

Does the Tail Wag the Dog? The Effect of Credit Default Swaps on Credit Risk*

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ABSTRACT

We use credit default swaps (CDS) trading data to demonstrate that the credit risk of reference firms, reflected in rating downgrades and bankruptcies, increases significantly upon the inception of CDS trading, a finding that is robust after controlling for the endogeneity of CDS trading. Additionally, distressed firms are more likely to file for bankruptcy if they are linked to CDS trading. Furthermore, firms with more “no restructuring” contracts than other types of CDS contracts (i.e., contracts that include restructuring) are more adversely affected by CDS trading, and the number of creditors increases after CDS trading begins, exacerbating creditor coordination failure in the resolution of financial distress.

Keywords: Credit default swaps, credit risk, bankruptcy, empty creditor

I. Introduction

Credit default swaps (CDS) are insurance-type contracts that offer buyers protection against default by a debtor. Like other derivatives, they are often viewed as “side bets” that do not affect the fundamentals of the underlying assets. However, CDS trading may affect decision makers’ incentives and induce suboptimal real decisions, in the spirit of Jensen and Meckling (1976) and Myers (1977). CDS contracts are traded over-the-counter by financial institutions, including the bank creditors of the reference entities. Hence, if creditors selectively trade the CDS linked to their borrowers, the CDS positions can change the creditor-borrower relationship and affect the borrower’s credit risk, which determines the CDS payoffs. CDS allow creditors to hedge their credit risk; therefore, these creditors may increase the supply of credit to the underlying firms. Such improved access to capital may increase the borrowers’ financial flexibility and resilience to financial distress.¹ In addition, CDS trading may reveal more information about the reference firm, strengthening monitoring and reducing credit risk. However, lenders may not be as vigilant in monitoring borrowers once their credit exposures are hedged. Thus, borrowers may take on more risky projects. Furthermore, CDS-protected creditors are likely to be tougher during debt renegotiations, refusing debt workouts and making distressed borrowers more vulnerable to bankruptcy.

We empirically examine the effects of CDS trading on the credit risk of reference entities using a comprehensive dataset dating back to the broad inception of the CDS market for corporate names in 1997. It is difficult to obtain accurate data on CDS transactions from a single source because CDS trading does not occur on centralized exchanges. (Even the central clearing of CDS is a relatively recent phenomenon.) Hence, our identification of CDS inception and transactions relies on multiple leading data sources, including GFI Group,

¹The invention of CDS is attributed to J.P. Morgan, which lent to Exxon Mobil in the aftermath of the Exxon Valdez oil spill in 1994 (Tett (2009)). In this pioneering transaction, J.P. Morgan bought protection from the European Bank for Reconstruction and Development against the default of Exxon Mobile.

CreditTrade, and Markit. Our dataset covers 901 North American firms with a CDS trading history during the period from 1997 to 2009. The list of bankruptcies for North American firms is comprehensively constructed from major data sources, covering 1,628 bankruptcy filings from 1997 to 2009.

Our first finding from the combined dataset, after controlling for fundamental credit risk determinants suggested by structural credit models, is that the likelihood of a rating downgrade and the likelihood of the bankruptcy of the reference firms both increase after CDS trading begins. This increase in credit risk is both statistically significant and economically meaningful: for our sample of CDS firms, credit ratings decline by approximately half a notch, on average, in the two years after the inception of CDS trading. Similarly, the likelihood of bankruptcy more than doubles (from 0.14% to 0.47%) once a firm begins being referenced by CDS trading.

Unobserved omitted variables may drive both the selection of firms for CDS trading and changes in bankruptcy risk. Moreover, CDS trading is more likely to be initiated when market participants anticipate the *future* deterioration in the credit quality of a reference firm. We address these two concerns in several ways. Specifically, we construct a model to predict CDS trading for individual firms. This model allows us to identify the effect of CDS inception using propensity score matching and full-information maximum likelihood estimation with instrumental variables. We employ two instrumental variables for CDS trading. The first is the foreign exchange hedging positions of lenders and bond underwriters. Lenders with larger foreign exchange hedging positions are more likely to trade the CDS of their borrowers. The second is lenders' Tier One capital ratio. Banks with lower capital ratios have a greater need to hedge the credit risk of their borrowers via CDS. We indeed find that both instrumental variables are significant determinants of CDS trading. It also appears valid to exclude both from the credit risk predictions of borrowing firms because they only affect borrowers' credit risk via CDS market activities. The Sargan (1958) over-identification tests fail to reject the

hypothesis that both instrumental variables are exogenous. We confirm that the positive relationship between CDS trading and bankruptcy risk remains significant even after controlling for the selection and endogeneity of CDS trading.

After establishing our primary finding that reference firms' credit risk increases after CDS trading begins, we investigate potential mechanisms that may channel the effect of CDS trading on credit risk. An intuitive mechanism is that CDS trading can affect firm fundamentals, such as leverage and interest burden. Indeed, we find that firm leverage increases significantly after CDS trading begins, consistent with Saretto and Tookes (2013). Therefore, we control for leverage (both before and after CDS trading begins) in our regression analysis to examine other possibilities. The credit risk of a firm can also increase if the firm is more vulnerable when it is in financial distress. This vulnerability may result from a creditor's unwillingness to work out troubled debt and the potential failure of coordination among a distressed firm's creditors due to their diverse and conflicting incentives.

Hu and Black (2008) term CDS-protected debt-holders as "empty creditors" who have all the same legal rights as creditors but do not have positive risk exposure to borrower default. Hence, the financial interests of empty creditors are not aligned with those of other creditors who do not enjoy such protection. The empty creditor problem is formally modeled by Bolton and Oehmke (2011). Their model predicts that, under mild assumptions, lenders would choose to become empty creditors by buying CDS protection. Consequently, they would be tougher in debt renegotiation should the firm come under stress. Empty creditors would even be willing to push the firm into bankruptcy if their total payoffs, including CDS payments, would be larger in that event. In their model, CDS sellers anticipate this empty creditor problem and price it into the CDS premium, but they cannot directly intervene in the debt renegotiation process (unless they buy bonds or loans to become creditors).

One implication of the Bolton and Oehmke (2011) model is that, conditioning on financial distress, firms with CDS trading are more likely to file for bankruptcy. We find evidence

consistent with this prediction. We further construct a more effective test of the tough creditor implications because our dataset includes details of the contract terms. Specifically, for each CDS contract, we know whether restructuring is covered as a credit event. Buyers of “no restructuring” CDS contracts will be paid only if the reference firm files for bankruptcy. However, buyers of CDS contracts that include restructuring as a credit event will be compensated even when the debt of the reference firm is restructured. Clearly, creditors with “no restructuring” CDS protection would have a stronger incentive to force the firm into bankruptcy than those without this restrictive clause. Indeed, we find that the effects of CDS trading are stronger when a larger fraction of CDS contracts contain the “no restructuring” credit event clause.

The availability of CDS contracts may render more banks willing to lend due to the possibility of risk mitigation and enhanced bargaining power via CDS contracts. However, the consequent expansion in the lender base can also hinder debt workouts: a greater number of lenders will make it more likely that some lenders will become empty creditors, and thus, the coordination problems will become more severe in a stressed situation where a workout may be necessary. Indeed, we find that more creditors lend to firms after CDS contracts referencing their debt become available. Furthermore, bankruptcy risk increases with the number of lenders and with changes in the number of creditors around CDS introduction, providing another channel for the adverse effect of CDS trading on bankruptcy risk.

We conclude that, although CDS are designed to provide insurance against borrower default, CDS trading can increase the likelihood of borrower default (“the tail wags the dog”). Our main contribution is to document the real effect of CDS trading on the survival probabilities of the reference firms. Thus, we are among the first to formally test and support the empty creditor model of Bolton and Oehmke (2011). Our study complements Ashcraft and Santos (2009) and Saretto and Tookes (2013), who find that the cost of debt of risky firms and their leverage increase after CDS trading is initiated.

The remainder of this paper is organized as follows. Section II develops testable hypotheses in relation to the prior literature. Our dataset is described in Section III. Section IV presents our empirical results regarding the effects of CDS trading, along with a detailed examination of the endogeneity concerns and the mechanisms of the observed effects. Section V presents the conclusions of this study.

II. Related Literature and Testable Hypotheses

CDS were originally developed to help banks transfer credit risk, maintain relationships with borrowers, and develop new business. Borrowers' credit quality may improve if lenders share some of the benefits from CDS trading with the borrowers (Allen and Carletti (2006)). Parlour and Winton (2013) demonstrate theoretically that CDS can increase lending efficiency for high-quality borrowers. Other researchers have argued that CDS trading could hurt banking relationships and is potentially harmful to borrowers (Duffee and Zhou (2001), Morrison (2005)). Moreover, Minton, Stulz, and Williamson (2009) find that banks' use of CDS is limited by CDS market liquidity. Saretto and Tookes (2013) find that the reference firms' leverage and debt maturity increase after the inception of CDS trading, implying that the bankruptcy risk of the firm will increase. Therefore, the overall effect of CDS trading on the borrowers' credit risk depends on the tradeoff of the costs and benefits; firms will become riskier after CDS trading is initiated on them if the costs in terms of additional risks outweigh the benefits of financial flexibility.

Hypothesis 1 (Baseline) *The credit risk of a firm, such as its likelihood of bankruptcy, increases after the introduction of CDS referencing its debt.*

Bolton and Oehmke (2011) model creditors' lending choices in the event that they can buy CDS after loan initiation. In their model, CDS protection increases banks' bargaining power in debt renegotiations and reduces borrowers' strategic defaults. Therefore, lenders are more

willing to lend. However, lenders can become excessively tough with distressed borrowers if their CDS positions are sufficiently large, triggering bankruptcy. From a different perspective, Che and Sethi (2012) argue that lenders may opt to sell CDS contracts instead of lending to the respective borrowers, reducing the credit supply.² Hence, it will be more difficult for distressed firms to roll over their debt if lenders choose to sell CDS protection instead of selling loans. Both the “tough creditor” and rollover risk concerns will exacerbate the credit risk of borrowers, particularly if the borrowers are financially distressed. Hence, the effect of CDS trading on the reference firms’ credit risk may depend on market conditions and firm characteristics (Campello and Matta (2012)). Therefore, the CDS effect is likely to be prominent when the borrower is already in financial distress.

Hypothesis 2 (Bankruptcy Conditional on Distress) *Once a firm is in financial distress, its likelihood of bankruptcy increases if CDS trading is referencing its default.*

The above hypothesis emphasizes the incentives of tough creditors, some of whom may be empty creditors.³ One could alternatively examine the related issue that CDS trading may reduce the restructuring success rates of distressed firms. This latter question has been addressed in complementary studies with conflicting results: Danis (2012) finds a significant impact of CDS trading on restructuring, whereas Bedendo, Cathcart, and El-Jahel (2012) fail to find such effects. However, whereas those two studies use relatively small samples, our empirical analysis applies to a large sample of both healthy and distressed firms. Moreover, bankruptcy provides a better testing context than restructuring because bankruptcy events are more easily observed. Also, defining distressed firms based on restructuring is a subjective assessment, which may account for the mixed evidence in the aforementioned studies. Therefore, we focus on bankruptcy filings in our analysis.

²Empirical evidence regarding the above theories appears inconclusive. Ashcraft and Santos (2009) find that, after CDS inception, the cost of debt increases for low-quality firms and decreases for high-quality firms. Hirtle (2009) finds no significant increase in the bank credit supply after CDS inception.

³The recent decline in the absolute priority deviation during bankruptcy resolution, documented by Jiang, Li, and Wang (2012) and Bharath, Panchapagesan, and Werner (2010), is consistent with tougher creditors and coincides with the development of the CDS market.

In addition, we develop a further hypothesis linked to the empty creditor model of Bolton and Oehmke (2011), which indicates that the lenders' willingness to restructure a firm's debt in the event of financial distress is affected by their respective CDS positions (a simple illustration is provided in the internet appendix). Some CDS-protected lenders may prefer the bankruptcy of borrowers if the resulting payoffs from their CDS positions will be sufficiently high.⁴ However, empty creditors would not fully prefer borrower bankruptcy if they were concerned about counterparty risk from CDS sellers (Thompson (2010)).

A unique advantage of our data is the specification of the credit event clause of the CDS contract. If a CDS contract covers restructuring as a default event, then the creditors will be compensated regardless of whether the distressed firm restructures or declares bankruptcy. However, if restructuring is not covered as a default event, creditors holding CDS will be compensated only if there is a failure to pay or the firm files for bankruptcy. Bolton and Oehmke (2011) endogenize the pricing of CDS contracts so that the CDS seller accounts for this additional "empty creditor" incentive (interested readers can find details in their model). Therefore, we hypothesize that the empty creditor mechanism is even more effective for "no restructuring" CDS:

Hypothesis 3 (No Restructuring) *The increase in bankruptcy risk of a firm after the introduction of trading in CDS contracts on its debt is larger if "no restructuring" contracts account for a large proportion of these CDS contracts.*

The above hypotheses emphasize the *ex post* effects (after the loan and CDS positions are given) of CDS associated with lenders who are tougher in debt renegotiations. However, becoming an empty creditor is likely not the first goal of every lender when making lending decisions. Thus, from an *ex ante* perspective, lenders will consider their use of CDS along with other factors, such as reputation. Bolton and Oehmke (2011) predict that more banks

⁴There could be other reasons why lenders may be unwilling to restructure the debt of a firm in financial distress. For example, they may believe that the borrower could eventually go bankrupt, even following a debt restructuring.

will be willing to lend to a firm when CDS are available.⁵ Such expansions in the lender base have two consequences. First, the likelihood of empty creditors is higher when there are more lenders. Second, the probability of bankruptcy is higher when there are more lenders due to the increased potential for coordination failure.

Hypothesis 4 (Lender Coordination) *(a) The number of (bank) lenders increases after the introduction of CDS trading. (b) Bankruptcy risk increases with the number of lenders.*

III. Dataset on CDS Trading and Bankruptcy

We use actual transaction records to identify firms with CDS contracts written on them, including the date when CDS trading began for each firm and the type of contract traded. Unlike voluntary dealer quotes, which are non-binding and may be based on hypothetical contract specifications, transaction data contain multi-dimensional information on actual CDS contracts, including price, volume, and settlement terms. Our CDS transaction data are obtained from two separate sources: CreditTrade and the GFI Group. CreditTrade was the main data source for CDS transactions during the initial phase of the CDS market before the GFI Group took over as the market leader. Combining data from these two sources allows us to assemble a comprehensive history of North American corporate CDS trading activities.

Our CreditTrade data cover the period from June 1997 to March 2006, and our GFI data cover the period from January 2002 to April 2009. Both datasets contain complete information on intra-day quotes and trades, such as type of contract, time of transaction, order type, and CDS price. Because CDS contracts are traded over-the-counter rather than on exchanges, the first trading date for each firm's CDS is difficult to identify with a time stamp. Using overlapping samples from these two data sources between January 2002 and March 2006, we

⁵Acharya and Johnson (2007) suggest that bank lenders engage in insider trading in the CDS market. Therefore, borrowers may also wish to broaden their lender base if they anticipate that the lenders can exploit informational advantages via their CDS positions.

can cross-check the two records to confirm the reliability of our identification of CDS firms and starting dates. The dates of the first appearance of a particular CDS in the two data sources are typically within several months of each other. To ensure greater accuracy, we also cross-check trading-based CDS data with the Markit CDS database, a commonly used CDS dealer quote source, to confirm our identifications.⁶

There are two important advantages of using the complete set of CDS transaction data in our empirical analysis. First, our sample starts in 1997, which is generally acknowledged to be the year of inception of the broad CDS market (Tett (2009)). Therefore, our identified first CDS trading dates are not contaminated by censoring of the data series. Second, our CDS transaction data include detailed contractual terms, such as the specification of the credit event, maturity, and security terms, for each contract. Aggregate position or quote data obtained from broker-dealers or, more recently, clearing houses or data aggregators, would generally not include such contract-level information. The credit event specification allows us to investigate the effect of restructuring clauses. Maturity information at the contract level allows us to calculate volumes of outstanding CDS positions at each point in time. Our sample of CDS introductions ends in April 2009 for an important institutional reason: the market practice in CDS changed significantly in April 2009 due to the “Big Bang” implemented by the International Swaps and Derivatives Association (ISDA), including, for example, the removal of restructuring as a standard credit event. In addition, an observation window of three years is required *after* the introduction of CDS trading to measure its potential effects, which extends the study period to 2012.

Based on our merged dataset, there are 901 North American firms with CDS inception during the 1997-2009 sample period. The industry distribution of the CDS firms in our sample is rather diverse.⁷ In our baseline analysis, we mainly utilize information about the first day

⁶Markit provides end-of-day “average” indicative quotes from contributing sell-side dealers using a proprietary algorithm. In contrast, both CreditTrade and GFI report trades and binding quotes.

⁷Most CDS firms in our sample are in the manufacturing (SIC 2, 3), the transportation, communications, and utilities (SIC 4), and the finance, insurance, and real estate (SIC 6) sectors. We control for industry fixed effects throughout our empirical analysis.

of CDS trading, comparing changes in firm default risk upon the onset of CDS trading. We also use the volume of CDS outstanding and the fraction of CDS contracts with various restructuring clauses based on more detailed transaction information to further assess how CDS trading affects credit risk.

We assemble a comprehensive bankruptcy dataset by combining data from various sources for North American corporations filing for bankruptcy in U.S. courts. Our initial bankruptcy sample is derived from New Generation Research's Public and Major Company Database, available at www.BankruptcyData.com. This database includes information on public companies filing for bankruptcy and significant bankruptcies of private firms. We further validate and augment this initial sample with additional bankruptcy data sources, including the Altman-NYU Salomon Center Bankruptcy List, the Mergent Fixed Income Securities Database (FISD), the UCLA-LoPucki Bankruptcy Research Database, and Moody's Annual Reports on Bankruptcy and Recovery.

We link the bankruptcy dataset with our CDS sample so as to identify the bankrupt firms that had CDS trading prior to their bankruptcy filings. Table I presents the yearly summary of our sample, including the number of bankrupt firms, the number of firms on which CDS are traded, and the number of bankrupt firms with and without CDS trading. The row labeled "total" indicates that there were a total of 1,628 bankruptcy filings during the 1997-2009 sample period. Our bankruptcy sample is comprehensive and larger than those of prior studies, which have used various filters. Many bankruptcies were filed in the 1999-2003 and 2008-2009 periods, accounting for 1,214 (74.6%) of the 1,628 bankruptcy events occurring during the entire sample period. The fourth and fifth columns of the table report the number of *New CDS* firms and the number of firms with *Active CDS* trading firms across the years, respectively. More CDS contracts were introduced in the 2000-2003 period than in earlier or later periods. Among the 901 distinct CDS trading firms, 60 (6.7%) subsequently filed for bankruptcy protection. Bankruptcies among CDS firms represent a small fraction of the total

number of bankruptcies because only relatively large firms, in terms of asset size and debt outstanding, have CDS traded on them. However, the bankruptcy rate of 6.7% for CDS firms is similar to the four-year overall (or 11-year BBB-rated) cumulative default rate of U.S. firms (Standard & Poor’s (2012)). We further link the CDS and bankruptcy sample with relevant financial and accounting data in CRSP and Compustat. In our final sample used in the regressions, there are 940 distinct bankrupt firms (58% of the raw number of bankruptcies), 42 of which are CDS firms (70% of the raw number of CDS bankruptcies). Additionally, 898 bankruptcies in the final sample are non-CDS firms, representing 57% of the raw number of non-CDS bankruptcies. The last four rows of Table I (as well as Tables A1 and A2 in the internet appendix) indicate that our raw sample, final regression sample, and other samples used in our later analysis have similar distributions of bankruptcies and CDS firms.

