indicating whether the bond is senior. *spread* is the difference between the yield on a given firm's bond and the yield on a maturity-matched Treasury bond. *sizeX* is a dummy variable equal to one if a given financial institution's size is in the top Xth percentile. *financial* is a dummy variable set to one if the firm is a financial firm (SIC code starting with 6). *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. *dd* is Merton's (1974) distance-to-default measure. *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. *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 Pre-Dodd-Frank is the time period before 2012. All regression models include month/year fixed effects. Standard errors are in parentheses below their coefficient estimates and are adjusted for both heteroscedasticity and within correlation clustering at issue and month/year. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% two-tailed levels, respectively.

VARIABLES	(1) pre-Dodd Frank log(spread)	(2) post-Dodd Frank log(spread)	(3) pre-Dodd Frank log(spread)	(4) post-Dodd Frank log(spread)
puttable	-0.248***	-0.210***	-0.124*	0.244***
	(0.058)	(0.040)	(0.071)	(0.048)
exchangeable	0.604*	0.651**	0.186	0.958
	(0.338)	(0.320)	(0.150)	(0.719)
fixed rate	1.745*	-0.210	0.000	0.481***
	(0.945)	(0.297)	(0.000)	(0.020)
enhanced	-0.259***	0.139***	0.331***	0.329***
	(0.090)	(0.017)	(0.064)	(0.014)
callable	0.175***	0.032	-0.127***	-0.150***
	(0.034)	(0.026)	(0.029)	(0.014)
redeemmable	-0.025	0.121***	0.136***	0.138***
	(0.033)	(0.026)	(0.029)	(0.021)
-log(dd)	0.415***	0.854***	0.533***	0.992***
	(0.036)	(0.022)	(0.058)	(0.018)
size90	-0.555***	-0.432***	-0.107	-0.549***
	(0.062)	(0.053)	(0.094)	(0.065)
size90 × -log(dd)	-0.239***	-0.143***	0.046	-0.194***
	(0.034)	(0.028)	(0.049)	(0.030)
financial		-0.541***		-0.510***
		(0.045)		(0.087)
financial × -log(dd)		-0.241***		-0.297***
		(0.025)		(0.044)
size90 × financial		-0.148*		0.630***
		(0.078)		(0.144)
financial × size90 × -log(dd)		-0.130***		0.298***
		(0.043)		(0.071)
Constant	-5.009***	-2.213***	-2.815***	-2.890***
	(0.951)	(0.298)	(0.112)	(0.045)
Year-Month FE and Controls	Yes	Yes	Yes	Yes
Observations	103,333	470,744	91,456	468,677
R-squared	0.432	0.509	0.395	0.555

Table C2: Spread-Risk sensitivity regressions with alternate TBTF definitions

This table presents regression results where the dependent variable is the natural logarithm of spreads. Panel A reports regression results using the interaction of the top two decile size dummies. Panel B reports results reports regression results using the interaction of the top 10 and top 20 size *ttm* is the time-to-maturity for a bond. *seniority* is a dummy variable indicating whether the bond is senior. *spread* is the difference between the yield on a given firm's bond and the yield on a maturity-matched Treasury bond. *size90, size80* are dummy variables set to one if a given financial institution's size is in the top 90th percentile and top 80th percentile respectively. *sizetop10, sizetop20* are dummy variables set to one if a given financial institution's is in the top 10 and top 20 respectively of firms ranked by size. *financial* is a dummy variable set to one if the firm is a financial firm (SIC code starting with 6). *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. *dd* is Merton's (1974) distance-to-default measure. *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. All regression models include month/year fixed effects. Standard errors are in parentheses below their coefficient estimates and are adjusted for both heteroscedasticity and within correlation clustering at issue and month/year. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% two-tailed levels, respectively.

