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

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ABSTRACT

Credit default swaps (CDS) are derivative contracts that are widely used as tools for credit risk management. However, in recent years, concerns have been raised about whether CDS trading itself affects the credit risk of the reference entities. We use a unique, comprehensive sample covering 901 CDS introductions on North American corporate issuers, between June 1997 and April 2009, to address this question. We find that the probability of both a credit rating downgrade and bankruptcy increase, with large economic magnitudes, after the inception of CDS trading. This finding is robust to controlling for the endogeneity of CDS trading in difference-in-difference analysis, propensity score matching, and treatment regressions with instruments. Beyond the CDS introduction effect, we show that firms with relatively larger amounts of CDS contracts outstanding, and those with relatively more "no restructuring" contracts than other types of CDS contracts covering restructuring, are more adversely affected by CDS trading.

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Credit default swaps (CDS) are derivative contracts that are widely used as tools for credit risk management. However, in recent years, concerns have been raised about whether CDS trading itself affects the credit risk of the reference entities. We use a unique, comprehensive sample covering 901 CDS introductions on North American corporate issuers, between June 1997 and April 2009, to address this question. We find that the probability of both a credit rating downgrade and bankruptcy increase, with large economic magnitudes, after the inception of CDS trading. This finding is robust to controlling for the endogeneity of CDS trading in difference-in-difference analysis, propensity score matching, and treatment regressions with instruments. Beyond the CDS introduction effect, we show that firms with relatively larger amounts of CDS contracts outstanding, and those with relatively more "no restructuring" contracts than other types of CDS contracts covering restructuring, are more adversely affected by CDS trading.

Keywords: Credit default swap, bankruptcy risk, empty creditor, restructuring

I. Introduction

Credit default swaps (CDS) are insurance-type contracts that offer buyers protection against default by a debtor. They are arguably the most controversial financial innovation of the past two decades, extolled by some and disparaged by others. Former Federal Reserve Chairman Alan Greenspan argued that "these increasingly complex financial instruments have contributed, especially over the recent stressful period, to the development of a far more flexible, efficient, and hence resilient financial system than existed just a quarter-century ago."[1] In striking contrast, Warren Buffett, the much acclaimed investor, weighed against derivatives, in general, by describing them as "time bombs, for the parties that deal in them and the economic system" and went on to conclude that "in my view, derivatives are financial weapons of mass destruction, carrying dangers that, while now latent, are potentially lethal."[2] In a similar vein, George Soros, a legendary hedge fund manager, argued that "CDS are toxic instruments whose use ought to be strictly regulated."[3] Which of these conclusions is valid? Although one can debate this issue based on theoretical arguments, it can ultimately be resolved only by empirical tests in specific contexts with clearly stated and refutable hypothesis. Our purpose in this paper is to present a careful empirical examination along these lines.

Despite the concerns expressed by regulators as well as market participants, the CDS market grew by leaps and bounds from about \$0.9 trillion at the end of 2001 to a high of about \$62 trillion at the end of 2007, measured by notional amount outstanding. Although the CDS market shrank considerably during the global financial crisis, it nevertheless stood at \$26 trillion by December 2010. Indeed, during this period, CDS trading was introduced in countries including China and India. At the same time, CDS played a prominent role during the credit crisis of 2007-2009 and the European sovereign debt crisis of 2010-2012. In particular, the bankruptcy of Lehman Brothers, and the collapse of Bear Stearns and AIG, were closely related to CDS trading. In spite of misgivings about the role of CDS in potentially destabilizing markets, their role as indicators of credit quality has, in fact, expanded. CDS spreads are widely quoted by practitioners and regulators for the assessment of credit risks of both individual corporate debtors and the overall sovereign risk of a country.

Many of the issues mentioned in the context of derivatives, in general, have also been raised in the specific case of CDS. The generic arguments about the deleterious effects of derivatives, as a group, rely on market mechanisms such as the possibility of market manipulation, accounting fraud, pressure on posting collateral and their liquidity consequences,

[1] "Economic Flexibility," Alan Greespan, Speech given to the Her Majesty's Treasury Enterprise Conference, London, January 26, 2004.

[2] Berkshire Hathaway Annual Report for 2002.