IV. CDS Trading and Credit Risk: Empirical Results

This section presents our empirical findings regarding the effects of CDS trading on firms’ credit risk. In our analysis, we use several common measures of credit risk, with a focus on the likelihood of bankruptcy. We first conduct an “event study” of the effects of the introduction of CDS trading on credit ratings to gain a high-level perspective on the evidence. We then report our baseline panel data regression results. Next, we address the issue of selection and endogeneity in the introduction of CDS trading. Finally, we investigate the channels and mechanisms through which CDS trading affects credit risk.

A. Credit Ratings Before and After the Introduction of CDS

An ordinal measure of a firm’s credit risk is its credit rating, a metric that is widely used in industry, regulations, and academia. Rating agencies are known to incorporate information on both bankruptcies and restructuring into their rating decisions (Moody’s (2009)). We

first analyze the credit ratings of CDS firms around the time of CDS introduction. Changes in credit quality around the introduction of CDS trading may be reflected in credit rating changes. A credit rating downgrade is often the first step toward bankruptcy and is an indicator of an increase in bankruptcy risk.

We obtain the time series of Standard & Poor’s (S&P) long-term issuer ratings from Compustat and FISD. We conduct a basic “within-firm” analysis, in which we compare the distribution of credit ratings in the year preceding the introduction of CDS trading (year $t - 1$) with the rating distribution two years after that (year $t + 2$), for all firms with such contracts traded at some point in our sample. These rating distributions are plotted in Figure 1. Our first observation from Figure 1 is that A and BBB ratings are the most common issuer ratings when CDS trading is initiated. The vast majority of firms in our sample (92%) are rated at the onset of CDS trading. Compared with the general corporate rating distribution documented in Griffin and Tang (2012), our sample includes more BBB-rated firms than other investment grade (AAA, AA, A-rated) firms but also fewer non-investment grade firms. Overall, firms in our sample are of relatively good credit quality at the time of CDS inception, as measured by their credit ratings.

Figure 1 displays a discernible shift to lower credit ratings after the introduction of CDS trading. Whereas the proportion of BBB-rated firms is approximately the same both before and after CDS trading begins, the proportion of AA-rated and A-rated firms decreases. At the same time, the proportion of non-investment grade and unrated firms increases. We examine the distributional differences before and after the introduction of CDS trading using the Kolmogorov-Smirnov test.⁸ We use the one-sided test for stochastic dominance. The D -statistic of the one-sided Kolmogorov-Smirnov test (the maximum difference between cumulative distributions) is significant at the 1% level, indicating that the credit rating distribution shifts to the right (lower rating quality) after CDS trading commences. In other words, the

⁸See Siegel and Castellan (1988) for the construction of the test and Busse and Green (2002) for a discussion and applications of the test.

ratings before CDS trading is introduced stochastically dominate the ratings afterwards.

At the firm level, 54% of firms maintain the same rating after as before the introduction of CDS trading, 37% of firms experience a rating downgrade, and only 9% of firms experience a rating improvement. We employ a difference-in-difference analysis to isolate the effect of the market trend using matched non-CDS firms with propensities for CDS trading similar to those of the CDS firms (the matching method is described in section C.2 below). We first compare the rating distribution for CDS firms and their non-CDS matched counterparts (see Figure A1 in the internet appendix). The distribution of the downgrades for CDS firms is similar to that for non-CDS firms. For both the CDS and non-CDS samples, the downgrades are mainly from the BBB category, which accounts for 50% and 76% of the downgrades in the two samples, respectively. We then regress rating *changes*, measured in terms of number of notches, on firm characteristics and the CDS indicator *CDS Active*. We convert letter ratings to numerical ratings (i.e., AAA=1, AA+=2) so that larger numbers indicate worse ratings. The regression results are reported in Table A3 of the internet appendix, and indicate that downgrades for CDS firms after CDS trading commences are an average of 0.23 notches larger than those for non-CDS firms within the same time period. We also find that the downgrading frequency is 2.6% higher for CDS firms than for non-CDS firms of a similar size from the same industry. These rating results provide preliminary evidence that the credit quality of the reference entities deteriorates following the inception of CDS trading.

B. Baseline Hazard Model Results on Downgrading and Bankruptcy

We next run multivariate analyses to obtain systematic statistical evidence regarding the effect of the inception of CDS trading on credit risk while controlling for other credit risk determinants. Our baseline model predicts both credit rating downgrades and bankruptcy filings. We confine the discussion to bankruptcy for brevity. We adopt a proportional hazard model using firm-month panel data. Specifically, we assume that the marginal probability

of bankruptcy over the next period follows a logistic distribution with parameters (α, β) and time-varying covariates X_{it-1} :

$$\Pr(Y_{it} = 1|X_{it-1}) = \frac{1}{1 + \exp(-\alpha - \beta'X_{it-1})}, \quad (1)$$

where Y_{it} is an indicator variable that equals one if firm i files for bankruptcy in period t , and X_{it-1} is a vector of explanatory variables observed at the end of the previous period: a higher level of $\alpha + \beta'X_{it-1}$ represents a higher probability of bankruptcy. We conduct several robustness checks on the model specification in the internet appendix.

Although firms are often delisted before they file for bankruptcy, delisting can also occur for other reasons, such as mergers and privatization. To account for these factors, we follow Shumway (2001) and Chava and Jarrow (2004) in treating the delisting date as the bankruptcy filing date for delisted firms that filed for bankruptcy within five years.

Our key explanatory variable of interest is *CDS Active*, which is a dummy variable that equals one after the inception of the firm's CDS trading and zero prior to it; *CDS Active* always equals zero for non-CDS firms. Following Ashcraft and Santos (2009) and Saretto and Tookes (2013), we use *CDS Firm* to control for unobservable differences between firms with and without CDS traded on them. *CDS Firm* is a dummy variable that equals one for firms with CDS traded at any point during our sample period. Hence, *CDS Active* captures the marginal impact of CDS introduction on bankruptcy risk. Because the variables *CDS Firm* and *CDS Active* are positively correlated, we report results both with and without controls for *CDS Firm* in our main analysis.

We follow Bharath and Shumway (2008) in including five fundamental determinants of default risk in X_{it-1} , constructed from CRSP and Compustat data: the logarithm of the firm's equity value $\ln(E)$, the firm's stock return in excess of market returns over the past year $r_{it-1} - r_{mt-1}$, the logarithm of the book value of the firm's debt $\ln(F)$, the inverse of the

firm's equity volatility $1/\sigma_E$, and the firm's profitability measured by the ratio of net income to total assets NI/TA . We also control for year and industry fixed effects in the panel data analysis. Because we have autocorrelated observations from the same firms in our panel data, we follow Petersen's (2009) suggestion and cluster the standard errors within firms.

The proportional hazard model estimation results are presented in Table II. Specifications 1 and 2 represent the analysis of credit rating downgrades, and Specifications 3 and 4 are the counterparts for bankruptcy filings. The coefficient estimates for *CDS Active* are positive and significant under all four specifications. Specifications 2 and 4 indicate that the effect of *CDS Active* is significant without controls for *CDS Firm*, indicating that the effect of *CDS Active* is not driven by fundamental differences between CDS firms and non-CDS firms. The coefficient estimates for the variable *CDS Firm* are statistically significant at the 1% level in Specifications 1 and 3 but have opposite signs: compared with non-CDS firms, CDS firms are more likely to be downgraded but less likely to go bankrupt. Such diametrically opposite effects in the case of *CDS Firm* contrast with the consistently positive *CDS Active* effect, further attenuating concern that the effect of *CDS Active* may be driven by multi-collinearity with *CDS Firm*.

The positive coefficients for *CDS Active* in Specifications 1 and 2 indicate that firms are more likely to be downgraded after the inception of CDS trading. In both specifications, the effect of CDS trading is statistically significant at the 1% level. The economic magnitude is also large: in Specification 1, the marginal effect of CDS trading on the probability of a downgrade is 0.39%, whereas the average downgrading probability is 0.59%. Specification 3 reports similar findings for bankruptcy filings. Bankruptcies are relatively rare events – the likelihood of bankruptcy in our overall sample is 0.14%. However, bankruptcy risk increases substantially after CDS trading is initiated: the marginal effect of CDS trading on the likelihood of bankruptcy is 0.33%. Furthermore, in Specification 3, the odds ratio for *CDS Active* (the likelihood of bankruptcy after CDS trading divided by the likelihood of bankruptcy

before CDS trading) for bankruptcy predictions is 10.73, indicating that bankruptcy is more likely to occur after CDS trading begins.⁹

The effect of *CDS Active* is not driven by industry characteristics, which are controlled for throughout our analysis. In addition, the estimation results for the other control variables in Table II are similar to the findings of prior studies. Larger firms and firms with higher stock returns are less likely to be downgraded or go bankrupt. Firms with higher leverage and greater equity volatility are more likely to be downgraded or go bankrupt with all else equal. Profitable firms are less likely to file for bankruptcy. Finally, the pseudo- R^2 s, approximately 15% for the downgrade regressions and 24% for the bankruptcy regressions, suggest that bankruptcy filings are better explained by these explanatory variables than are downgrades.

Our baseline results are consistent with Hypothesis 1 that the credit quality of reference firms declines after CDS trading begins. Although this hypothesis specifically concerns the worsening of credit quality, one may wonder whether the effect is symmetric, i.e., whether CDS trading may predict both a higher probability of credit quality deterioration and a lower probability of credit quality improvement. We categorize rating changes into upgrades, no change, and downgrades. The results in Table A4 of the internet appendix indicate that *CDS Active* can predict rating downgrades but has no predictive power with respect to rating upgrades. In addition, the results demonstrate that we cannot distinguish an upgrade from no change in the credit rating. These findings justify our focus on downgrades. Our main results also survive other robustness checks pertaining to sample period, data frequency, model specification, and alternative measures, as reported in Tables A5-A13 of the internet appendix.

⁹Both the odds ratio and marginal effect provide more intuitive interpretations of the logistic regression coefficients. However, these two numbers can differ significantly: the odds ratio is calculated as the exponential of the coefficient estimates (e.g., $\exp(2.373) = 10.730$), whereas the marginal probability is calculated using the event probability at the chosen setting of the predictors (p) and the parameter estimate for *CDS Active*, ($\beta_{CDSActive}$), i.e., the marginal effect= $p(1-p)\beta_{CDSActive}$.

C. Selection and Endogeneity in CDS Trading

The previous section demonstrates a strong statistical association between the introduction of CDS trading on a firm and a subsequent increase in its credit risk. However, to infer whether CDS trading causes a decrease in credit quality, we must consider the possibility that firms may be selected into CDS trading based on certain characteristics. Moreover, CDS trading may be initiated on firms for which market participants anticipate an increase in credit risk. To address these concerns, we consider the joint determination of bankruptcy filings and CDS trading. The main equation that we estimate relates to bankruptcy prediction with binary outcomes:

$$\begin{aligned}
 \textit{Bankruptcy}^* &= \alpha + \beta \textit{CDSActive} + \mu X + \varepsilon & (2) \\
 \textit{Bankruptcy} &= 1 \text{ if } \textit{Bankruptcy}^* > 0; \text{ and } \textit{Bankruptcy} = 0 \text{ otherwise,}
 \end{aligned}$$

where X is a vector of control variables, and $\textit{Bankruptcy}^*$ and $\textit{Bankruptcy}$ are the index and indicator variables of bankruptcy, respectively. The key explanatory variable of interest is $\textit{CDS Active}$, which is a binary outcome variable. The initiation of CDS trading on a firm can be partly anticipated by investors, as in the following specification:

$$\begin{aligned}
 \textit{CDSActive}^* &= \gamma_0 + \gamma_1 X + \gamma_2 Z + \nu; & (3) \\
 \textit{CDSActive} &= 1 \text{ if } \textit{CDSActive}^* > 0; \text{ and } \textit{CDSActive} = 0 \text{ otherwise,}
 \end{aligned}$$

where Z is a vector of instrumental variables, and $\textit{CDS Active}^*$ and $\textit{CDS Active}$ are the CDS trading variables. Endogeneity concerns arise when the correlation between the residuals of the outcome and treatment equations, $\textit{corr}(\varepsilon, \nu)$, is not zero. For example, there could be a feedback loop: the anticipated increase in bankruptcy risk induces CDS trading, and then CDS trading induces higher bankruptcy risk. This “binary outcome model with a binary

endogenous explanatory variable” is also analyzed by Jiang, Li, and Wang (2012). They adopt the estimation method of Wooldridge (2002, Chapter 15.7.3) using maximum likelihood estimation methods. We use a similar estimation approach.

We first select instrumental variables for CDS trading and then use two standard econometric approaches to address the selection issues (see Li and Prabhala (2007) and Roberts and Whited (2012) for detailed discussions): propensity score matching and full-information maximum likelihood.

C.1. *Determinants of CDS Trading*

We seek the most appropriate model for the selection of CDS trading on firms, as this model will enable us to adjust for this selectivity in our analysis of credit risk changes after the inception of CDS trading. We follow Ashcraft and Santos (2009) and Saretto and Tookes (2013), who face similar endogeneity concerns in the specification of their CDS selection models. We also consider other explanatory variables given that our focus is explicitly on credit risk.

One way to uncover the true effect of CDS trading is by using an instrumental variable that has a direct effect on CDS trading but only affects bankruptcy via its effect on CDS trading. We employ two such instruments: foreign exchange hedging activities by banks and underwriters, *Lender FX Hedging*, and the Tier One capital ratio of lenders, *Lender Tier 1 Capital*.¹⁰ We first identify lenders and bond underwriters for our sample firms based on DealScan data (for lenders) and FISD data (for bond underwriters). We then obtain Federal Reserve call report data for the FX derivative positions of these lenders and bond

¹⁰Saretto and Tookes (2013) also use the first of these instrumental variables, *Lender FX Hedging*, which is motivated by the findings of Minton, Stulz, and Williamson (2009). We have also considered two other instrumental variables: *TRACE Coverage* and *Post CFMA*. The likelihood of CDS trading increases after the implementation of TRACE and after the enactment of the Commodity Futures Modernization Act (CFMA). The CDS effect is also significant using those instruments, although those two instrumental variables are not our first choices.

underwriters. For each firm in each quarter, *Lender FX Hedging* is constructed as the average of the notional volume of FX derivatives used for hedging purposes, relative to total assets, across the banks that have served as either lenders or bond underwriters for the firm over the previous five years. We use the Compustat Bank file containing lenders' Tier One capital ratio data to construct the second instrument, *Lender Tier 1 Capital*, defined as the average of the Tier One capital ratios across the banks that have served as either lenders or bond underwriters for a particular firm over the previous five years.¹¹

In addition to these two instruments for CDS trading, we also include firm size and other characteristics as explanatory variables. The choice of these variables is dictated by their role in capturing hedging interest, credit risk, and lender characteristics. Size is clearly important, as larger firms naturally attract more attention from CDS traders given that the hedging demands of investors are likely to be greater for larger firms. In addition, we include a set of firm characteristics, namely, sales, tangible assets, working capital, cash holdings, and capital expenditure, to capture the potential hedging interests of investors. Furthermore, we include credit risk variables, such as leverage, profitability, equity volatility, the credit ratings of the firm, and the senior unsecured debt status of the firm, to predict the inception of CDS trading. Finally, we use lender size and lenders' total credit derivatives positions as additional explanatory variables for CDS trading.

We use data from 1997 until the first month of CDS trading for CDS firms and all observations in our sample for non-CDS firms to estimate a model of the introduction of CDS trading for a firm. The model is estimated using a probit framework: the dependent variable equals one after the firm starts CDS trading and zero beforehand. The probit regression results are reported in Table III. The results indicate that CDS contracts are more likely to be traded

¹¹Because we are using average FX hedging activity across all lenders and underwriters for a firm, the potential selection effect due to the possibility that "bad banks switch their lending to bad borrowers" at the individual bank level will be mitigated considerably. Furthermore, this selection effect is likely to be small because firms' banking relationships are generally stable and do not change dramatically over time. The same argument regarding the mitigation of the selection effects due to aggregation across all bank lenders in the case of *Lender FX Hedging* also applies in the case of *Lender Tier 1 Capital*.

on larger firms than on smaller firms. CDS trading is more likely for firms with higher leverage but with investment grade ratings, whereas CDS contracts are less likely to be traded on unrated firms. Firms with high profitability, tangibility, and large amounts of working capital are all more likely to have CDS trading. Overall, firms with relatively *high* credit quality and visibility (a stronger balance sheet and larger size) are more likely to be selected for CDS trading. Both of our instruments, *Lender FX Hedging* and *Lender Tier 1 Capital*, are significant predictors of CDS trading even after controlling for all other variables. After including bank size and bank credit derivative positions, our instrumental variables remain significant determinants of CDS trading. Moreover, the Sargan (1958) over-identification test fails to reject the null hypothesis that both instrumental variables are exogenous.¹²

Table III illustrates that CDS trading can be explained reasonably well by the chosen variables, with pseudo- R^2 s of approximately 39% across the three model specifications (Models 1 and 2 include one instrumental variable at a time, and Model 3 includes both instrumental variables). In the following analysis, we use these CDS trading prediction models to control for endogeneity in CDS trading and re-examine the relationship between CDS trading and credit risk. In the remainder of the analysis, we focus on the likelihood of bankruptcy.

C.2. Propensity Score Matching

Propensity score matching is among the most common techniques used to address endogeneity concerns, as noted by Roberts and Whited (2012) in their survey, due to the simplicity of its matching methodology. Once the matched sample has been determined, actual estimation involves only a one-equation system. The key advantage of the matching method is that it avoids specification of the functional form: matching methods do not rely on a clear source of exogenous variation for identification.

¹²The χ^2 test statistic is 2.436 (p -value=0.119 for one degree of freedom) in our sample for the two instrumental variables with one endogenous variable, *CDS Active*.

The propensity score matching approach conditions on the one-dimensional propensity score, defined as the probability of receiving treatment, conditional on the covariates. The potential outcomes are taken as independent of the treatment assignment, conditional on the propensity score. One disadvantage of this approach is that the latter assumption is strong and untestable. To quote Roberts and Whited (2012): “Matching will not solve a fundamental endogeneity problem. However, it can offer a nice robustness test.” Therefore, we use propensity score matching as an alternative methodology to control for the expected increase in credit risk accompanying CDS trading.

We now re-estimate our baseline model using a propensity score-matched sample. The “treatment effect” from the propensity score matching estimation is the difference between the CDS firms and the counterfactual matched non-CDS firms with similar propensities for CDS trading, as measured by the coefficient of *CDS Active*. For each CDS firm, we find one matching non-CDS firm with the nearest propensity score for CDS trading using the CDS prediction models from Table III with all the explanatory variables. We then perform the hazard model on this matched sample. Given the limitations of the propensity score matching procedure, in that we do not observe the full model for CDS trading, we use three different matching criteria: (1) the one non-CDS firm with the nearest distance to the CDS firm in terms of propensity score; (2) the one firm with the nearest propensity score but within a difference of 1%; and (3) the two firms with propensity scores closest to the CDS firm.

We first compare the relevant characteristics of the CDS firms and the propensity score-matched non-CDS firms. There are no significant differences in either the propensity scores or the *Z*-scores between the CDS firms and the matched firms with the nearest propensity scores (see Table A14 in the internet appendix). Nevertheless, the CDS firms are slightly larger but have slightly poorer credit ratings than their matched counterparts. Therefore, we control for these variables in the bankruptcy prediction model. The CDS firms have slightly better credit ratings but similar distances-to-default relative to the non-CDS matched firms.