Panel A: Separating size90 from size80

	(1)	(2)	(3)	(4)
	pre-Dodd Frank	post-Dodd Frank	pre-Dodd Frank	post-Dodd Frank
VARIABLES	log(spread)	log(spread)	log(spread)	log(spread)
size90	-0.625***	-0.510***	-0.306***	-0.823***
	(0.074)	(0.177)	(0.075)	(0.170)
size80	-0.354***	-0.470**	-0.225***	-0.101
	(0.075)	(0.225)	(0.072)	(0.206)
-log(dd)	0.427***	0.422***	0.859***	0.877***
	(0.042)	(0.080)	(0.029)	(0.064)
size90 × -log(dd)	-0.241***	-0.018	-0.058	-0.230***
	(0.042)	(0.095)	(0.035)	(0.086)
size80 × -log(dd)	-0.056	-0.029	-0.035	0.103
	(0.037)	(0.121)	(0.035)	(0.105)
financial			-0.600***	-0.566***
			(0.070)	(0.172)
size90 × financial			-0.300***	0.452*
			(0.098)	(0.248)
size80 × financial			-0.073	-0.141
			(0.105)	(0.335)
financial × -log(dd)			-0.260***	-0.274***
			(0.036)	(0.085)
size90 × financial × -log(dd)			-0.174***	0.181
			(0.053)	(0.123)
size80 × financial × -log(dd)			-0.006	-0.081
			(0.053)	(0.169)
Constant	-3.316***	-2.784***	-2.525***	-1.954***
	(0.081)	(0.157)	(0.063)	(0.119)
Year-Month FE and Controls	Yes	Yes	Yes	Yes
Observations	61,873	27,422	169,749	56,469
R-squared	0.453	0.492	0.530	0.575

Panel B: TBTF based on top 10 and top 20 by size

VARIABLES	(1) pre-Dodd Frank log(spread)	(2) post-Dodd Frank log(spread)	(3) pre-Dodd Frank log(spread)	(4) post-Dodd Frank log(spread)
sizetop10	-0.388***	-0.059	0.279***	0.554***
	(0.058)	(0.193)	(0.081)	(0.203)
sizetop20	1.114***	1.090***	0.595***	1.182***
	(0.270)	(0.391)	(0.161)	(0.387)
-log(dd)	0.375***	0.245**	0.825***	0.794***
	(0.037)	(0.097)	(0.026)	(0.059)
sizetop10 × -log(dd)	-0.185***	0.072	0.102***	0.183*
	(0.034)	(0.103)	(0.039)	(0.096)
sizetop20× -log(dd)	0.435***	0.324*	0.197**	0.304*
	(0.125)	(0.166)	(0.098)	(0.177)
financial			-0.561***	-0.231
			(0.055)	(0.191)
sizetop10× financial			-0.657***	-0.463*
			(0.094)	(0.269)
sizetop20× financial			0.366	0.067
			(0.288)	(0.481)
financial × -log(dd)			-0.263***	-0.182*
			(0.027)	(0.093)
sizetop10× financial × -log(dd)			-0.288***	-0.120
			(0.048)	(0.134)
sizetop20× financial × -log(dd)			0.147	0.099
			(0.145)	(0.228)
Constant	-3.478***	-3.217***	-2.690***	-2.326***
	(0.075)	(0.191)	(0.053)	(0.131)
Year-Month FE and Controls	Yes	Yes	Yes	Yes
Observations	61,873	27,422	169,749	56,469
R-squared	0.447	0.450	0.529	0.562

Table C3: Equity Return sensitivity of Bond Returns sing a Larger Sample

This table presents regression results where the dependent variable is the change in spread. *ttm* is the time-to-maturity for a bond. *seniority* is a dummy variable indicating whether the bond is senior. *spread* is the difference between the yield on a given firm's bond and the yield on a maturity-matched Treasury bond. *Size90* is a dummy variable equal to one if a given financial institution's size is in the top 90th percentile. *financial* is a dummy variable set to one if the firm is a financial firm (SIC code starting with 6). *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. *assetvol* is asset volatility computed from the Merton model. *illiquidity* 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. *Ereturn return* is the monthly equity return. *Dreturn* is the monthly bond return multiplied by 100. *hedgeratio* is the equity hedge ratio from the Merton (1974) model described in the Appendix. Pre-Dodd-Frank is the time period before 2012. All regression models include month/year fixed effects. Standard errors are in parentheses below their coefficient estimates and are adjusted for both heteroscedasticity and within correlation clustering at issue and month/year. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% two-tailed levels, respectively.