Table IV presents the regression results for our CDS-trading propensity-matched sample. In all specifications, the coefficient estimates for *CDS Active* are significantly positive. We use “nearest one” matching as a benchmark case in the first specification. When we modify the matching criterion from “nearest one” to “nearest one with propensity score difference within 1%”, the results are similar to those in column 2 without the 1% restriction. As an alternative, we choose the two matching firms with the nearest propensity scores and continue to find a significant coefficient estimate for *CDS Active*. Therefore, the likelihood of bankruptcy increases after CDS trading begins even after adjusting for the propensity for CDS trading. *CDS Firm* is not significant in any of the specifications. Therefore, CDS firms are no longer statistically significantly different from non-CDS firms in terms of credit quality deterioration after matching by propensity for CDS trading, indicating the effectiveness of our matching procedure.

We also employ alternative CDS prediction models, using one of the two instruments at a time, with nearest-one propensity score matching. These models produce different matched samples due to variations in the data available to calculate propensity scores for each prediction model. *CDS Active* is significant in both of these specifications, as shown in Table A15 of the internet appendix.

C.3. Full-Information Maximum Likelihood (FIML)

Given the strong assumption in propensity score matching that the matching is based on observable information, we consider an alternative estimation approach that employs the full-information maximum likelihood (FIML) procedure, which is more efficient provided that the model is correctly specified. FIML estimation considers all information regarding the joint distribution of the bankruptcy determination and CDS trading variables, $f(\varepsilon, \nu)$, in Equations 2 and 3 by using the conditional distribution, $f(\varepsilon|\nu)$, and the marginal distribution, $f(\nu)$, simultaneously. The FIML estimate is asymptotically efficient when the error terms are

normally distributed.¹³

The estimation results are reported in Table V. For brevity, we only present the estimation results for our main equation for bankruptcy prediction, and not for CDS trading, which is estimated simultaneously. The two specifications with and without the *CDS Firm* control yield positive and significant (at the 1% level) coefficient estimates for *CDS Active*. In addition, we provide the estimated correlation of the residuals from the selection equation and the outcome equation. The likelihood ratio test rejects the exogeneity of CDS trading at the 1% level. The coefficient estimates translate into economically large odds ratios for *CDS Active*.

We perform two robustness checks of our FIML estimation results. First, we remove the crisis period observations from our sample. The results are reported in the first column of Table A16 of the internet appendix, illustrating that the FIML estimate of the coefficient for *CDS Active* is similar to the full sample estimate in Table V in terms of economic magnitude and statistical significance. In our second robustness check, we consider an alternative but related estimation approach. Although the FIML estimator is efficient, it is computationally burdensome. Due to the lack of a closed-form expression for the likelihood function, the estimator and its derivatives must be estimated through numerical approximation. Moreover, the FIML estimates are sensitive to model specification. Any mis-specification may lead to inconsistent estimates across all equations. Therefore, we also employ limited-information maximum likelihood (LIML) estimation.¹⁴ The estimation results are reported in Table A16 of the internet appendix. The coefficient estimates for *CDS Active* are significant at the 1% level in both the full sample (column 2) and the pre-crisis period sub-sample (third column). Therefore, the maximum likelihood estimates, which are more efficient than alternative ap-

¹³We thank an anonymous referee for suggesting this method. Edmans, Goldstein, and Jiang (2012) and Hochberg and Lindsey (2010) provide thorough discussions of the FIML estimation approach. We implement the FIML estimation using *Stata*.

¹⁴The LIML estimator is more efficient than the two-stage least squares estimator but not as sensitive to model specification. In addition, LIML is a special case of FIML in which only a single equation is over-identified. LIML estimation is used and discussed in detail by Hochberg and Lindsey (2010). The Heckman two-stage analysis is also a LIML. The results reported in Table A17 of the internet appendix demonstrate that the effect of *CDS Active* is significant. However, the estimation results could be inconsistent because the outcome variable in our bankruptcy analysis is binary. Therefore, we focus on other econometric approaches.

proaches, support our previous finding that bankruptcy risk is greater following CDS trading, after considering the endogeneity of CDS trading.

D. Channels and Mechanisms for the Effect of CDS on Credit Risk

The baseline result that the reference firms' credit risk increases after the inception of CDS trading is not linked to any specific theory. In this section, we first demonstrate that, in addition to the mere presence of CDS trading, the volume of CDS trading affects credit risk. We then test the other three hypotheses stated in Section II. We document that firms in financial distress are more likely to face bankruptcy if they are referenced in CDS trading. We demonstrate that the effect of CDS mainly arises from the "no restructuring" type of contract. Finally, the number of creditors increases after the initiation of CDS trading. Therefore, CDS firms become more susceptible to bankruptcy because it is more difficult for the creditors to coordinate and develop a restructuring plan if the firm gets into financial distress.

D.1. CDS Contracts Outstanding

Our analysis thus far has focused on the CDS introduction effect captured by a binary variable, *CDS Active*, which is a permanent regime variable. That is, once CDS trading is initiated for a firm, it cannot return to being a non-CDS firm. Such a regime variable ignores much of the information in the *variation* in CDS trading over time. Indeed, CDS trading activity varies considerably over time and across firms. Such variation may have additional implications for the effects of CDS trading on credit risk. The CDS effect may be less pronounced if the CDS trading activity of a firm is very thin or illiquid. Additionally, a larger outstanding position in CDS may have greater monetary consequences for CDS traders. Similarly, if CDS trading causes credit risk changes, then its influence on credit risk should disappear when all outstanding CDS contracts mature or are extinguished. Moreover, as noted by Li and Prabhala (2007), the magnitude of the selection variable, the notional amount of

CDS contracts outstanding in our setting, aids identification of the treatment effect. In this subsection, we test for such a continuous effect of CDS trading.

We calculate the ratio of the notional dollar amount of CDS contracts outstanding to the total dollar amount of debt outstanding at a given point in time, *CDS Notional Outstanding/Total Debt*, for each firm in each month.¹⁵ We scale the CDS position by total debt to relate the dollar amount of CDS outstanding to the creditors' exposure. We conjecture that bankruptcy risk will be higher when *CDS Notional Outstanding/Total Debt* is larger. The estimation results, reported in column 1 of Table VI, show that a firm is more likely to file for bankruptcy when the dollar amount of outstanding CDS contracts referencing its debt is large relative to its outstanding debt.

One possible objection to the use of *CDS Notional Outstanding/Total Debt* as an explanatory variable is that traders choose the amount of CDS they wish to buy or sell; therefore, the CDS exposure variable may itself be endogenous. To address this concern, we construct a two-stage model in which we first estimate the quantity of CDS outstanding. As shown in Table A18 of the internet appendix, the metric of CDS exposure, *CDS Notional Outstanding/Total Debt*, is smaller for investment-grade firms and for profitable firms. The model appears to be reasonably well specified, with an adjusted R^2 of 0.59 in Specification 2. This analysis also suggests that CDS contracts are used, at least partially, for hedging purposes. We then use the instrumented *CDS Notional Outstanding/Total Debt* in the second stage, in Specification 2 of Table VI, and continue to find a significant positive coefficient estimate for the instrumented variable, *Instrumented CDS Notional Outstanding/Total Debt*. The results are significant when *CDS Firm* is not included in the regression. The results are also significant when only CDS firms (in a within-CDS firm analysis) are included. These results, using an alternative quantitative measure of CDS exposure, suggest that the source of the *CDS*

¹⁵The maximum value of *CDS Notional Outstanding/Total Debt* is 4.14, which is suggestive of over-insurance for such firms and the potential presence of "empty creditors". We thank an anonymous referee for observing that this measure could be contaminated by the positions of speculators in the CDS market. Unfortunately, we cannot consider this issue in this analysis because we do not have access to investor-level data.

Active effect documented in the prior sections is indeed CDS trading.

D.2. Likelihood of Bankruptcy Conditioning on Distress

One specific prediction of the “empty creditor” model presented by Bolton and Oehmke (2011) is that creditors will become tougher in the course of renegotiations with financially distressed borrowers if their potential losses are protected by CDS. Consequently, bankruptcy is more likely than restructuring, as illustrated by Internet Appendix I. This result implies that distressed firms are less likely to free themselves from financial distress and more likely to file for bankruptcy if they are referenced in CDS trading.¹⁶ We test the specific prediction (Hypothesis 2) that, conditioning on financial distress, CDS firms are more likely to file for bankruptcy.

We follow Gilson, John, and Lang (1990) and Demiroglu and James (2013) in identifying firms in financial distress. If a firm’s stock return is in the bottom 5% of the market for two consecutive years, we classify it as financially distressed in the third year. According to this definition, there are 655 financially distressed firms in our sample period, providing sufficient information for our analysis. We perform a cross-sectional regression using CDS and non-CDS firms in financial distress. The estimation results are reported in Table VII. In line with Hypothesis 2, Model 1 shows that, once a firm is in financial distress, it is more likely to file for bankruptcy if it is referenced by CDS trading. This effect is economically large. Compared to the default rate of 17.71% for all financially distressed firms, the marginal effect of CDS trading is 19.84%.

We select those firms that are in the bottom 10% of stock returns for two consecutive years as an alternative financial distress sample, as a robustness check, identifying 1,229

¹⁶CDS firms can also become more exposed to credit risk if they take on more debt after CDS trading begins. Indeed, Saretto and Tookes (2013) demonstrate that firm leverage increases following the inception of CDS trading. We also confirm that firms exhibit higher leverage after the start of CDS trading (see Table A19 of the internet appendix). We control for firm leverage before and after CDS trading begins in our regressions.

financially distressed firms based on this definition. The regression results for this alternative sample, presented in Model 2, display a pattern similar to that observed above. In Model 3, we remove the financial crisis period (using the 5% definition of financial distress) and demonstrate that the results are both quantitatively and qualitatively similar to the above results. Finally, adding variables for senior secured debt, the presence of bonds and loans (a measure of capital structure complexity), and tangibility does not alter the effect of *CDS Active*.¹⁷ Overall, the conditional analysis using a different sample (distressed firms) supports Hypothesis 2 and the empty creditor model.

D.3. “No Restructuring” CDS

In this section, we present an alternative test of the “empty creditor” model prediction. Empty creditors will clearly prefer firms to declare bankruptcy rather than restructure their debt *only if* their total payoffs are greater under bankruptcy than under restructuring. One such situation arises when bankruptcy, but not restructuring, triggers a credit event for CDS contracts and generates payments to the CDS buyers. In this case, as shown in internet appendix, creditors’ incentives to encourage borrower bankruptcy will be even stronger if restructuring is not covered by the CDS contracts. Empty creditors will not have this incentive to the same degree if their CDS contracts also cover restructuring as a credit event. Thus, the probability of bankruptcy will be positively associated with a no restructuring clause in a CDS contract if the empty creditor effect is present.

We investigate the effects of differences in contractual terms on the credit risk consequences of CDS trading. The appendix describes the restructuring clauses used in CDS contracts and their historical evolution. There are four types of CDS contracts based on different definitions of credit events: full restructuring (FR), modified restructuring (MR), modified-

¹⁷We also find that firms are less likely to encounter financial distress after the inception of CDS trading (Table A20 of the internet appendix). However, this finding is not robust. Although the coefficient estimate for *CDS Active* is always negative, it becomes less significant when we cluster standard errors by firm or use an instrumented measure.

modified restructuring (MMR), and no restructuring (NR). For FR contracts, any type of restructuring qualifies as a trigger event, and any debt obligation with a maturity of up to 30 years can be delivered in that event. Any restructuring is considered a credit event under MR as well; however, in this type of contract, deliverable obligations are limited to those with maturities within 30 months of the CDS contract's maturity. For MMR contracts, the deliverable obligations are relaxed to include those with maturities within 60 months of the CDS contract's maturity for restructured debt and 30 months for other obligations. Restructuring is excluded as a credit event under NR. Firms with a greater proportion of NR contracts are more strongly subject to the empty creditor threat than those with other types of contracts. Similarly, FR contracts will not be as strongly influenced by empty creditor incentives.

Figure 2 plots the number of contracts of each type in each year, as observed in our CDS transaction records. The majority of firms in our sample have the MR type of clause in their CDS contracts. The FR and MMR contracts have a negligible presence in our sample, which is representative of the market as a whole, although there may be some variation at the firm level. Figure 2 illustrates that there were very few NR CDS contracts prior to 2002. Packer and Zhu (2005) demonstrate that, in their sample period, MR contracts were slightly more expensive than NR contracts. In such circumstances, CDS buyers would likely buy MR contracts rather than NR contracts. The proportion of CDS contracts with NR specifications has increased dramatically in recent years, particularly in 2007. The median (mean) fraction of NR contracts out of all CDS contracts for a reference entity is 0.61 (0.55). There is wide variation across firms in terms of the proportions of NR contracts used.

We account for differences in contractual specifications in the estimations reported in Table VIII, which include variables measuring the type of CDS contract. *No Restructuring CDS* is the fraction of CDS contracts with NR clauses among all CDS contracts on a given reference entity. This measure is zero for firms without CDS. The results in Table VIII indicate a

significant positive relationship between CDS trading using NR contracts and bankruptcy risk. We include year dummies in our regressions to control for potential time series patterns in the composition of CDS contract types. The result is significant regardless of whether we include *CDS Firm* in the regression (the coefficient estimates for *CDS Firm* are insignificant).

Because CDS contract terms are chosen by traders, there may be concern over the choice of contract type, i.e., CDS buyers who believe bankruptcy is more likely than restructuring will buy CDS contracts that only cover bankruptcy. Table A21 of the internet appendix illustrates that firms with more tangible assets, low stock returns, and junk ratings are more likely to have NR CDS traded on them, as are all firms after the year 2003. We look at this finding more closely using *After January 2003* as an instrument. Our instrumented NR CDS continues to be significant, as shown in the third and fourth columns of Table VIII. We present our results for the test of our specification for the NR CDS effect within the CDS sample in the final column of Table VIII. The result is significant for this sample as well, supporting Hypothesis 3.

The above discussion indicates that the effect of *CDS Active* is driven by CDS contracts with NR clauses. This finding regarding restructuring will likely be relevant to many more reference names in the future, as an increasing number of corporate CDS contracts are using NR as the credit event specification (e.g., all CDS index constituents of the North America investment grade index CDX.NA.IG), particularly since the CDS Big Bang in 2009.

The results for *CDS Notional Outstanding/Total Debt*, bankruptcy conditioned on financial distress, and *No Restructuring CDS* are consistent with the empty creditor model. We repeated the analysis using distance-to-default and found similar results for instrumented CDS exposure and NR CDS, as reported in Table A22 of the internet appendix. Therefore, one source of the CDS effect on credit risk is creditors becoming tougher in debt renegotiations, thus causing firms to file for bankruptcy.

D.4. Number of Creditors

In addition to tough creditors causing bankruptcy on an individual basis, creditor coordination is another important consideration when it comes to debt workout. If firms borrow money from a larger group of lenders after the inception of CDS trading, then creditor coordination will be more difficult and bankruptcy more likely when firms seek to restructure. Lead banks will likely not wish to appear to be driving their borrowers into bankruptcy, as the long-run reputational damage may outweigh the short-run gains from empty creditor trading profits. However, other lenders, such as hedge funds or private equity players, who are not similarly constrained, may exploit CDS trading more intensively. Therefore, CDS trading may affect the size and composition of a firm's lenders.

We investigate the impact of the introduction of CDS on the creditor relationships of a firm. The overall creditor relationship is represented in our analysis by the lending relationships available from DealScan LPC data.¹⁸ For each firm in a given month, we examine the prior five-year period for any syndicated loan facilities in place for this firm. Summing over all such active facilities, we compute the number of unique banks lending to the firm. Δ *Number of Banks* is the change in the number of bank relationships from one year before the inception of CDS trading to two years after its inception.

We match each CDS firm with a non-CDS firm with a close propensity score for CDS trading using the CDS prediction model with all explanatory variables, as discussed above. First, based on a univariate difference-in-difference analysis, we find that the number of bank relationships of a firm increases significantly, by 1.4, one year after the inception of CDS trading, and by 3, two years after CDS trading begins, compared to a matched non-CDS firm.

Second, we regress Δ *Number of Banks* from the year before to two years after the start of

¹⁸The construction of the dataset is detailed by Chava and Roberts (2008). We thank Michael Roberts for providing the DealScan-Compustat linking file.

CDS trading on a set of firm characteristics and the *CDS Active* variable. The sample includes both CDS firms and matched non-CDS firms. These “event study” results are reported in Panel A of Table IX. In this cross-sectional regression, we find that CDS trading significantly increases the number of lenders for a firm. On average, controlling for the propensity for CDS trading, and for other factors that may affect the number of lenders, such as firm size and leverage, CDS firms have 2.4 more lenders than non-CDS firms two years following CDS introduction.

The relationship between the number of lenders and bankruptcy risk has previously been documented by Gilson, John, and Lang (1990) and Brunner and Krahen (2008), among others. We present similar evidence using our sample, including the effect of CDS trading, in Panel B of Table IX. We include the *Number of Banks* as an additional explanatory variable in the hazard model of the firm’s likelihood of bankruptcy. The results indicate that a firm’s bankruptcy risk increases with the number of banking relationships, even after controlling for the direct impact of CDS trading. Column 2 in Panel B analyzes the effect of changes in the number of bank relationships of the CDS firms: CDS firms with larger increases in the number of lenders around the time of CDS introduction are more likely to file for bankruptcy. Therefore, the results in Table IX support Hypothesis 4, in that CDS trading increases the number of creditors, which in turn increases the bankruptcy risk of a reference firm.

V. Conclusion

Using a comprehensive dataset of North American corporate CDS transaction records over the 1997-2009 period, we find strong evidence that the bankruptcy risk of reference firms increases after the inception of CDS trading. This effect of CDS trading on credit risk is economically significant: the likelihood of bankruptcy for the average firm more than doubles after the initiation of CDS trading. This finding is robust to the selection and endogeneity

of CDS trading. Firms in financial distress are more likely to file for bankruptcy if they are referenced by CDS trading than if they are not. The effect of CDS trading on bankruptcy risk is more pronounced when CDS payments in the event of default do not cover restructuring. Moreover, the number of lenders increases after the initiation of CDS trading, exacerbating the problems of creditor coordination.

This study reveals a real consequence of CDS trading and contributes to a better understanding of this important derivative market. Although our findings indicate that firms become more vulnerable to bankruptcy once CDS are traded on them, we emphasize that this finding does *not* imply that CDS trading necessarily reduces social welfare. The benefits of the higher firm leverage that results from the mitigation of risk may, for some agents, outweigh the greater bankruptcy costs. Future work can examine the tradeoff between the potential benefits and the bankruptcy vulnerability caused by CDS, shedding light on the overall impact of CDS trading on allocative efficiency.

Appendix:

Credit Default Swaps' Credit Event Definitions

Credit default swaps (CDS) provide insurance protection against the default of a reference entity's debt. For the buyer of protection to obtain a payoff from a CDS contract, a credit event must be triggered. Following such an event, the CDS contract can be settled either by physical delivery (by delivering the reference security and receiving the notional principal) or by payment of cash (by receiving the difference between the notional principal and the price of the reference security). The trade organization of participants in the derivatives market, the International Swaps and Derivatives Association (ISDA), sets the standards for the contractual terms of CDS contracts, including the definition of trigger events, the delivery and settlement process, and other details.

Based on the 1999 ISDA Credit Event Definitions, there are six categories of trigger events used to define a default for different obligors: bankruptcy, failure to pay, obligation acceleration, obligation default, repudiation/moratorium, and restructuring. For CDS linked to corporate debt, the primary trigger events are bankruptcy, failure to pay and restructuring. Under this definition, known as full restructuring (FR), *any* restructuring qualifies as a trigger event, and *any* obligation with a maturity of up to 30 years can be delivered. This creates a "cheapest to deliver" option for protection buyers, who will benefit by delivering the least expensive instrument in the event of default. The broad definition of deliverable obligations was intended to create a standard hedge contract with a wide range of protection possibilities for the credit risk of the reference entity.

However, the restructuring of Conseco Finance on September 22, 2000 highlighted the problems with the 1999 ISDA Credit Event Definitions. The bank debt of Conseco Finance was restructured to the benefit of the debt holders. Yet, the restructuring event still triggered payments from outstanding CDS contracts. To settle the CDS position, CDS holders also utilized the cheapest-to-deliver option created by the broad definition of deliverable obligations

and delivered long-maturity, deeply discounted bonds in exchange for the notional amount. To address this obvious lacuna, ISDA modified CDS contracts and defined a new structure known as modified restructuring (MR). Under this 2001 ISDA Supplement Definition, *any* restructuring is defined as a credit event. However, deliverable obligations are limited to those with maturities within 30 months of the CDS contract's maturity.

In March 2003, ISDA made another change and introduced modified-modified restructuring contracts (MMR) to relax the limitation on deliverable obligations. The definition of deliverable obligations was relaxed to include those with maturities within 60 months of the CDS contract's maturity for restructured debt, and 30 months for other obligations. Thus, according to the 2003 ISDA Credit Derivative Definitions, there are four types of restructuring clauses: full restructuring (FR), modified restructuring (MR), modified-modified restructuring (MMR) and no restructuring (NR). For CDS contracts with NR as the restructuring clause, restructuring is excluded as a credit event: the credit event has to be either bankruptcy or failure to pay. To further standardize the CDS market, since April 2009, ISDA has not included restructuring as a credit event for North American CDS contracts.

To sum up, based on the 2003 ISDA Credit Derivative Definitions, there are four types of restructuring clauses: FR, MR, MMR and NR. The credit event in all cases includes bankruptcy and failure to pay. For CDS contracts under FR, the event also includes restructuring. Under NR, restructuring is excluded as a credit event. The other types include restructuring as a credit event, but differ in terms of the maturity of the deliverable obligations, MR being more restrictive than MMR. By 2009, the rules essentially excluded restructuring as a credit event for all North American corporate CDS contracts.

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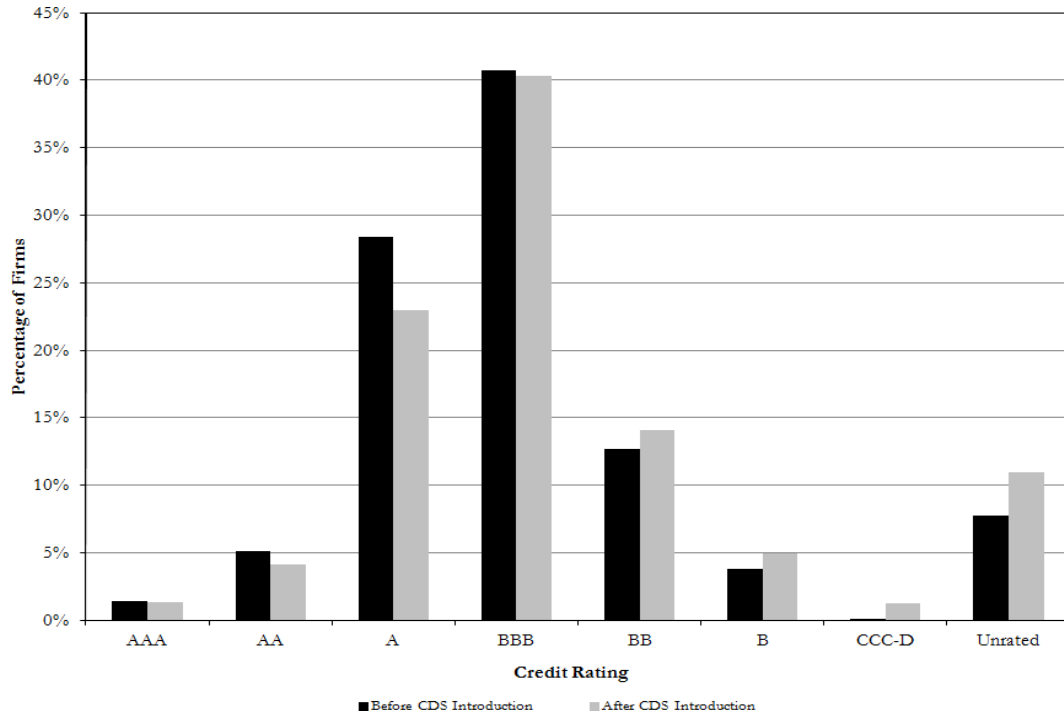


Figure 1: Rating Distribution Around the Introduction of Credit Default Swaps. This figure plots the credit rating distributions for firms with credit default swaps (CDS), before the inception of CDS trading and two years after the inception of CDS trading. The credit ratings are taken from S&P Credit Ratings. The CDS data come from CreditTrade and the GFI Group. There are 901 firms in our sample that have CDS traded at some point during the sample period of June 1997 to April 2009.

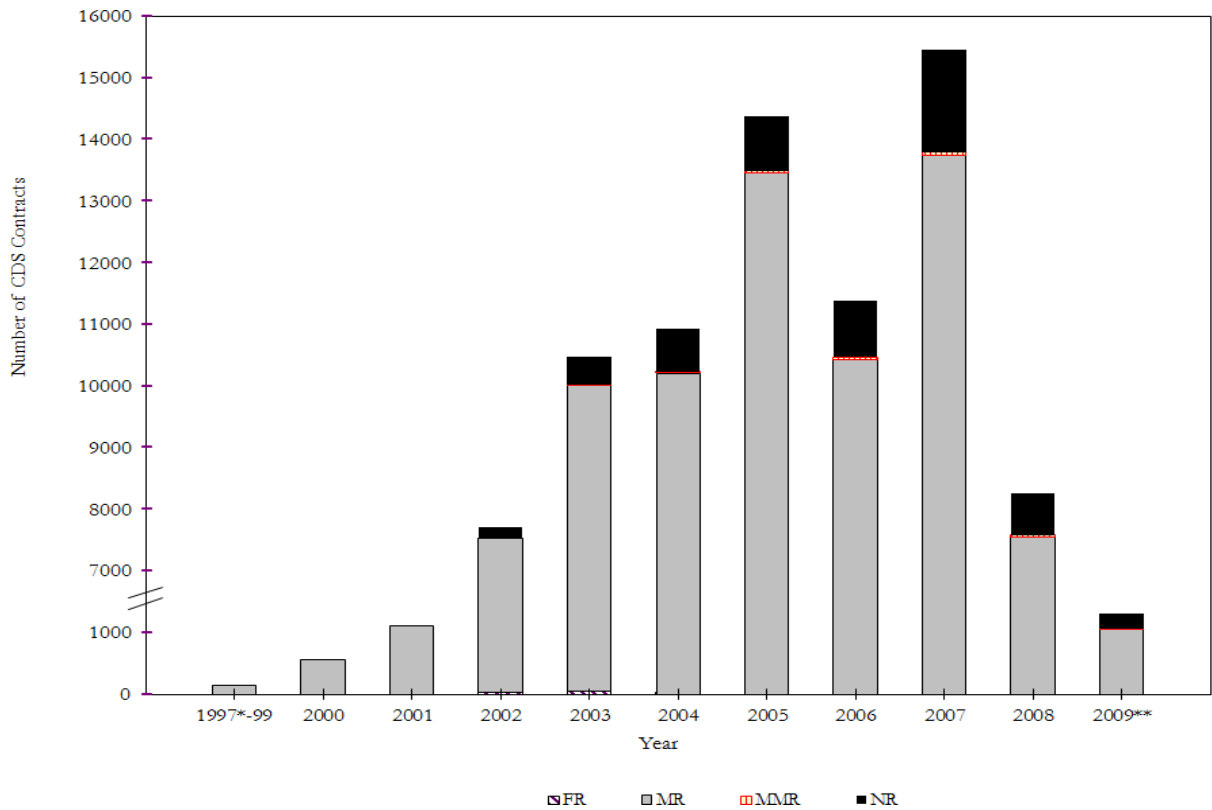


Figure 2: Credit Default Swaps' Restructuring Clauses by Year. This figure plots the distribution of credit default swaps' (CDS') restructuring clauses, by year, in our sample, between 1997 and 2009. The CDS data are taken from CreditTrade and the GFI Group. There are four types of contract terms related to restructuring: full restructuring (FR), modified restructuring (MR), modified-modified restructuring (MMR), and no restructuring (NR). For firms with NR in the restructuring clause, the credit events do not include restructuring, while for the other types, they do. MR and MMR contracts impose restrictions on the type of bond that can be delivered in the event of default.

Table I
Credit Default Swaps Trading and Bankruptcies by Year

This table reports the distribution of firms, including those with credit default swaps (CDS) traded, and bankruptcy events, by year, in our sample, between 1997 and 2009. The sample of all firms is drawn from Compustat, and includes all companies in the database during 1997-2009. The CDS data are taken from CreditTrade and the GFI Group. There are 901 firms in our sample that have CDS traded at some point during the sample period of June 1997 to April 2009. The bankruptcy data are obtained from New Generation Research’s “Public and Major Company Database”, the UCLA-LoPucki Bankruptcy Research Database (BRD), the Altman-NYU Salomon Center Bankruptcy List, the Fixed Income Securities Database (FISD) and Moody’s Annual Reports on Bankruptcy and Recovery. The combined database includes all public companies that filed for bankruptcy during the period; it also includes selected private firms that are deemed significant. The first column in the table is the year. The second column in the table shows the total number of U.S. companies included in the Compustat database. The third column shows the number of bankruptcies in the year. The fourth column reports the number of firms for which CDS trading was initiated during the year in question. The fifth column presents firms with active CDS trading during each year. The last two columns report the number of CDS firms that filed for bankruptcy and the number of non-CDS firms that filed for bankruptcy, respectively. The last three rows report the number of bankruptcies (or firms) in the final sample, the propensity score-matched sample, and the propensity score-matched final sample, as percentages of the raw sample. ([†] from June 1997, [‡] until April 2009)

(1)	(2)	(3)	(4)	(5)	(6)	(7)
Year	Total # of Firms	# of Bankruptcies	# of New CDS Firms	# of Active CDS Firms	# of CDS Bankruptcies	# of Non-CDS Bankruptcies
1997 [†]	9366	50	22	22	0	50
1998	9546	92	58	72	0	92
1999	9545	118	55	106	0	118
2000	9163	158	102	196	1	157
2001	8601	257	172	334	8	249
2002	8190	225	221	547	12	213
2003	7876	156	93	582	5	151
2004	7560	86	58	593	0	86
2005	7318	76	73	629	5	71
2006	6993	49	28	533	2	47
2007	6651	61	9	418	1	60
2008	6223	121	9	375	4	117
2009 [‡]	5686	179	1	234	22	157
Total		1628	901		60	1568
Final Sample		57.7%	61.6%		70.0%	57.3%
Matched Sample		3.1%	56.7%		56.7%	1.0%
Matched Final		2.8%	53.3%		51.7%	0.9%

Table II
Impact of Credit Default Swaps Trading on Credit Quality

This table presents the estimates of the probabilities of credit downgrades and bankruptcy, using a logistic model in a sample including firms with credit default swaps (CDS) and all non-CDS firms. $\ln(E)$ is the logarithm of the firm's market value of equity. $\ln(F)$ is the logarithm of the book value of the firm's debt, where book debt is the sum of short-term debt and 50% of long-term debt. $1/\sigma_E$ is the inverse of the firm's annualized equity volatility. $r_{it-1} - r_{mt-1}$ is the firm's excess return over the past year, and NI/TA is the firm's ratio of net income to total assets. To estimate the impact of CDS trading on the probability of a credit downgrade or bankruptcy, we include CDS variables in the model specification. *CDS Firm* equals one if the firm is in the CDS sample and zero otherwise. *CDS Active* is a dummy variable that equals one after the inception of CDS trading and zero before CDS trading. The coefficient of interest is that of *CDS Active*, which captures the impact of CDS trading on the probability of a credit downgrade or bankruptcy after the inception of CDS trading. The sample period is 1997-2009, based on monthly observations. (***) significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level. The numbers in parentheses are standard errors.)

	Probability of Downgrade		Probability of Bankruptcy	
	(1)	(2)	(3)	(4)
$\ln(E)$	-0.735*** (0.022)	-0.736*** (0.022)	-0.713*** (0.026)	-0.710*** (0.026)
$\ln(F)$	0.507*** (0.024)	0.503*** (0.024)	0.711*** (0.026)	0.713*** (0.026)
$1/\sigma_E$	-0.062* (0.035)	-0.017 (0.032)	-1.626*** (0.251)	-1.675*** (0.251)
$r_{it-1} - r_{mt-1}$	-0.281*** (0.061)	-0.252*** (0.059)	-1.320*** (0.192)	-1.331*** (0.192)
NI/TA	-0.003 (0.008)	-0.000 (0.008)	-0.038*** (0.009)	-0.038*** (0.009)
<i>CDS Firm</i>	0.755*** (0.088)		-2.009*** (0.720)	
<i>CDS Active</i>	0.691*** (0.096)	1.371*** (0.067)	2.373*** (0.736)	0.400** (0.179)
<i>CDS Active Odds Ratio</i>	1.925	3.939	10.730	1.492
<i>CDS Active Marginal Effect</i>	0.39%	0.78%	0.33%	0.06%
Time Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Clustered Standard Error	Yes	Yes	Yes	Yes
Pseudo R^2	15.08%	14.75%	24.18%	24.06%
N	658966	658966	658966	658966
% of CDS Observations	10.83%	10.83%	10.83%	10.83%
% of CDS Downgrades (Bankruptcies)	34.74%	34.74%	4.47%	4.47%
Sample Probability of a Downgrade (Bankruptcy)	0.59%	0.59%	0.14%	0.14%

Table III
Probability of Credit Default Swaps Trading

This table presents the estimates of the probability of credit default swaps (CDS) trading, obtained using a probit model. Propensity scores are estimated based on the model parameters. $\ln(\text{Assets})$ is the logarithm of the firm's total asset value. *Leverage* is defined as the ratio of book debt to the sum of book debt and market equity, where book debt is the sum of short-term debt and 50% of long-term debt, and market equity is the measure of the number of common shares outstanding multiplied by the stock price. *ROA* is the firm's return on assets. $r_{it-1} - r_{mt-1}$ is the firm's excess return over the past year. *Equity Volatility* is the firm's annualized equity volatility. *PPENT/Total Asset* is the ratio of property, plant and equipment to total assets. *Sales/Total Asset* is the ratio of sales to total assets. *EBIT/Total Asset* is the ratio of earnings before interest and tax to total assets. *WCAP/Total Asset* is the ratio of working capital to total assets. *RE/Total Asset* is the ratio of retained earnings to total assets. *Cash/Total Asset* is the ratio of cash to total assets. *CAPX/Total Asset* is the ratio of capital expenditure to total assets. *Rated* is a dummy variable that equals one if the firm is rated. *Senior Unsecured Debt* is the ratio of senior unsecured debt to total debt. *Lender Size* is a measure of the size of the lending banks and underwriters. *Lender Credit Derivatives* measures the credit derivative activities of the lenders. *Lender FX Hedging* is a measure of the FX hedging activities of the lending banks and underwriters, and *Lender Tier 1 Capital* is the Tier One capital ratio of the lenders. The sample period is 1997-2009, based on monthly observations. (***) significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level. The numbers in parentheses are standard errors.)

	Probability of CDS Trading		
	CDS Prediction Model 1	CDS Prediction Model 2	CDS Prediction Model 3
<i>Ln(Assets)</i>	0.790*** (0.006)	0.804*** (0.006)	0.797*** (0.006)
<i>Leverage</i>	0.429*** (0.025)	0.440*** (0.025)	0.431*** (0.026)
<i>ROA</i>	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)
$r_{it-1} - r_{mt-1}$	-0.104*** (0.011)	-0.104*** (0.011)	-0.104*** (0.011)
<i>Equity Volatility</i>	0.063*** (0.017)	0.069*** (0.017)	0.067*** (0.017)
<i>PPENT/Total Asset</i>	0.306*** (0.031)	0.321*** (0.031)	0.307*** (0.031)
<i>Sales/Total Asset</i>	-0.026*** (0.009)	-0.027*** (0.003)	-0.026*** (0.003)
<i>EBIT/Total Asset</i>	0.315*** (0.064)	0.375*** (0.064)	0.338*** (0.064)
<i>WCAP/Total Asset</i>	0.142*** (0.024)	0.145*** (0.024)	0.143*** (0.024)
<i>RE/Total Asset</i>	0.022*** (0.005)	0.023*** (0.005)	0.024*** (0.005)
<i>Cash/Total Asset</i>	0.290*** (0.023)	0.302*** (0.023)	0.294*** (0.023)
<i>CAPX/Total Asset</i>	-1.611*** (0.122)	-1.677*** (0.122)	-1.604*** (0.122)
<i>Rated</i>	0.667*** (0.203)	0.645*** (0.205)	0.638*** (0.205)
<i>Senior Unsecured Debt</i>	0.375*** (0.014)	0.377*** (0.014)	0.375*** (0.014)
<i>Lender Size</i>	0.369*** (0.011)	0.378*** (0.011)	0.385*** (0.011)
<i>Lender Credit Derivatives</i>	1.006*** (0.024)	1.013*** (0.024)	1.019*** (0.025)
<i>Lender FX Hedging</i>	8.979*** (0.788)		9.104*** (0.789)
<i>Lender Tier 1 Capital</i>		-3.865*** (0.756)	-4.000*** (0.757)
F-statistic (instruments)	129.89	26.13	159.74
p-value (F-statistic)	0.000	0.000	0.000
Credit Rating Controls	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
Clustered Standard Error	Yes	Yes	Yes
Pseudo R^2	38.96%	38.79%	38.99%
N	690111	690111	690111
% of CDS Observations	6.15%	6.15%	6.15%

Table IV
Credit Default Swaps Trading and Probability of Bankruptcy:
Propensity Score Matching

This table presents the estimates of the probability of bankruptcy, using a logistic model in a sample including firms with credit default swaps (CDS) and non-CDS propensity score-matched firms. Propensity score-matched firms are selected based on propensity scores estimated from the model of the probability of CDS trading presented in Table III. $\ln(E)$ is the logarithm of the firm's market value of equity. $\ln(F)$ is the logarithm of the book value of the firm's debt, where book debt is the sum of short-term debt and 50% of long-term debt. $1/\sigma_E$ is the inverse of the firm's annualized equity volatility. $r_{it-1} - r_{mt-1}$ is the firm's excess return over the past year, and NI/TA is the firm's ratio of net income to total assets. To estimate the impact of CDS trading on the probability of bankruptcy, we include CDS variables in the model specification. *CDS Firm* equals one if the firm is in the CDS sample and zero otherwise. *CDS Active* is a dummy variable that equals one after the inception of CDS trading and zero before CDS trading begins. The coefficient of interest is that of *CDS Active*, which captures the impact of the inception of CDS trading on the probability of bankruptcy. The second column presents the analysis in the baseline matched sample, i.e., the "nearest one" propensity score-matched firms, selected based on CDS prediction model 3 in Table III. The third column presents the same analysis, but for the "nearest one" with a propensity score difference within 1%. The fourth column uses the two matching firms with the nearest propensity scores. The sample period is 1997-2009, based on monthly observations. (***) significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level. The numbers in parentheses are standard errors.)