	Pre-Dodd-Frank		Post-Dodd-Frank	
	(1)	(2)	(3)	(4)
VARIABLES	Dreturn	Dreturn	Dreturn	Dreturn
ttm	0.013	0.014*	0.007	0.005
	(0.014)	(0.008)	(0.009)	(0.007)
senior	-0.013	-0.008	0.119**	0.090
	(0.079)	(0.074)	(0.058)	(0.069)
roa	-2.284	-1.185	-7.154***	-1.920**
	(4.785)	(1.275)	(2.009)	(0.846)
mb	0.039	0.007	-0.066	0.013*
	(0.051)	(0.006)	(0.045)	(0.007)
mismatch	0.254	-0.039	0.718**	0.140
	(0.454)	(0.271)	(0.315)	(0.097)
liquidity	-0.072*	-0.038	-0.122***	-0.110***
	(0.040)	(0.028)	(0.037)	(0.027)
size90	-0.136	0.008	0.161**	-0.035
	(0.141)	(0.098)	(0.079)	(0.049)
Ereturn x hedgeratio	50.125***	83.217***	108.447***	42.577*
	(13.821)	(18.163)	(34.726)	(24.061)
Ereturn x hedgeratio x size90	-41.350***	36.714	-7.559	29.346
	(11.265)	(27.992)	(47.777)	(46.562)
Ereturn x financial		-33.164		71.079
		(24.323)		(42.995)
financial x size90		-0.142		0.329***
		(0.142)		(0.101)
Ereturn x hedgeratio x size90 x financial		-79.386**		8.243
		(32.099)		(69.571)
Constant	0.516***	0.532***	0.731***	0.476***
	(0.138)	(0.104)	(0.101)	(0.076)
Year-Month FE	Yes	Yes	Yes	Yes
Observations	36,284	73,086	29,130	53,020
R-squared	0.207	0.165	0.112	0.136

Table C4: Credit Default Swap risk-sensitivity

This table presents regression results where the dependent variable is the natural logarithm of month-end 5-year credit default spreads. *Size* is the natural logarithm of firms' assets. *financial* is a dummy variable set to one if the firm is a financial firm (SIC code starting with 6). *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. *dd* is Merton's (1974) distance-to-default measure. *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. Pre-Dodd-Frank is the time period before 2012. All regression models include month/year fixed effects. Standard errors are in parentheses below their coefficient estimates and are adjusted for both heteroscedasticity and within correlation clustering at issue and month/year. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% two-tailed levels, respectively.

Panel A: pre-Dodd-Frank Act Period

	(1)	(2)	(3)	(4)
VARIABLES	log(CDS)	log(CDS)	log(CDS)	log(CDS)
roa	-0.858	-0.828	-1.714***	-1.790***
	(0.578)	(0.596)	(0.301)	(0.292)
mb	-0.000	0.000	-0.001	-0.001
	(0.008)	(0.008)	(0.001)	(0.001)
mismatch	0.225	0.205	-0.016	-0.022
	(1.209)	(1.185)	(0.064)	(0.062)
size	-0.238***	-0.273***	-0.102***	0.170**
	(0.067)	(0.072)	(0.034)	(0.067)
-log(dd)	1.103***	1.347**	1.315***	-0.172
	(0.199)	(0.650)	(0.066)	(0.285)
-log(dd)*size		-0.025		0.164***
		(0.056)		(0.031)
financial			-0.007	3.714***
			(0.250)	(0.708)
-log(dd)*financial			-0.103	1.538***
			(0.147)	(0.554)
size*financial				-0.411***
				(0.084)
-log(dd)*financial*size				-0.187***
				(0.055)
constant	8.729***	9.063***	7.578***	5.139***
	(0.644)	(0.724)	(0.293)	(0.592)
Year-Month FE	Yes	Yes	Yes	Yes
Observations	1,342	1,342	32,234	32,234
R-squared	0.656	0.656	0.617	0.628

Panel B: post-Dodd-Frank Act Period

	(1)	(2)	(3)	(4)
VARIABLES	log(CDS)	log(CDS)	log(CDS)	log(CDS)
roa	-4.569	-4.788	-0.614*	-0.657*
	(6.180)	(6.010)	(0.338)	(0.332)
mb	0.003	0.003	-0.000	-0.000
	(0.004)	(0.004)	(0.001)	(0.001)
mismatch	-0.800	-0.684	-0.041	-0.046
	(1.566)	(1.437)	(0.075)	(0.074)
size	-0.216	-0.109	-0.197***	-0.080
	(0.166)	(0.370)	(0.023)	(0.074)
-log(dd)	0.756	0.128	1.165***	0.564*
	(0.646)	(2.631)	(0.061)	(0.320)
-log(dd)*size		0.060		0.063*
		(0.230)		(0.035)
financial			0.424	0.208
			(0.650)	(4.560)
-log(dd)*financial			0.103	0.213
			(0.343)	(2.935)
size*financial				0.024
				(0.438)
-log(dd)*financial*size				-0.009
				(0.268)
constant	8.391***	7.308	8.561***	7.466***
	(1.451)	(4.066)	(0.196)	(0.659)
Year-Month FE	Yes	Yes	Yes	Yes
Observations	744	744	25,966	25,966
R-squared	0.532	0.533	0.602	0.604