	Probability of Bankruptcy		
	Nearest One Matching	Nearest One PS Diff<1%	Nearest Two Matching
$\ln(E)$	-1.206*** (0.246)	-1.350*** (0.309)	-0.993*** (0.195)
$\ln(F)$	1.274*** (0.211)	1.319*** (0.248)	1.008*** (0.203)
$1/\sigma_E$	-0.078 (1.043)	0.048 (0.904)	-0.612 (1.208)
$r_{it-1} - r_{mt-1}$	-2.054* (1.190)	-1.655 (1.046)	-1.59 (1.290)
NI/TA	-0.026 (0.106)	-2.919*** (0.753)	0.034 (0.095)
<i>CDS Firm</i>	-0.262 (1.050)	-0.279 (1.261)	-0.555 (0.879)
<i>CDS Active</i>	1.858** (0.910)	2.261** (1.082)	1.771** (0.802)
<i>CDS Active Odds Ratio</i>	6.411	9.593	5.877
<i>CDS Active Marginal Effect</i>	0.07%	0.07%	0.07%
Time Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
Clustered Standard Error	Yes	Yes	Yes
Pseudo R^2	37.29%	38.53%	36.81%
N	119710	108401	168600
% of CDS Observations	57.49%	56.58%	40.82%
% of CDS Bankruptcies	68.89%	71.43%	49.21%
Sample Probability of a Bankruptcy	0.03%	0.03%	0.03%

Table V
Credit Default Swaps Trading and Probability of Bankruptcy:
Full-Information Maximum Likelihood

This table presents the full-information maximum likelihood (FIML) results of the impact of credit default swaps (CDS) on a firm's probability of bankruptcy. $\ln(E)$ is the logarithm of the firm's market value of equity. $\ln(F)$ is the logarithm of the book value of the firm's debt, where book debt is the sum of short-term debt and 50% of long-term debt. $1/\sigma_E$ is the inverse of the firm's annualized equity volatility. $r_{it-1} - r_{mt-1}$ is the firm's excess return over the past year, and NI/TA is the firm's ratio of net income to total assets. To estimate the impact of CDS trading on the probability of bankruptcy, we include CDS variables in the model specification. *CDS Firm* equals one if the firm is in the CDS sample and zero otherwise. *CDS Active* is a dummy variable that equals one after the inception of CDS trading and zero before CDS trading begins. The coefficient of interest is that of *CDS Active*, which captures the impact of the inception of CDS trading on the probability of bankruptcy. The sample period is 1997-2009, based on monthly observations. (***) significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level. The numbers in parentheses are standard errors.)

	Probability of Bankruptcy	
	(1)	(2)
$\ln(E)$	-0.581*** (0.022)	-0.580*** (0.022)
$\ln(F)$	0.628*** (0.024)	0.630*** (0.024)
$1/\sigma_E$	-0.284*** (0.044)	-0.298*** (0.044)
$r_{it-1} - r_{mt-1}$	-0.072** (0.028)	-0.074*** (0.028)
NI/TA	-0.288*** (0.031)	-0.288*** (0.031)
<i>CDS Firm</i>	-0.340** (0.147)	
<i>CDS Active</i>	0.864*** (0.175)	0.552*** (0.111)
Time Fixed Effects	Yes	Yes
Industry Fixed Effects	Yes	Yes
Clustered Standard Error	Yes	Yes
N	558376	558376
% of CDS Observations	11.98%	11.98%
% of CDS Bankruptcies	4.47%	4.47%
Endogeneity Test		
Rho	0.038***	0.035***

Table VI
Credit Default Swaps Outstanding and Probability of Bankruptcy

This table shows the impact of credit default swaps (CDS) on a firm's probability of bankruptcy. $\ln(E)$ is the logarithm of the firm's market value of equity. $\ln(F)$ is the logarithm of the book value of the firm's debt, where book debt is the sum of short-term debt and 50% of long-term debt. $1/\sigma_E$ is the inverse of the firm's annualized equity volatility. $r_{it-1} - r_{mt-1}$ is the firm's excess return over the past year, and NI/TA is the firm's ratio of net income to total assets. $CDS Firm$ equals one if the firm has CDS trading at any point in time and zero otherwise. The CDS impact is measured as the total notional CDS outstanding, scaled by the book value of the total debt ($CDS Notional Outstanding/Total Debt$) or the *Instrumented CDS Notional Outstanding/Total Debt*. The sample period is 1997-2009, based on monthly observations. (***) significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level. The numbers in parentheses are standard errors.)

	Probability of Bankruptcy	
$\ln(E)$	-0.689*** (0.028)	-0.674*** (0.083)
$\ln(F)$	0.652*** (0.028)	0.631*** (0.085)
$1/\sigma_E$	-1.533*** (0.121)	-2.027*** (0.371)
$r_{it-1} - r_{mt-1}$	-0.620*** (0.102)	-0.830*** (0.237)
NI/TA	-0.076*** (0.025)	-0.111*** (0.023)
$CDS Firm$	-0.582*** (0.206)	-0.487 (0.477)
$CDS Notional Outstanding/Total Debt$	0.071** (0.030)	
$Instrumented CDS Notional Outstanding/Total Debt$		0.946*** (0.213)
Time Fixed Effects	Yes	Yes
Industry Fixed Effects	Yes	Yes
Clustered Standard Error	Yes	Yes
Pseudo R^2	15.82%	15.25%
N	658966	658966
% of CDS Observations	10.83%	10.83%
% of CDS Bankruptcies	4.47%	4.47%
Sample Probability of a Bankruptcy	0.14%	0.14%

Table VII
Bankruptcy Prediction for Distressed Firms

This table shows the results of a bankruptcy analysis conducted in a sample of distressed firms with and without credit default swaps (CDS) traded. The information on the firms at the time of distress is used to predict the probability of bankruptcy. Distressed firms are defined as firms in the bottom 5% (Models 1, 3, 4) or 10% (Model 2) of stock returns in two consecutive years, following Gilson, John, and Lang (1990) and Demiroglu and James (2013). Model 3 excludes crisis periods from the prediction. Model 4 includes additional controls. $\ln(E)$ is the logarithm of the firm's market value of equity. $\ln(F)$ is the logarithm of the book value of the firm's debt, where book debt is the sum of short-term debt and 50% of long-term debt. $1/\sigma_E$ is the inverse of the firm's annualized equity volatility. $r_{it-1} - r_{mt-1}$ is the firm's excess return over the past year, and NI/TA is the firm's ratio of net income to total assets. *Senior Secured Debt* is the ratio of senior secured debt to total debt. *Both Bond and Loan* is a dummy variable that equals one if the firm has both bonds and loans. *PPENT/Total Asset* is the ratio of property, plant and equipment to total assets. *CDS Active* is a dummy variable that equals one after the inception of CDS trading. (***) significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level. The numbers in parentheses are standard errors.)

	Probability of Bankruptcy			
	(1)	(2)	(3)	(4)
$\ln(E)$	-0.492*** (0.089)	-0.398*** (0.077)	-0.495*** (0.103)	-0.430*** (0.093)
$\ln(F)$	0.504*** (0.089)	0.461*** (0.071)	0.506*** (0.103)	0.457*** (0.092)
$1/\sigma_E$	-0.353 (0.532)	-1.072*** (0.376)	0.071 (0.654)	-0.462 (0.542)
$r_{it-1} - r_{mt-1}$	-0.074 (0.224)	-0.085 (0.088)	-0.076 (0.271)	-0.100 (0.223)
NI/TA	-0.046 (0.033)	0.002 (0.026)	-0.049 (0.033)	-0.043 (0.033)
<i>Senior Secured Debt</i>				0.273 (3.648)
<i>Both Bond and Loan</i>				0.690** (0.323)
<i>PPENT/Total Asset</i>				0.422 (0.643)
<i>CDS Active</i>	1.626** (0.663)	1.064** (0.484)	1.655** (0.821)	1.368** (0.671)
<i>CDS Active Odds Ratio</i>	5.083	2.898	5.233	3.927
<i>CDS Active Marginal Effect</i>	19.84%	9.99%	15.66%	16.51%
Time Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Pseudo R^2	23.24%	19.91%	31.31%	24.33%
N	655	1229	625	655
% of CDS Observations	2.29%	3.25%	1.92%	2.29%
% of CDS Bankruptcies	6.11%	5.96%	5.81%	6.11%
Sample Probability of a Bankruptcy	17.71%	12.29%	13.76%	17.71%

Table VIII

Restructuring Clauses of Credit Default Swaps and Probability of Bankruptcy

This table shows the results from our investigation of the impact of the restructuring clauses of credit default swaps (CDS) on the probability of bankruptcy of the firms. The CDS impact is expected to be more significant for firms with more contracts in which “no restructuring” is specified as the restructuring clause. In Models 1 and 2, for each CDS firm, we include a variable *No Restructuring CDS*, which is the total amount of active CDS contracts with “no restructuring” as the restructuring clause, scaled by the total number of CDS contracts trading on the firm. In Models 3-5, for each CDS firm, we include *Instrumented NR CDS*, which is the instrumented *No Restructuring CDS* from the model predicting the amount of “no restructuring” CDS contracts. Models 1-4 investigate the impact of No Restructuring CDS in a sample including firms with and without CDS traded. Model 5 conducts the analysis in the CDS sample. *CDS Firm* equals one if the firm has CDS trading on it at any point in time and zero otherwise. The coefficients of interest are those of *No Restructuring CDS* and *Instrumented NR CDS*, which capture the impact of CDS. $\ln(E)$ is the logarithm of the firm’s market value of equity. $\ln(F)$ is the logarithm of the book value of the firm’s debt, where book debt is the sum of short-term debt and 50% of long-term debt. $1/\sigma_E$ is the inverse of the firm’s annualized equity volatility. $r_{it-1} - r_{mt-1}$ is the firm’s excess return over the past year, and NI/TA is the firm’s ratio of net income to total assets. The sample period is 1997-2009, based on monthly observations. (***) significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level. The numbers in parentheses are standard errors.)

	Probability of Bankruptcy				
	(1)	(2)	(3)	(4)	(5)
$\ln(E)$	-0.716*** (0.026)	-0.713*** (0.026)	-0.714*** (0.026)	-0.710*** (0.026)	-1.379*** (0.160)
$\ln(F)$	0.715*** (0.026)	0.715*** (0.026)	0.713*** (0.026)	0.713*** (0.026)	1.381*** (0.157)
$1/\sigma_E$	-1.636*** (0.254)	-1.656*** (0.250)	-1.642*** (0.253)	-1.678*** (0.250)	0.200 (0.330)
$r_{it-1} - r_{mt-1}$	-1.327*** (0.192)	-1.330*** (0.193)	-1.330*** (0.193)	-1.335*** (0.193)	-2.126*** (0.708)
NI/TA	-0.037*** (0.009)	-0.037*** (0.009)	-0.037*** (0.009)	-0.037*** (0.009)	-2.554*** (0.658)
<i>CDS Firm</i>	-0.206 (0.187)		-0.609** (0.277)		
<i>No Restructuring CDS</i>	1.315** (0.517)	1.023** (0.438)			
<i>Instrumented NR CDS</i>			0.658*** (0.192)	0.324*** (0.110)	0.776** (0.363)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
Clustered Standard Error	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	24.06%	24.05%	24.11%	24.07%	39.67%
N	658966	658966	658966	658966	71338
% of CDS Observations	10.83%	10.83%	10.83%	10.83%	100%
% of CDS Bankruptcies	4.47%	4.47%	4.47%	4.47%	100%
Sample Probability of a Bankruptcy	0.14%	0.14%	0.14%	0.14%	0.06%

Table IX

Credit Default Swaps Trading, Bank Relationships and Probability of Bankruptcy

This table shows the results of an analysis of the impact of credit default swaps (CDS) on firm-creditor relationships. The creditor relationships are measured by bank relationships obtained from Dealscan LPC. For each firm, on a given date, we look back five years for any syndicated loan facilities extended to this firm. Summing over all such active facilities, we compute, on each date, the number of unique bank relationships. Panel A investigates the effect of CDS on the number of lenders to the firm. Panel B shows the effect of bank relationships on the bankruptcy risk of the firm. Model 1 in Panel B conducts the analysis in a sample including firms with and without CDS traded. Model 2 in Panel B conducts the analysis in the CDS sample. Δ *Number of Banks* is the change in the number of bank relationships from one year before to two years after the inception of CDS trading. $\Delta \ln(Asset)$ is the change in the logarithm of the firm's total asset value. ΔROA is the change in the firm's return on assets. $\Delta Leverage$ is the change in leverage. $\Delta PPENT/Total Asset$ is the change in the ratio of property, plant and equipment to total assets. *CDS Active* is a dummy variable that equals one after and zero before the inception of CDS trading. $\ln(E)$ is the logarithm of the firm's equity value. $\ln(F)$ is the logarithm of the book value of the firm's debt, where book debt is the sum of short-term debt and 50% of long-term debt. $1/\sigma_E$ is the inverse of the firm's annualized equity volatility. $r_{it-1} - r_{mt-1}$ is the firm's excess return over the past year, and NI/TA is the firm's ratio of net income to total assets. *CDS Firm* equals one if the firm has CDS trading on it at any point in time and zero otherwise. *Number of Banks* is the number of existing bank relationships. The coefficients of interest are those of *CDS Active* and *Number of Banks*. (***) significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level. The numbers in parentheses are standard errors.)

Panel A: CDS and Bank Relationships		Panel B: Bank Relationships and Bankruptcy Risk		
Δ Number of Banks		Probability of Bankruptcy		
		(1)	(2)	
$\Delta \ln(Asset)$	6.291*** (1.849)	$\ln(E)$	-0.669*** (0.029)	-1.299*** (0.324)
ΔROA	-0.396 (2.760)	$\ln(F)$	0.683*** (0.027)	1.445*** (0.419)
$\Delta Leverage$	8.581* (5.201)	$1/\sigma_E$	-1.763*** (0.266)	-0.974** (0.480)
$\Delta PPENT/Total Asset$	-1.586 (10.840)	$r_{it-1} - r_{mt-1}$	-1.339*** (0.192)	0.556 (0.341)
<i>CDS Active</i>	2.432** (1.069)	NI/TA	-0.040*** (0.009)	-2.500 (9.361)
Time Fixed Effects	Yes	<i>CDS Firm</i>	-2.210*** (0.722)	
Industry Fixed Effects	Yes	<i>CDS Active</i>	2.378*** (0.736)	
R^2	9.75%	<i>Number of Banks</i>	0.153*** (0.035)	
N	496	Δ <i>Number of Banks</i>		0.043*** (0.016)
		<i>CDS Active Odds Ratio</i>	10.783	
		<i>CDS Active Marginal Effect</i>	0.33%	
		Time Fixed Effects	Yes	Yes
		Industry Fixed Effects	Yes	Yes
		Clustered Standard Error	Yes	
		Pseudo R^2	24.32%	33.54%
		N	658966	480
		% of CDS Observations	10.83%	100%
		% of CDS Bankruptcies	4.47%	100%
		Sample Probability of a Bankruptcy	0.14%	5.83%

Internet Appendix

(not to be included for publication)

I. Illustration of CDS Effects on Bankruptcy Risk

We use a simple example of a reduced-form nature to illustrate how CDS trading by creditors affects the likelihood of bankruptcy. The example is intended to convey the basic intuition about the incentives of creditors with CDS positions, and is based on the model of Bolton and Oehmke (2011).

First, consider the case where there are no CDS traded on a firm. Assume that creditors lend X to the firm. If the firm is in financial distress and consequently declares bankruptcy, creditors will recover $r \times X$, where r is the recovery rate in bankruptcy. Consider, on the other hand, that the creditors allow the firm to restructure the debt, since the recovery value of the assets in bankruptcy is less than the firm's value as a going concern. Suppose the firm offers the creditors part of the difference between the "going concern" value and the recovery value of the assets in bankruptcy, and agrees to pay them, say, $R \times X$, with $R > r$. Clearly, the creditors would consider such a restructuring favorably, and try to avoid bankruptcy.¹⁹ In general, restructuring would dominate bankruptcy.

Suppose, next, that the creditors can also buy CDS protection against the firm's credit events. Clearly, bankruptcy will always be defined as a credit event. However, restructuring may or may not be, as per the clauses of the CDS contract. If restructuring is included as a credit event, we call the contract a "full restructuring" (FR) CDS. If it is not, we call it a "no restructuring" (NR) CDS.²⁰ In the case of FR CDS, assume that the CDS premium (price) is F , in present value terms, at the time of default and that the creditors buy CDS against Y of the notional value of the CDS. If the firm defaults, the creditors' total payoff with CDS

¹⁹The precise size of R would be determined in a bargaining process between the creditors and the shareholders of the firm.

²⁰Other types of CDS contracts exist, but are not relevant for the purpose of this simple illustration. See Appendix B for a discussion of contract clauses.

protection is $[r \times X + (1 - r - F) \times Y]$ in the event of bankruptcy, and $[R \times X + (1 - R - F) \times Y]$ if the debt is restructured. Therefore, the creditors are better off with bankruptcy than with restructuring if

$$[r \times X + (1 - r - F) \times Y] > [R \times X + (1 - R - F) \times Y],$$

i.e., when $Y > X$, since $R > r$. Hence, bankruptcy dominates restructuring as a choice for creditors for whom the amount of CDS purchased exceeds the bonds held (“empty creditors”), even when restructuring is covered by the CDS. In the equilibrium model of Bolton and Oehmke (2011), CDS sellers fully anticipate this incentive of CDS buyers, and price it into the CDS premium. Although CDS sellers may have an incentive to bail out the reference firms (by injecting more capital as long as it is less than the CDS payout) in order not to trigger CDS payments, they cannot do so unilaterally; the empty creditors, who are the CDS buyers, and other creditors, will mostly decide the fate of the company, as any new financing would require the existing creditors’ approval, and CDS sellers are not part of this negotiation process.

Now consider the case of NR CDS. Assume that the CDS premium, in this case, is f in present value terms, where $f < F$. Suppose again that the creditors buy CDS against Y of the notional value of the CDS. Therefore, if the firm defaults, the creditors’ total payoff with CDS protection is $[r \times X + (1 - r - f) \times Y]$ in the event of bankruptcy, and $[R \times X - f \times Y]$ if the debt is restructured. Bankruptcy is a preferred outcome for the creditors if

$$[r \times X + (1 - r - f) \times Y] > [R \times X - f \times Y],$$

or if

$$Y > \frac{R - r}{1 - r} X,$$

which can be true even when $Y < X$, since $R < 1$. Thus, for NR CDS, bankruptcy is

preferred when even a relatively small amount of CDS is purchased; hence, bankruptcy is the preferred outcome for a larger range of holdings of NR CDS by the creditors. It is also evident that buying CDS protection with NR CDS contracts will be more profitable in the event of bankruptcy than a restructuring without CDS protection would have been, so long as

$$[r \times X + (1 - r - f) \times Y] > R \times X,$$

which is equivalent to saying that ²¹

$$Y > \frac{R - r}{1 - r - f} X.$$

The above condition is met when $Y > X$, as long as $R < 1 - f$, which is almost always true as the cost of CDS protection is usually lower than the loss in the event of restructuring. Even if $Y < X$, the condition is likely to hold for reasonable values of R and f . Further, the greater the difference between Y and X , the greater will be the incentive for creditors to push the firm into bankruptcy.

Our parsimonious illustration skips many details of the equilibrium model of Bolton and Oehmke (2011) in order to capture the main intuition and predictions. We refer interested readers to Bolton and Oehmke's (2011) theory for a more rigorous treatment. To recap, we demonstrate that (a) creditors have an incentive to over-insure and push the firm into bankruptcy, (b) this incentive increases with the difference between Y and X , i.e., the amount of CDS contracts outstanding relative to the firm's debt, and (c) the probability of bankruptcy occurring is greater for NR CDS contracts.

²¹The calculation for the FR CDS is the same, except that the fee is F instead of f . The precise range of values for Y relative to X will be smaller than for the NR CDS, as argued above.

II. Robustness Checks of the Baseline Results

We run a battery of robustness checks on our baseline results. We first show in internet appendix Table A5 that our findings are consistent in different sample periods. The CDS effect is significant when we use the data before the credit crisis and when we extend the sample to cover bankruptcies in the post-crisis period ending in 2012. Second, we use annual data to reduce the clustering of firm observations and continue to find a significant CDS effect (internet appendix Table A6). We further reduce the clustering and include only one observation per firm for the CDS and matched non-CDS firms. These cross-sectional regression results are reported in internet appendix Table A7, which shows that CDS firms are again more likely to go bankrupt than non-CDS firms.

Third, we use an alternative bankruptcy prediction model proposed by Campbell, Hilscher, and Szilagyi (2008) and again find a significant CDS effect (internet appendix Table A8). Fourth, we match CDS firms with non-CDS firms by their initial ratings and recent rating changes, and continue to find a significant CDS effect on bankruptcy (internet appendix Table A9). Fifth, we match firms by distance-to-default and find a significant CDS effect (internet appendix Table A10). Sixth, we use the distance-to-default as the dependent variable. This alternative continuous measure of credit quality allows more estimation flexibility with the firm fixed effect (so that we do not need the *CDS Firm* control). The results in internet appendix Table A11 confirm the presence of a significant CDS effect.

Finally, we further analyze our bankruptcy prediction and consider the impact of other firm exits, although, in our main tests, we did carefully check for delisting in our bankruptcy sample and classified delisted firms as bankrupt at the time of delisting if they subsequently went bankrupt, and for our CDS and non-CDS matched sample, we carefully checked the default outcomes for these firms.²² We find that 23 non-CDS firms were delisted (but did not

²²We use the CRSP definitions to define four outcomes: active, bankrupt, merged, and delisted. We further determine three reasons for delisting: moving to another exchange, going private, and poor performance (such as share price below one dollar for a consecutive period of time).

subsequently go bankrupt) and 36 CDS firms went bankrupt (Panel A of internet appendix Table A12). We use CDS trading to predict different types of exit. Panel B of internet appendix Table A12 shows that CDS trading positively predicts bankruptcies, negatively predicts mergers, but has no predictive power for delisting. Although non-CDS firms are more likely to be acquired, we find that non-CDS firms with a merger event do not perform significantly worse than other non-CDS firms in our sample. Our finding is not driven by mergers, as another exit for poorly performing non-CDS firms. Furthermore, excluding mergers and delistings from our sample does not affect the estimation of the *CDS Active* effect (internet appendix Table A13).

III. Additional Figures and Tables

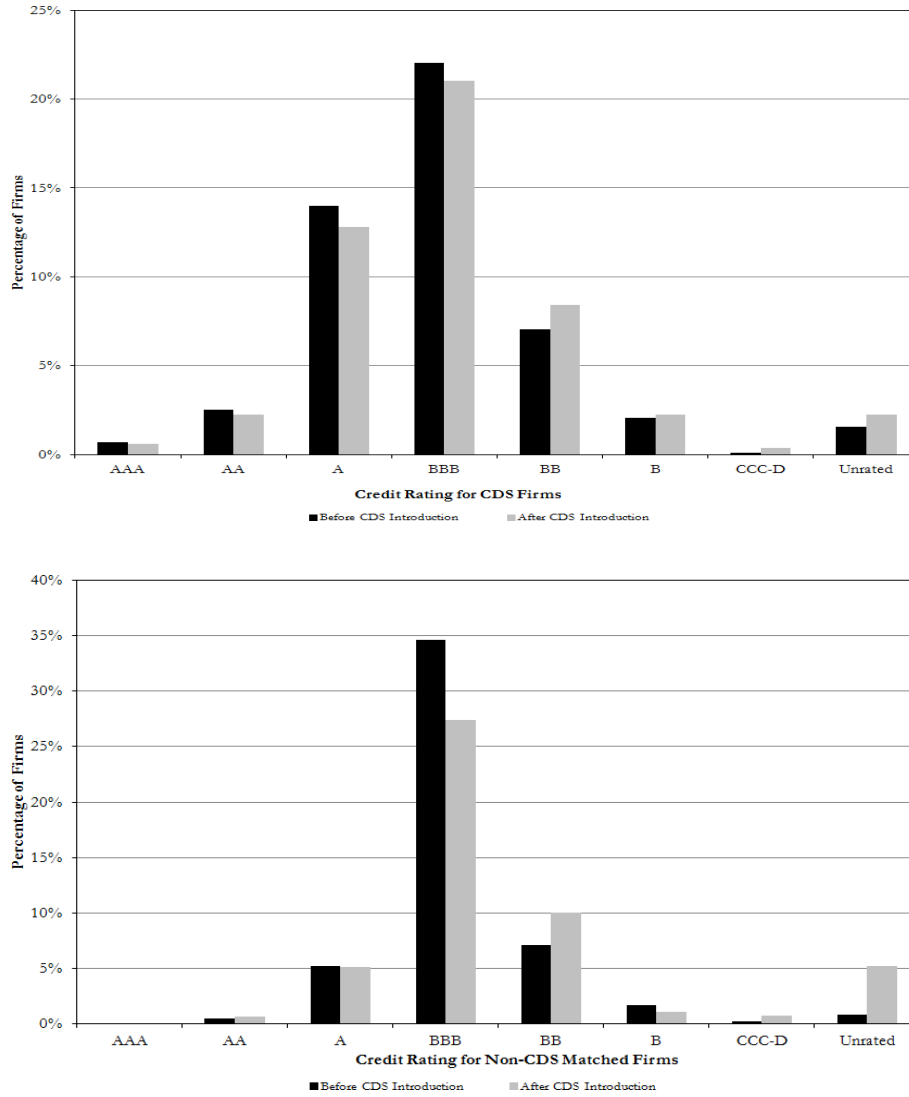


Figure A1: Rating Distribution for CDS Firms and Non-CDS Matched Firms. This figure plots the credit rating distributions for firms with and without credit default swaps (CDS). Non-CDS matched firms are selected based on propensity scores from a model predicting the probability of CDS trading. The credit ratings are taken from S&P Credit Ratings. The CDS data come from CreditTrade and the GFI Group.

Table A1
Industry Distributions of Raw and Final Samples of Bankruptcies

This table compares the industry distributions of the raw and final samples of bankruptcies. The raw bankruptcy data are obtained from New Generation Research’s “Public and Major Company Database”, the UCLA-LoPucki Bankruptcy Research Database (BRD), the Altman-NYU Salomon Center Bankruptcy List, the Fixed Income Securities Database (FISD) and Moody’s Annual Reports on Bankruptcy and Recovery. In our raw sample of bankruptcies, there are 1628 bankruptcies (1565 distinct bankrupt firms), 60 of which are CDS firms. In our final sample of bankruptcies, there are 940 distinct bankrupt firms, 42 of which are CDS firms.

	Raw Sample	Final Sample	Final Sample/Raw Sample
<i>Agriculture, Forestry and Fishing</i>	2	1	0.5
<i>Mining</i>	87	51	0.6
<i>Manufacturing</i>	590	386	0.7
<i>Transportation, Communications etc.</i>	223	133	0.6
<i>Wholesale Trade</i>	53	42	0.8
<i>Retail Trade</i>	166	99	0.6
<i>Finance, Insurance and Real Estate</i>	130	18	0.1
<i>Service</i>	291	198	0.7
<i>Non-classifiable</i>	23	12	0.5
Total	1565	940	0.6

Table A2
Additional Summary Statistics

This table provides additional summary statistics for our sample. Panel A summarizes the bankruptcy distribution in our final sample. Panel B provides summary statistics for the bankruptcy data in the propensity score-matched sample. Panel C compares the number of CDS firms in the raw sample, the final sample and the propensity score-matched sample.

Panel A: Summary Statistics for Final Sample

	Final # of Bankruptcies		Final # of CDS Bankruptcies		Final # of Non-CDS Bankruptcies	
	Number	% Raw	Number	% Raw	Number	% Raw
1997	23	46%	0	—	23	46%
1998	60	65%	0	—	60	65%
1999	79	67%	0	—	79	67%
2000	93	59%	1	100%	92	59%
2001	164	64%	4	50%	160	64%
2002	131	58%	8	67%	123	58%
2003	87	56%	2	40%	85	56%
2004	49	57%	0	—	49	57%
2005	38	50%	4	80%	34	48%
2006	30	61%	2	100%	28	60%
2007	27	44%	1	100%	26	43%
2008	60	50%	3	75%	57	49%
2009	99	55%	17	77%	82	52%
Total	940	58%	42	70%	898	57%

Panel B: Summary Statistics for Propensity Score-Matched Sample

	Raw # of Bankruptcies			Final # of Bankruptcies			
	Total	CDS	Non-CDS	Total	Final/Raw	CDS	Non-CDS
1997	0	0	0	0	–	0	0
1998	0	0	0	0	–	0	0
1999	0	0	0	0	–	0	0
2000	2	2	0	1	0.5	1	0
2001	6	4	2	5	0.8	3	2
2002	9	6	3	9	1.0	6	3
2003	3	2	1	2	0.7	2	0
2004	2	0	2	2	1.0	0	2
2005	6	4	2	5	0.8	3	2
2006	1	1	0	1	1.0	1	0
2007	1	1	0	1	1.0	1	0
2008	2	1	1	1	0.5	1	0
2009	18	13	5	18	1.0	13	5
Total	50	34	16	45	0.9	31	14

Panel C: Summary Statistics for CDS Sample

	# of New CDS Firms					
	Raw	Final	Final/Raw	Matching Raw	Matching Final	Matching Final/Raw
1997	22	13	0.6	12	11	0.9
1998	58	35	0.6	34	34	1.0
1999	55	32	0.6	31	29	0.9
2000	102	76	0.7	63	60	1.0
2001	172	139	0.8	117	109	0.9
2002	221	118	0.5	121	112	0.9
2003	93	50	0.5	45	43	1.0
2004	58	35	0.6	27	25	0.9
2005	73	37	0.5	42	39	0.9
2006	28	13	0.5	14	13	0.9
2007	9	4	0.4	1	1	1.0
2008	9	3	0.3	4	4	1.0
2009	1	0	0.0	0	0	–
Total	901	555	0.6	511	480	0.9

Table A3
Rating Change around CDS Introduction

This table investigates the change in credit ratings around the introduction of credit default swaps (CDS) trading, in a sample including CDS firms and propensity score-matched firms. Propensity score-matched firms are selected based on CDS prediction model 3 in Table III. $\Delta Rating$ is the change in the firm's credit rating around the CDS introduction date. $\Delta \ln(E)$ is the change in the logarithm of the firm's market value of equity. $\Delta \ln(F)$ is the change in the logarithm of the book value of the firm's debt, where book debt is the sum of short-term debt and 50% of long-term debt. $\Delta 1/\sigma_E$ is the change in the inverse of the firm's annualized equity volatility. $\Delta r_{it-1} - r_{mt-1}$ is the change in the firm's excess return over the past year, and $\Delta NI/TA$ is the change in the firm's ratio of net income to total assets. *CDS Active* is a dummy variable that equals one after the inception of CDS trading. The coefficient of interest is that of *CDS Active*, which captures the impact of CDS trading on the credit rating after the inception of CDS trading. (***) significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level. The numbers in parentheses are standard errors.)

	$\Delta Rating$
$\Delta \ln(E)$	-0.147** (0.063)
$\Delta \ln(F)$	-0.062 (0.085)
$\Delta 1/\sigma_E$	-0.029 (0.034)
$\Delta r_{it-1} - r_{mt-1}$	0.351*** (0.049)
$\Delta NI/TA$	0.085 (1.335)
<i>CDS Active</i>	0.230*** (0.083)
R^2	14.45%
N	744

Table A4
CDS Effect on Rating Upgrades

This table presents the estimates of the probabilities of credit upgrades, in a sample including firms with credit default swaps (CDS) and all non-CDS firms. Panel A presents the result of a multinomial logit regression where the base case is no change in credit rating (No Change). Panel B models the probability of upgrades using the logistic model. $\ln(E)$ is the logarithm of the firm's market value of equity. $\ln(F)$ is the logarithm of the book value of the firm's debt, where book debt is the sum of short-term debt and 50% of long-term debt. $1/\sigma_E$ is the inverse of the firm's annualized equity volatility. $r_{it-1} - r_{mt-1}$ is the firm's excess return over the past year, and NI/TA is the firm's ratio of net income to total assets. To estimate the impact of CDS trading, we include CDS variables in the model specification. *CDS Firm* equals one if the firm is in the CDS sample and zero otherwise. *CDS Active* is a dummy variable that equals one after the inception of CDS trading and zero before CDS trading. The coefficient of interest is that of *CDS Active*. The sample period is 1997-2009, based on monthly observations. (***) significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level. The numbers in parentheses are standard errors.)

Panel A: Multinomial Logit for Rating Change				
Probability of Rating Change				
	Downgrades Versus No Change		Upgrades Versus No Change	
	(1)	(2)	(3)	(4)
$\ln(E)$	-0.293*** (0.017)	-0.309*** (0.016)	0.013 (0.027)	0.011 (0.027)
$\ln(F)$	0.283*** (0.015)	0.300*** (0.015)	-0.020 (0.026)	-0.018 (0.026)
$1/\sigma_E$	-0.410*** (0.031)	-0.447*** (0.031)	-0.344*** (0.047)	-0.348*** (0.047)
$r_{it-1} - r_{mt-1}$	-0.508*** (0.038)	-0.519*** (0.038)	0.156*** (0.018)	0.156*** (0.018)
NI/TA	-1.386*** (0.131)	-1.429*** (0.131)	2.751*** (0.534)	2.741*** (0.534)
<i>CDS Firm</i>	-0.453*** (0.057)		-0.031 (0.077)	
<i>CDS Active</i>	0.534*** (0.067)	0.149*** (0.045)	-0.041 (0.097)	-0.066 (0.075)
N	658966	658966	658966	658966
% of CDS Observations	10.83%	10.83%	10.83%	10.83%
# of Downgrades	3863	3863		
# of Upgrades			1409	1409

Panel B: Probability of Rating Upgrade

	Probability of Rating Upgrade	
	(1)	(2)
$\ln(E)$	0.026 (0.038)	0.025 (0.038)
$\ln(F)$	-0.033 (0.037)	-0.031 (0.038)
$1/\sigma_E$	-0.335*** (0.054)	-0.338*** (0.053)
$r_{it-1} - r_{mt-1}$	0.160*** (0.024)	0.160*** (0.024)
NI/TA	2.810*** (0.704)	2.798*** (0.702)
<i>CDS Firm</i>	-0.033 (0.111)	
<i>CDS Active</i>	-0.049 (0.132)	-0.075 (0.097)
Time Fixed Effects	Yes	Yes
Industry Fixed Effects	Yes	Yes
Clustered Standard Error	Yes	Yes
N	658966	658966
% of CDS Observations	10.83%	10.83%
# of Upgrades	1409	1409

Table A5

Robustness Check for Baseline Model: Non-crisis Period and Extended Sample

This table presents the results of the robustness check of the baseline results in Table II, using a sample excluding the credit crisis period and an extended bankruptcy sample. Models 1 and 2 present the analysis for the sample excluding the recent credit crisis period. Models 3 and 4 conduct the analysis in the extended bankruptcy sample, covering 1997-2012. $\ln(E)$ is the logarithm of the firm's market value of equity. $\ln(F)$ is the logarithm of the book value of the firm's debt, where book debt is the sum of short-term debt and 50% of long-term debt. $1/\sigma_E$ is the inverse of the firm's annualized equity volatility. $r_{it-1} - r_{mt-1}$ is the firm's excess return over the past year, and NI/TA is the firm's ratio of net income to total assets. To estimate the impact of CDS trading on the probability of bankruptcy, we include CDS variables in the model specification. *CDS Firm* equals one if the firm is in the CDS sample and zero otherwise. *CDS Active* is a dummy variable that equals one after the inception of CDS trading and zero before CDS trading. The coefficient of interest is that of *CDS Active*, which captures the impact of the inception of CDS trading on the probability of bankruptcy. The analysis is based on monthly observations. (***) significant at the 1% level, (**) significant at the 5% level, and (*) significant at the 10% level. The numbers in parentheses are standard errors.)

	Probability of Bankruptcy			
	Non-Crisis Period		Extended Sample Period	
	(1)	(2)	(3)	(4)
$\ln(E)$	-0.708*** (0.027)	-0.704*** (0.027)	-0.712*** (0.025)	-0.709*** (0.025)
$\ln(F)$	0.701*** (0.027)	0.703*** (0.027)	0.714*** (0.025)	0.716*** (0.025)
$1/\sigma_E$	-1.483*** (0.250)	-1.540*** (0.250)	-1.593*** (0.236)	-1.638*** (0.236)
$r_{it-1} - r_{mt-1}$	-1.275*** (0.192)	-1.287*** (0.192)	-1.371*** (0.187)	-1.381*** (0.187)
NI/TA	-0.041*** (0.009)	-0.041*** (0.009)	-0.037*** (0.009)	-0.037*** (0.009)
<i>CDS Firm</i>	-2.083*** (0.719)		-1.994*** (0.720)	
<i>CDS Active</i>	2.503*** (0.740)	0.471** (0.197)	2.231*** (0.735)	0.368** (0.172)
<i>CDS Active Odds Ratio</i>	12.219	1.602	9.309	1.445
<i>CDS Active Marginal Effect</i>	0.35%	0.05%	0.28%	0.05%
Time Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Clustered Standard Error	Yes	Yes	Yes	Yes
Pseudo R^2	23.07%	22.92%	24.59%	24.49%
N	578008	578008	770837	770837
# of Bankruptcies	846	846	1003	1003
Sample Probability of a Bankruptcy	0.14%	0.14%	0.13%	0.13%

Table A6
Robustness Check for Baseline Model: Annual Data

This table presents the results of the robustness check of the baseline results in Table II with annual observations. $\ln(E)$ is the logarithm of the firm's market value of equity. $\ln(F)$ is the logarithm of the book value of the firm's debt, where book debt is the sum of short-term debt and 50% of long-term debt. $1/\sigma_E$ is the inverse of the firm's annualized equity volatility. $r_{it-1} - r_{mt-1}$ is the firm's excess return over the past year, and NI/TA is the firm's ratio of net income to total assets. To estimate the impact of CDS trading on the probability of bankruptcy, we include CDS variables in the model specification. *CDS Firm* equals one if the firm is in the CDS sample and zero otherwise. *CDS Active* is a dummy variable that equals one after the inception of CDS trading and zero before CDS trading. The coefficient of interest is that of *CDS Active*, which captures the impact of the inception of CDS trading on the probability of bankruptcy. The sample period is 1997-2009, based on annual observations. (***) significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level. The numbers in parentheses are standard errors.)

	Probability of Bankruptcy	
	(1)	(2)
$\ln(E)$	-0.682*** (0.028)	-0.678*** (0.028)
$\ln(F)$	0.678*** (0.028)	0.680*** (0.028)
$1/\sigma_E$	-1.157*** (0.245)	-1.207*** (0.245)
$r_{it-1} - r_{mt-1}$	-1.718*** (0.243)	-1.725*** (0.243)
NI/TA	-0.033*** (0.011)	-0.033*** (0.011)
<i>CDS Firm</i>	-1.961*** (0.722)	
<i>CDS Active</i>	2.276*** (0.736)	0.357** (0.169)
<i>CDS Active Odds Ratio</i>	9.738	1.429
<i>CDS Active Marginal Effect</i>	2.98%	0.47%
Time Fixed Effects	Yes	Yes
Industry Fixed Effects	Yes	Yes
Clustered Standard Error	Yes	Yes
Pseudo R^2	33.16%	33.00%
N	60136	60136
# of Bankruptcies	940	940
Sample Probability of a Bankruptcy	1.56%	1.56%

Table A7
Cross-sectional Bankruptcy Prediction Model

This table presents the cross-sectional regression analysis for the probability of bankruptcy using information from just before CDS introduction. The analysis is conducted in the sample of CDS firms and propensity score-matched firms. $\ln(E)$ is the logarithm of the firm's market value of equity. $\ln(F)$ is the logarithm of the book value of the firm's debt, where book debt is the sum of short-term debt and 50% of long-term debt. $1/\sigma_E$ is the inverse of the firm's annualized equity volatility. $r_{it-1} - r_{mt-1}$ is the firm's excess return over the past year, and NI/TA is the firm's ratio of net income to total assets. To estimate the impact of CDS trading on the probability of bankruptcy, we include CDS variables in the model specification. *CDS Active* is a dummy variable that equals one after the inception of CDS trading. The coefficient of interest is that of *CDS Active*, which captures the impact of the inception of CDS trading on the probability of bankruptcy. (***) significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level. The numbers in parentheses are standard errors.)

	Probability of Bankruptcy
$\ln(E)$	-0.575*** (0.001)
$\ln(F)$	0.540*** (0.001)
$1/\sigma_E$	-1.025*** (0.002)
$r_{it-1} - r_{mt-1}$	0.276*** (0.004)
NI/TA	-14.594*** (0.104)
<i>CDS Active</i>	0.901*** (0.004)
<i>CDS Active Odds Ratio</i>	2.462
<i>CDS Active Marginal Effect</i>	4.76%
Time Fixed Effects	Yes
Industry Fixed Effects	Yes
Pseudo R^2	17.73%
# of Bankruptcies	45
Sample Probability of a Bankruptcy	7.10%
N	893

Table A8

Impact of Credit Default Swaps Trading on Bankruptcy: Alternative Model

This table presents estimates of the effect of CDS trading on firms' bankruptcy risk, based on the model in Campbell, Hilscher, and Szilagyi (2008). *NIMTAAVG* is the weighted average profitability ratio of net income to market-valued total assets, which includes lagged information about profitability, as defined in Campbell, Hilscher, and Szilagyi (2008). *TLMTA* is total liabilities over the market value of total assets. *EXRETAVG* is the weighted average excess return over the value-weighted S&P 500 return, which includes lagged information about excess returns. *Sigma* is the square root of the sum of squared firm stock returns over a 3-month period. *Rsize* is the relative size of each firm, measured as the log ratio of its market capitalization to that of the S&P 500 index, and *CASHMTA* is the stock of cash and short-term investments over the market value of total assets. *MB* is the market-to-book ratio of the firm, and *PRICE* is the firm's log price per share, truncated above at \$15. To estimate the impact of CDS trading on firms' bankruptcy risk, we include CDS variables in the model specification. *CDS Firm* equals one if the firm is in the CDS sample and zero otherwise. *CDS Active* is a dummy variable that equals one if the firm has CDS traded on its debt one year before month *t*. The sample period is 1997-2009, based on monthly observations. (***) significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level. The numbers in parentheses are standard errors.)

	Probability of Bankruptcy	
	(1)	(2)
<i>NIMTAAVG</i>	-18.007*** (1.680)	-17.918*** (1.678)
<i>TLMTA</i>	3.154*** (0.177)	3.268*** (0.179)
<i>EXRETAVG</i>	-1.272 (0.830)	-1.273 (0.825)
<i>Sigma</i>	0.829*** (0.144)	0.800*** (0.143)
<i>Rsize</i>	0.114*** (0.030)	0.203*** (0.035)
<i>CASHMTA</i>	-2.368*** (0.400)	-2.436*** (0.401)
<i>MB</i>	0.001*** (0.000)	0.001** (0.000)
<i>PRICE</i>	-0.429*** (0.076)	-0.485*** (0.076)
<i>CDS Firm</i>		-2.284*** (0.452)
<i>CDS Active</i>		1.749*** (0.479)
<i>CDS Active Odds Ratio</i>		5.749
<i>CDS Active Marginal Effect</i>		0.23%
Time Fixed Effects	Yes	Yes
Industry Fixed Effects	Yes	Yes
Clustered Standard Error	Yes	Yes
Pseudo R^2	12.35%	12.77%
N	682053	682053
% of CDS Observations	10.30%	10.30%
# of Bankruptcies	888	888
Sample Probability of a Bankruptcy	0.13%	0.13%

Table A9
Rating Drift and the Impact of Credit Default Swaps

This table presents the estimates of the probability of bankruptcy using a logistic model, in a sample including firms with credit default swaps (CDS) and non-CDS firms matched by credit rating. Models 1 and 2 select matched firms as firms with the same credit rating as the CDS firm and the closest asset size at the time of CDS introduction. Models 3 and 4 select matched firms as firms with the same credit rating, the same rating change, and the closest asset size to that of the CDS firm at the time of CDS introduction. $\ln(E)$ is the logarithm of the firm's equity value. $\ln(F)$ is the logarithm of the book value of the firm's debt. $1/\sigma_E$ is the inverse of the firm's annualized equity volatility. $r_{it-1} - r_{mt-1}$ is the firm's excess return over the past year, and NI/TA is the firm's ratio of net income to total assets. To estimate the impact of CDS trading on the probability of credit downgrades/bankruptcy, we include CDS variables in the model specification. *CDS Firm* equals one if the firm is in the CDS sample and zero otherwise. *CDS Active* is a dummy variable that equals one if the firm has CDS traded on its debt one year before month t . The coefficient of interest is that of *CDS Active*, which captures the impact of the inception of CDS trading on the probability of bankruptcy. The sample period is 1997-2009, based on monthly observations. (***) significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level. The numbers in parentheses are standard errors.)

	Probability of Bankruptcy			
	(1)	(2)	(3)	(4)
$\ln(E)$	-1.552*** (0.283)	-1.562*** (0.287)	-1.589*** (0.294)	-1.600*** (0.301)
$\ln(F)$	1.449*** (0.261)	1.463*** (0.265)	1.483*** (0.270)	1.500*** (0.278)
$1/\sigma_E$	-0.548 (1.033)	-0.528 (1.029)	-0.437 (0.999)	-0.422 (1.010)
$r_{it-1} - r_{mt-1}$	-0.695 (0.598)	-0.733 (0.583)	-0.787 (0.612)	-0.868 (0.607)
NI/TA	-4.102*** (0.710)	-4.118*** (0.699)	-4.180*** (0.702)	-4.175*** (0.686)
<i>CDS Firm</i>	-0.530 (1.009)		-0.978 (0.975)	
<i>CDS Active</i>	2.431*** (0.918)	2.134*** (0.641)	2.341** (0.910)	1.796*** (0.587)
<i>CDS Odds Ratio</i>	11.37	8.449	10.392	6.025
<i>CDS Marginal Effect</i>	0.10%	0.09%	0.10%	0.07%
Time Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Clustered Standard Error	Yes	Yes	Yes	Yes
Pseudo R^2	39.95%	39.91%	41.53%	41.38%
N	141006	141006	139040	139040
# of Bankruptcies	65	65	65	65
Sample Probability of a Bankruptcy	0.05%	0.05%	0.05%	0.05%

Table A10
Impact of Credit Default Swaps Trading on Credit Quality:
Distance-to-Default Matching

This table presents the estimates of the probability of credit downgrades/bankruptcy using a logistic model, in a sample including firms with credit default swaps (CDS) and non-CDS firms matched by distance-to-default (DD). Each matched firm selected is the one firm with the closest DD to the target firm. DD is calculated from the Merton (1974) model. $\ln(E)$ is the logarithm of the firm's equity value. $\ln(F)$ is the logarithm of the book value of the firm's debt. $1/\sigma_E$ is the inverse of the firm's annualized equity volatility. $r_{it-1} - r_{mt-1}$ is the firm's excess return over the past year, and NI/TA is the firm's ratio of net income to total assets. To estimate the impact of CDS trading on the probability of bankruptcy, we include CDS variables in the model specification. *CDS Firm* equals one if the firm is in the CDS sample and zero otherwise. *CDS Active* is a dummy variable that equals one if the firm has CDS traded on its debt one year before month t. The coefficient of interest is that of *CDS Active*, which captures the impact of the inception of CDS trading on the probability of bankruptcy. The sample period is 1997-2009, based on monthly observations. (***) significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level. The numbers in parentheses are standard errors.)

	Probability of Bankruptcy	
	(1)	(2)
$\ln(E)$	-0.923*** (0.142)	-0.891*** (0.138)
$\ln(F)$	0.853*** (0.144)	0.865*** (0.145)
$1/\sigma_E$	-1.905*** (0.382)	-1.971*** (0.387)
$r_{it-1} - r_{mt-1}$	-0.076 (0.325)	-0.101 (0.346)
NI/TA	-0.331 (0.205)	-0.994*** (0.204)
<i>CDS Firm</i>	-1.809** (0.772)	
<i>CDS Active</i>	2.196*** (0.751)	0.773** (0.339)
<i>CDS Active Odds Ratio</i>	8.989	2.166
<i>CDS Active Marginal Effect</i>	0.12%	0.04%
Time Fixed Effects	Yes	Yes
Industry Fixed Effects	Yes	Yes
Clustered Standard Error	Yes	Yes
Pseudo R^2	23.16%	23.05%
N	119143	119143
# of Bankruptcies	67	67
Sample Probability of a Bankruptcy	0.05%	0.05%

Table A11
Distance-to-Default and Credit Default Swaps Trading

This table presents estimates of the effect of CDS trading on firms' distance-to-default (DD). DD is calculated from the Merton (1974) model. $\ln(E)$ is the logarithm of the firm's equity value. $\ln(F)$ is the logarithm of the firm's debt. $1/\sigma_E$ is the inverse of the firm's annualized equity volatility. $r_{it-1} - r_{mt-1}$ is the firm's excess return over the past year, and NI/TA is the firm's ratio of net income to total assets. To estimate the impact of CDS trading on firms' DD, we include CDS variables in the model specification. *CDS Active* is a dummy variable that equals one if the firm has CDS traded on its debt, one year before month t . The sample period is 1997-2009, based on monthly observations. The regression controls for firm fixed effects and time fixed effects. (***) significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level. The numbers in parentheses are standard errors.)

	Distance-to-Default			
	(1)	(2)	(3)	(4)
$\ln(E)$	0.667*** (0.002)	0.667*** (0.024)	0.553*** (0.002)	0.553*** (0.009)
$\ln(F)$	-0.644*** (0.002)	-0.644*** (0.023)	-0.530*** (0.002)	-0.530*** (0.009)
$1/\sigma_E$	1.603*** (0.003)	1.603*** (0.055)	1.566*** (0.003)	1.566*** (0.052)
$r_{it-1} - r_{mt-1}$	0.099*** (0.001)	0.099* (0.055)	0.220*** (0.001)	0.220*** (0.010)
NI/TA	0.031*** (0.002)	0.031 (0.019)	0.017*** (0.002)	0.017* (0.010)
<i>CDS Active</i>	-0.249*** (0.008)	-0.249*** (0.031)		
<i>Instrumented CDS Active</i>			-0.426*** (0.014)	-0.426*** (0.055)
Time Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Clustered Standard Error	No	Yes	No	Yes
R^2	82.76%	82.76%	80.00%	80.00%
N	648242	648242	648242	648242
% of CDS Observations	10.89%	10.89%	10.89%	10.89%

Table A12
Firm Exits in Propensity Score-Matched Sample

This table investigates different firm exits and the CDS effect in our propensity score-matched sample. Panel A presents the distribution of delistings for our sample firms based on CRSP delisting codes. *Active* means that the issue is still trading on the NYSE/NYSE MKT or NASDAQ. *Bankruptcy* means that the firm has filed for bankruptcy protection. *Mergers* means that the issue has been acquired in a merger etc. *Delisting: Exchanges* means that the issue was exchanged for trading on NYSE etc. *Delisting: Going private* means that the issue has gone private. *Delisting: Bad performance* means that the issue was delisted by the current exchange due to poor performance. Panel B shows the results of the cross-sectional analysis of the impact of CDS trading on the probability of bankruptcy, merger and delisting. $\ln(E)$ is the logarithm of the firm's market value of equity. $\ln(F)$ is the logarithm of the book value of the firm's debt, where book debt is the sum of short-term debt and 50% of long-term debt. $1/\sigma_E$ is the inverse of the firm's annualized equity volatility. $r_{it-1} - r_{mt-1}$ is the firm's excess return over the past year, and NI/TA is the firm's ratio of net income to total assets. *CDS Active* is a dummy variable that equals one after the inception of CDS trading.

Panel A: Distribution of Delistings		
	Non-CDS	CDS
Active	211	334
Bankruptcy	25	36
Mergers	252	131
Delisting	23	10
Delisting: Exchanges	7	6
Delisting: Going private	15	0
Delisting: Bad performance	1	4
Total Firms	511	511

Panel B: Probability of Bankruptcy/Merger/Delisting			
	Probability of Bankruptcy	Probability of Merger	Probability of Delisting
$\ln(E)$	-0.575*** (0.001)	-0.092 (0.072)	-1.282*** (0.319)
$\ln(F)$	0.540*** (0.001)	-0.042 (0.099)	1.252*** (0.347)
$1/\sigma_E$	-1.025*** (0.002)	-0.015 (0.151)	0.645 (0.551)
$r_{it-1} - r_{mt-1}$	0.276*** (0.004)	0.086 (0.132)	0.111 (0.305)
NI/TA	-14.594*** (0.104)	3.122 (3.100)	16.275 (16.735)
<i>CDS Active</i>	0.901*** (0.004)	-1.080*** (0.168)	-0.809 (0.629)
<i>CDS Active Odds Ratio</i>	2.462	0.340	0.445
<i>CDS Active Marginal Effect</i>	4.76%	-18.91%	-1.44%
Time Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
Pseudo R^2	17.73%	25.97%	46.34%
N	893	893	893
Sample Probability of an Event	7.10%	31.91%	2.46%

Table A13

Bankruptcy Prediction Excluding Firms with Mergers and Delisting

This table presents the estimates of the probability of bankruptcy using a logistic model, in a sample excluding firms with a merger or delisting event. Model 1 excludes firms with mergers. Model 2 excludes firms with delistings or mergers before 2009. Model 3 excludes firms with delistings or mergers before 2010. $\ln(E)$ is the logarithm of the firm's market value of equity. $\ln(F)$ is the logarithm of the book value of the firm's debt, where book debt is the sum of short-term debt and 50% of long-term debt. $1/\sigma_E$ is the inverse of the firm's annualized equity volatility. $r_{it-1} - r_{mt-1}$ is the firm's excess return over the past year, and NI/TA is the firm's ratio of net income to total assets. To estimate the impact of CDS trading on the probability of bankruptcy, we include CDS variables in the model specification. *CDS Firm* equals one if the firm is in the CDS sample and zero otherwise. *CDS Active* is a dummy variable that equals one after and zero before the inception of CDS trading. The coefficient of interest is that of *CDS Active*, which captures the impact of the inception of CDS trading on the probability of bankruptcy. The sample period is 1997-2009, based on monthly observations. (***) significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level. The numbers in parentheses are standard errors.)

	Probability of Bankruptcy		
	(1)	(2)	(3)
$\ln(E)$	-0.685*** (0.027)	-0.661*** (0.026)	-0.640*** (0.026)
$\ln(F)$	0.697*** (0.026)	0.678*** (0.026)	0.661*** (0.026)
$1/\sigma_E$	-1.907*** (0.202)	-2.156*** (0.289)	-2.195*** (0.292)
$r_{it-1} - r_{mt-1}$	-1.380*** (0.204)	-1.282*** (0.187)	-1.289*** (0.188)
NI/TA	-0.033** (0.010)	-0.257 (0.182)	-0.255 (0.180)
<i>CDS Firm</i>	-1.755** (0.722)	-2.345*** (0.720)	-2.361*** (0.720)
<i>CDS Active</i>	1.985*** (0.744)	2.544*** (0.737)	2.488*** (0.736)
<i>CDS Active Odds Ratio</i>	7.279	12.730	12.037
<i>CDS Active Marginal Effect</i>	0.30%	0.53%	0.55%
Time Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
Clustered Standard Error	Yes	Yes	Yes
Pseudo R^2	25.20%	29.82%	30.02%
N	563771	419876	396785
# of Bankruptcies	839	940	940
Sample Probability of a Bankruptcy	0.15%	0.22%	0.24%

Table A14
Comparison between CDS and Propensity Score-Matched Firms

This table compares the difference in characteristics between CDS and propensity score-matched firms. *Distance-to-Default* is the firm's distance-to-default calculated from Merton (1974). *Leverage* is defined as the ratio of book debt to the sum of book debt and market equity, where book debt is the sum of short-term debt and 50% of long-term debt, and market equity is the measure of the number of common shares outstanding multiplied by the stock price. *ln(Asset)* is the logarithm of the firm's total asset value. *B/M* is the book-to-market ratio. *ROA* is the firm's return on assets. *Bank Relationship* is the firm's bank relationships, obtained from Dealscan LPC. *Rating* is the firm's credit rating. *ROE* is the firm's return on equity. *Propensity Score* is the propensity score estimated from the model of probability of CDS trading presented in Table III.

	CDS Firm	Matching Firm	Difference
<i>Distance-to-Default</i>	2.734	2.681	0.053
<i>Leverage</i>	0.193	0.177	0.016
<i>ln(Asset)</i>	8.597	8.492	0.105*
<i>B/M</i>	0.600	0.849	-0.249**
<i>ROA</i>	0.136	-0.003	0.138***
<i>Bank Relationship</i>	25.952	19.727	6.225***
<i>Rating</i>	8.390	8.883	-0.494***
<i>ROE</i>	-0.012	-0.172	0.161
<i>Propensity Score</i>	0.561	0.556	0.005

Table A15
Credit Default Swaps Trading and Credit Quality:
Robustness Check for Propensity Score Matching

This table presents the estimates of the probability of bankruptcy using a logistic model, in a sample including firms with credit default swaps (CDS) and non-CDS propensity score-matched firms. Propensity score-matched firms are selected based on the nearest propensity scores estimated from Models 1 and 2 of the probability of CDS trading presented in Table III. $\ln(E)$ is the logarithm of the firm's market value of equity. $\ln(F)$ is the logarithm of the book value of the firm's debt, where book debt is the sum of short-term debt and 50% of long-term debt. $1/\sigma_E$ is the inverse of the firm's annualized equity volatility. $r_{it-1} - r_{mt-1}$ is the firm's excess return over the past year, and NI/TA is the firm's ratio of net income to total assets. To estimate the impact of CDS trading on the probability of bankruptcy, we include CDS variables in the model specification. *CDS Firm* equals one if the firm is in the CDS sample and zero otherwise. *CDS Active* is a dummy variable that equals one after the inception of CDS trading and zero before CDS trading. The coefficient of interest is that of *CDS Active*, which captures the impact of the inception of CDS trading on the probability of bankruptcy. The sample period is 1997-2009, based on monthly observations. (***) significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level. The numbers in parentheses are standard errors.)

	Probability of Bankruptcy	
	CDS Prediction Model 1	CDS Prediction Model 2
$\ln(E)$	-0.960*** (0.172)	-0.997*** (0.226)
$\ln(F)$	0.938*** (0.177)	1.053*** (0.207)
$1/\sigma_E$	-0.44 (1.233)	-0.707 (1.335)
$r_{it-1} - r_{mt-1}$	-2.357* (1.354)	-1.359 (1.124)
NI/TA	-0.013 (0.088)	-0.084 (0.089)
<i>CDS Firm</i>	-1.352 (0.853)	-0.856 (0.881)
<i>CDS Active</i>	1.671** (0.811)	2.049** (0.826)
<i>CDS Odds Ratio</i>	5.317	7.760
<i>CDS Marginal Effect</i>	0.07%	0.07%
Time Fixed Effects	Yes	Yes
Industry Fixed Effects	Yes	Yes
Clustered Standard Error	Yes	Yes
Pseudo R^2	36.29%	32.62%
N	116651	118103
# of Bankruptcies	58	49
Sample Probability of a Bankruptcy	0.03%	0.04%

Table A16
Credit Default Swaps Trading and Probability of Bankruptcy:
Robustness Check for Full-Information Maximum Likelihood

This table presents the robustness checks for the full-information maximum likelihood (FIML) results for the CDS effect. Model 1 estimates the bankruptcy model with FIML in a sample excluding the crisis period. Model 2 estimates the bankruptcy model with limited-information maximum likelihood (LIML). Model 3 estimates the bankruptcy model with LIML in a sample excluding the crisis period. $\ln(E)$ is the logarithm of the firm's market value of equity. $\ln(F)$ is the logarithm of the book value of the firm's debt, where book debt is the sum of short-term debt and 50% of long-term debt. $1/\sigma_E$ is the inverse of the firm's annualized equity volatility. $r_{it-1} - r_{mt-1}$ is the firm's excess return over the past year, and NI/TA is the firm's ratio of net income to total assets. To estimate the impact of CDS trading on the probability of bankruptcy, we include CDS variables in the model specification. *CDS Firm* equals one if the firm is in the CDS sample and zero otherwise. *CDS Active* is a dummy variable that equals one after the inception of CDS trading and zero before CDS trading begins. The coefficient of interest is that of *CDS Active*, which captures the impact of the inception of CDS trading on the probability of bankruptcy. The sample period is 1997-2009, based on monthly observations. (***) significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level. The numbers in parentheses are standard errors.)

	Probability of Bankruptcy		
	(1)	(2)	(3)
$\ln(E)$	-0.522*** (0.023)	-0.530*** (0.046)	-0.485*** (0.047)
$\ln(F)$	0.556*** (0.025)	0.540*** (0.050)	0.490*** (0.051)
$1/\sigma_E$	-0.405*** (0.046)	-0.418*** (0.141)	-0.544*** (0.102)
$r_{it-1} - r_{mt-1}$	-0.076*** (0.028)	-0.062*** (0.018)	-0.065*** (0.018)
NI/TA	-0.781*** (0.052)	-0.279 (0.223)	-0.764 (0.525)
<i>CDS Firm</i>	-0.225 (0.145)	-5.744*** (1.244)	-4.026*** (1.063)
<i>CDS Active</i>	0.709*** (0.180)	9.185*** (1.862)	7.171*** (1.741)

Table A17
Credit Default Swaps Trading and Probability of Bankruptcy:
Heckman Treatment Effects Model with Instrumental Variables

This table presents the second-stage estimation results of the two-stage Heckman treatment effects model. The second-stage analysis is for the probability of bankruptcy, using a logistic model in a sample including firms with credit default swaps (CDS) and all non-CDS firms. The *Inverse Mills Ratio* is calculated from the first-stage probit regression, modeling the probability of CDS trading presented in Table III CDS prediction Model 3. $\ln(E)$ is the logarithm of the firm's market value of equity. $\ln(F)$ is the logarithm of the book value of the firm's debt, where book debt is the sum of short-term debt and 50% of long-term debt. $1/\sigma_E$ is the inverse of the firm's annualized equity volatility. $r_{it-1} - r_{mt-1}$ is the firm's excess return over the past year, and NI/TA is the firm's ratio of net income to total assets. To estimate the impact of CDS trading on the probability of bankruptcy, we include CDS variables in the model specification. *CDS Firm* equals one if the firm is in the CDS sample and zero otherwise. *CDS Active* is a dummy variable that equals one after the inception of CDS trading and zero before CDS trading. The coefficient of interest is that of *CDS Active*, which captures the impact of the inception of CDS trading on the probability of bankruptcy. The sample period is 1997-2009, based on monthly observations. (***) significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level. The numbers in parentheses are standard errors.)

	Probability of Bankruptcy		
	(1)	(2)	(3)
<i>Inverse Mills Ratio</i>	0.187*** (0.028)	0.003 (0.114)	0.081 (0.132)
$\ln(E)$		-0.635*** (0.024)	-0.639*** (0.024)
$\ln(F)$		0.647*** (0.024)	0.646*** (0.024)
$1/\sigma_E$		-1.449*** (0.233)	-1.410*** (0.232)
$r_{it-1} - r_{mt-1}$		-1.340*** (0.188)	-1.330*** (0.188)
NI/TA		-0.032*** (0.008)	-0.032*** (0.008)
<i>CDS Firm</i>			-2.297*** (0.718)
<i>CDS Active</i>		0.443** (0.209)	2.773*** (0.755)
<i>CDS Active Odds Ratio</i>		1.557	16.007
<i>CDS Active Marginal Effect</i>		0.06%	0.39%
Time Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
Clustered Standard Error	Yes	Yes	Yes
Pseudo R^2	2.34%	22.24%	22.42%
N	657438	657438	657438
# of Bankruptcies	940	940	940
Sample Probability of a Bankruptcy		0.14%	0.14%

Table A18
Determinants of CDS Notional Outstanding/Total Debt

This table presents the estimates of the determinants of *CDS Notional Outstanding/Total Debt*. *Lender Size* is a measure of the size of lending banks and underwriters. *Lender Credit Derivatives* measures the credit derivative activities of the lenders. *Lender FX Hedging* is a measure of the FX hedging activities of the lending banks and underwriters and *Lender Tier 1 Capital* is the Tier One capital ratio of the lenders. *Senior Secured Debt* is the ratio of senior secured debt to total debt. $\ln(Assets)$ is the logarithm of the firm's total assets value. *Leverage* is defined as the ratio of book debt to the sum of book debt and market equity, where book debt is the sum of short-term debt and 50% of long-term debt, and market equity is the measure of the number of common shares outstanding multiplied by the stock price. *ROA* is the firm's return on assets. $r_{it-1} - r_{mt-1}$ is the firm's excess return over the past year. *Equity Volatility* is the firm's annualized equity volatility. *PPENT/Total Asset* is the ratio of property, plant and equipment to total assets. *Sales/Total Asset* is the ratio of sales to total assets. *EBIT/Total Asset* is the ratio of earnings before interest and tax to total assets. *WCAP/Total Asset* is the ratio of working capital to total assets. *RE/Total Asset* is the ratio of retained earnings to total assets. *Cash/Total Asset* is the ratio of cash to total assets. *CAPX/Total Asset* is the ratio of capital expenditure to total assets. *Rated* is a dummy variable that equals one if the firm is rated. *Investment Grade* is a dummy variable that equals one if the firm has an investment grade credit rating. The sample period is 1997-2009, based on monthly observations. (***) significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level. The numbers in parentheses are standard errors.)

	CDS Notional Outstanding/Total Debt	
	(1)	(2)
<i>Lender Size</i>	0.525*** (0.126)	0.521*** (0.123)
<i>Senior Unsecured Debt</i>	0.281*** (0.036)	0.263*** (0.035)
<i>Lender Credit Derivatives</i>	-0.473*** (0.134)	-0.421*** (0.146)
<i>Lender FX Hedging</i>	4.256*** (1.079)	3.919*** (0.959)
<i>Lender Tier 1 Capital</i>	1.384*** (0.381)	1.331*** (0.370)
<i>Ln(Assets)</i>	0.026 (0.034)	0.034 (0.033)
<i>Leverage</i>	0.152* (0.084)	0.085 (0.079)
<i>ROA</i>	0.000 (0.000)	0.000 (0.000)
$r_{it-1} - r_{mt-1}$	-0.004 (0.004)	-0.005 (0.004)
<i>Equity Volatility</i>	0.091*** (0.021)	0.084*** (0.021)
<i>PPENT/Total Asset</i>	-0.549*** (0.197)	-0.390** (0.186)
<i>Sales/Total Asset</i>	-0.054 (0.037)	-0.044 (0.031)
<i>EBIT/Total Asset</i>	-0.045** (0.018)	-0.039** (0.016)
<i>WCAP/Total Asset</i>	0.022 (0.015)	0.018 (0.013)
<i>RE/Total Asset</i>	0.005** (0.002)	0.004** (0.002)
<i>Cash/Total Asset</i>	0.118*** (0.031)	0.112*** (0.030)
<i>CAPX/Total Asset</i>	0.072 (0.062)	0.081 (0.064)

(continued)

Table A18—*Continued*

	CDS Notional Outstanding/Total Debt	
	(1)	(2)
<i>Rated</i>	0.149*	0.391
	(0.080)	(0.346)
<i>Investment Grade</i>	−1.013***	
	(0.233)	
<i>AAA</i>		−10.272***
		(1.537)
<i>AA</i>		−6.064***
		(0.930)
<i>A</i>		−2.918***
		(0.539)
<i>BBB</i>		−0.800**
		(0.407)
<i>BB</i>		−0.129
		(0.351)
<i>B</i>		−0.134
		(0.348)
<i>CCC</i>		−0.481
		(0.343)
<i>Lower Ratings</i>		0.029
		(0.605)
Firm Fixed Effect	Yes	Yes
Time Fixed Effect	Yes	Yes
Clustered Standard Error	Yes	Yes
Pseudo R^2	57.69%	59.36%

Table A19**Changes in Leverage Around the Introduction of Credit Default Swaps**

This table presents a univariate analysis of changes in leverage from one year before to two years or three years after the introduction of credit default swaps (CDS) trading. The changes in leverage of CDS-trading firms are compared with those of the matching firms. Matching firms are selected based on propensity scores estimated from the models for the probability of CDS trading presented in Table III. The change in leverage is defined as the change in the ratio of book debt to the sum of book debt and market equity, where book debt is the sum of short-term debt and 50% of long-term debt, and market equity is the measure of the number of common shares outstanding multiplied by the stock price. (***) significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level.)

	Year <i>t-1 to t+2</i>			Year <i>t-1 to t+3</i>		
	Nearest One	Nearest One PS Diff <1%	Nearest Two	Nearest One	Nearest One PS Diff <1%	Nearest Two
CDS Prediction Model 1	0.013*	0.015**	0.015**	0.012***	0.016**	0.014**
CDS Prediction Model 2	0.007*	0.005**	0.005**	0.013***	0.008**	0.006**
CDS Prediction Model 3	0.008**	0.013**	0.011**	0.007**	0.015**	0.016**

Table A20
CDS Trading and Probability of Distress

This table investigates the impact of credit default swaps (CDS) on the probability of distress in a sample including firms with and without CDS traded. Models 1 and 2 include time and industry fixed effects. Model 3 clusters the standard error at the firm level. Model 4 uses *Instrumented CDS Active* with standard error clustered at the firm level. $\ln(E)$ is the logarithm of the firm's market value of equity. $\ln(F)$ is the logarithm of the book value of the firm's debt, where book debt is the sum of short-term debt and 50% of long-term debt. $1/\sigma_E$ is the inverse of the firm's annualized equity volatility. $r_{it-1} - r_{mt-1}$ is the firm's excess return over the past year, and NI/TA is the firm's ratio of net income to total assets. To estimate the impact of CDS trading on the probability of bankruptcy, we include CDS variables in the model specification. *CDS Firm* equals one if the firm has CDS trading at any point in time and zero otherwise. *CDS Active* is a dummy variable that equals one after the inception of CDS trading and zero before CDS trading. *Instrumented CDS Active* is the instrumented *CDS Active* from the model predicting the probability of CDS trading. The coefficients of interest are those of *CDS Active* and *Instrumented CDS Active*, which capture the impact of the inception of CDS trading on the probability of distress. The sample period is 1997-2009, based on monthly observations. (***) significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level. The numbers in parentheses are standard errors.)

	Probability of Distress			
	(1)	(2)	(3)	(4)
$\ln(E)$	-0.291*** (0.008)	-0.291*** (0.008)	-0.291*** (0.026)	-0.285*** (0.027)
$\ln(F)$	0.337*** (0.008)	0.337*** (0.008)	0.337*** (0.029)	0.319*** (0.030)
$1/\sigma_E$	-3.134*** (0.043)	-3.134*** (0.043)	-3.134*** (0.135)	-3.251*** (0.145)
$r_{it-1} - r_{mt-1}$	-0.463*** (0.019)	-0.463*** (0.019)	-0.463*** (0.055)	-0.445*** (0.055)
NI/TA	0.021*** (0.004)	0.021*** (0.004)	0.021** (0.010)	0.019* (0.011)
<i>CDS Firm</i>	-0.132 (0.133)		-0.132 (0.454)	0.116 (0.374)
<i>CDS Active</i>	-0.404** (0.160)	-0.533*** (0.094)	-0.404 (0.562)	
<i>Instrumented CDS Active</i>				-1.276* (0.767)
<i>CDS Odds Ratio</i>	0.668	0.587	0.668	0.279
<i>CDS Marginal Effect</i>	-0.44%	-0.58%	-0.44%	-1.53%
Time Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Clustered Standard Error	No	No	Yes	Yes
Pseudo R^2	22.92%	22.92%	22.92%	21.09%
N	711475	711475	711475	711475
Sample Probability of a Distress	1.18%	1.18%	1.18%	1.29%

Table A21
Determinants of No-Restructuring CDS

This table presents the estimates of the determinants of *No Restructuring CDS*, which is the total amount of active CDS contracts on a firm with “no restructuring” as the restructuring clause, scaled by the total number of CDS contracts trading on the firm. *Instrumented No Restructuring CDS* are estimated based on the model parameters. *After January 2003* is a dummy variable that equals one for the period after January 2003. *PPENT/Total Asset* is the ratio of property, plant and equipment to total assets. *Senior Secured Debt* is the ratio of senior secured debt to total debt. $\ln(\text{Assets})$ is the logarithm of the firm’s total asset value. *Leverage* is defined as the ratio of book debt to the sum of book debt and market equity, where book debt is the sum of short-term debt and 50% of long-term debt, and market equity is the measure of the number of common shares outstanding multiplied by the stock price. *ROA* is the firm’s return on assets. $r_{it-1} - r_{mt-1}$ is the firm’s excess return over the past year. *Equity Volatility* is the firm’s annualized equity volatility. *Sales/Total Asset* is the ratio of sales to total assets. *EBIT/Total Asset* is the ratio of earnings before interest and tax to total assets. *WCAP/Total Asset* is the ratio of working capital to total assets. *RE/Total Asset* is the ratio of retained earnings to total assets. *Cash/Total Asset* is the ratio of cash to total assets. *CAPX/Total Asset* is the ratio of capital expenditure to total assets. *Rated* is a dummy variable that equals one if the firm is rated. *Investment Grade* is a dummy variable that equals one if the firm has an investment grade credit rating. The sample period is 1997-2009, based on monthly observations. (***) significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level. The numbers in parentheses are standard errors.)

	No Restructuring CDS
<i>After January 2003</i>	0.095** (0.046)
<i>PPENT/Total Assets</i>	1.908** (0.815)
<i>Senior Secured Debt</i>	1.305 (1.012)
<i>Ln(Assets)</i>	0.109 (0.182)
<i>Leverage</i>	-0.217 (0.457)
<i>ROA</i>	0.083 (0.111)
$r_{it-1} - r_{mt-1}$	-0.105** (0.041)
<i>Equity Volatility</i>	-0.163 (0.119)
<i>Sales/Total Asset</i>	0.328 (0.428)
<i>EBIT/Total Asset</i>	0.733 (0.687)
<i>WCAP/Total Asset</i>	-0.000 (0.357)
<i>RE/Total Asset</i>	-0.066 (0.094)
<i>Cash/Total Asset</i>	-0.501 (0.509)
<i>CAPX/Total Asset</i>	0.322 (1.580)
<i>Rated</i>	0.511** (0.224)
<i>Investment Grade</i>	-0.665*** (0.188)
Time Fixed Effects	Yes
Firm Fixed Effects	Yes
Clustered Standard Error	Yes
R^2	46.53%

Table A22
Instrumented CDS Exposure Measures and Distance-to-Default

This table investigates the impact of instrumented CDS exposure measures on a firm's distance-to-default. $\ln(E)$ is the logarithm of the firm's market value of equity. $\ln(F)$ is the logarithm of the book value of the firm's debt, where book debt is the sum of short-term debt and 50% of long-term debt. $1/\sigma_E$ is the inverse of the firm's annualized equity volatility. $r_{it-1} - r_{mt-1}$ is the firm's excess return over the past year, and NI/TA is the firm's ratio of net income to total assets. *Instrumented CDS Outstanding/Total Debt* is instrumented *CDS Outstanding/Total Debt* estimated from the model predicting that variable. *Instrumented No Restructuring CDS* is instrumented *No Restructuring CDS* estimated from the model predicting that variable. The sample period is 1997-2009, based on monthly observations. (***) significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level. The numbers in parentheses are standard errors.)

	Distance-to-Default	
$\ln(E)$	0.180*** (0.012)	0.868*** (0.030)
$\ln(F)$	-0.168*** (0.012)	-0.847*** (0.028)
$1/\sigma_E$	0.497*** (0.020)	2.019*** (0.067)
$r_{it-1} - r_{mt-1}$	-0.034*** (0.005)	0.118* (0.067)
NI/TA	0.081 (0.049)	0.012 (0.009)
<i>Instrumented CDS Outstanding/Total Debt</i>	-0.249*** (0.026)	
<i>Instrumented No Restructuring CDS</i>		-0.336*** (0.028)
Time Fixed Effects	Yes	Yes
Firm Fixed Effects	Yes	Yes
Clustered Standard Error	Yes	Yes
R^2	67.09%	90.37%

Table A23
Number of Banks and Probability of Bankruptcy: Cross-sectional Analysis in Matched Sample

This table conducts the cross-sectional analysis of the impact of the number of banks on a firm's probability of bankruptcy. Models 1 and 3 present the results for the propensity score-matched sample. Model 2 conducts the analysis in the propensity score-matched sample with a positive change in the number of banks. $\ln(E)$ is the logarithm of the firm's market value of equity. $\ln(F)$ is the logarithm of the book value of the firm's debt, where book debt is the sum of short-term debt and 50% of long-term debt. $1/\sigma_E$ is the inverse of the firm's annualized equity volatility. $r_{it-1} - r_{mt-1}$ is the firm's excess return over the past year, and NI/TA is the firm's ratio of net income to total assets. *Change in Number of Banks* is the change in the number of banks from CDS introduction to two years after CDS introduction. *Average Number of Banks* is the average number of banks after the inception of CDS trading. (***) significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level. The numbers in parentheses are standard errors.)

	Probability of Bankruptcy		
	(1)	(2)	(3)
$\ln(E)$	-0.982*** (0.224)	-1.459*** (0.527)	-0.547*** (0.001)
$\ln(F)$	1.023*** (0.271)	1.679** (0.688)	0.442*** (0.001)
$1/\sigma_E$	-0.401 (0.354)	-1.668** (0.742)	-1.145*** (0.002)
$r_{it-1} - r_{mt-1}$	0.393* (0.237)	-0.240 (0.634)	0.172*** (0.004)
NI/TA	-8.714 (5.482)	-12.513 (8.361)	-13.890*** (0.105)
<i>CDS Active</i>	1.511*** (0.534)	2.148* (1.176)	0.584*** (0.005)
<i>Change in Number of Banks</i>	0.033** (0.017)	0.074** (0.033)	
<i>Average Number of Banks</i>			0.029*** (0.000)
Time Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
Pseudo R^2	29.58%	47.44%	21.92%
N	775	390	893

References for the Internet Appendix

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