[3] "One Way to Stop Bear Raids," *Wall Street Journal*, March 24, 2009.

and counterparty credit risk. These arguments challenge the hitherto accepted notion that derivatives are redundant securities, as assumed in most pricing and hedging models, and hence have no effect, adverse or benign, on the price of the underlying asset or the integrity of markets.[4]

Apart from the above concerns that apply to all derivatives, CDS contracts are somewhat different for several reasons: Buyers of CDS protection can influence the financial decisions, and hence, the credit risk of the reference entities which determine the payoffs. CDS contracts are traded over-the-counter, where price transparency and discovery are less clear-cut than exchanges where most equity derivatives are traded. Moreover, institutions including the bank creditors of the reference entities are major participants of the CDS market. CDS typically have much longer maturities than most exchange-traded derivatives, allowing the traders more flexibility in adjusting their positions. Therefore, the general conclusions drawn from the equity derivatives market may not be applicable to CDS and the underlying credit risk. Specifically, in structural models of credit risk along the lines of Merton (1974), default risk is driven principally by leverage and asset volatility. In the spirit of that framework, CDS are regarded as "side-bets" on the value of the firm, and hence, have no effect on the credit risk associated with the individual claims issued by the firm. In particular, in such models, CDS trading does not affect the probability of bankruptcy, or indeed, even the possibility of a credit rating downgrade.

In contrast to the redundancy argument, illustrative evidence from corporate restructuring and bankruptcy suggests that CDS positions play an important role for distress resolution. To cite one such instance, CIT Group attempted to work out its debt from late 2008 to mid-2009. In the event, however, some creditors with CDS protection (e.g., Goldman Sachs) rejected the firm's exchange offer.[5] CIT Group eventually filed for Chapter 11 bankruptcy on November 1, 2009. Appendix A lists other cases of a similar nature, demonstrating that the example cited is not that unique. Hu and Black (2008) term such debt-holders, whose exposures are insured with CDS, "empty creditors," meaning that they are creditors with an economic interest in the firm's claims, but no risk alignment with the other bondholders who do not enjoy such protection.[6] Along the same lines, Henry Hu, one of the coauthors of Hu and Black (2008), named Goldman Sachs as AIG's empty creditor in an op-ed piece, shortly before becoming the director of the U.S. Securities and Exchange Commission (SEC)

[4]At a general level, there is evidence from the equity market that derivatives trading can affect the pricing of the underlying asset. See, for example, an early survey by Damodaran and Subrahmanyam (1992), and Sorescu (2000), for examples of such studies.

[5]"Goldman Purchase Puts CDS in Focus," *Financial Times*, October 4, 2009. "Goldman Sachs May Reap $1 Billion in CIT Bankruptcy", *Bloomberg*, October 5, 2009.

[6]The use of equity derivatives such as options or swaps in the context of equities creates the analogous issue of "empty voters" who enjoy voting rights in the firm, but without any financial risk, by breaking the link between cash flow rights and control rights.

Division of Risk, Strategy, and Financial Innovation.[7] In an eye-popping case, when Delphi Corporation filed for bankruptcy on October 8, 2005, the total amount of CDS contracts outstanding was roughly thirty times the face value of its bonds outstanding! It is highly likely that some of Delphi's creditors had become empty creditors.[8]

Although restructuring and bankruptcy are the ultimate eventualities for a financially troubled firm, the potential threat of credit deterioration occurs early on in the firm's life. Typically, the firm is placed on credit watch with a negative outlook, and then downgraded, perhaps several times, before the likelihood of restructuring or bankruptcy comes to the fore. Thus, if the empty creditor problem increases the probability of bankruptcy to some degree, it may manifest itself much earlier with credit downgrading, as rating agencies may anticipate the increase in credit risk and take such action. Therefore, the empty creditor problem is not confined to the probability of ultimate bankruptcy, but also applies to the earlier, and more widespread phenomenon of credit downgrades. More generally, the threat of empty creditors is latent even for firms that are currently healthy in terms of credit quality. Analyzing the bankruptcy event using the full sample also yields broader implications than focusing only on distressed firms' terminal outcomes.

The empty creditor problem is formally modeled by Bolton and Oehmke (2011).[9] Their model predicts that some lenders will choose to "over-insure" their credit exposure by buying CDS protection, and thus, becoming empty creditors. Consequently, they have different economic interests from other creditors, and are tougher in negotiation of debt restructuring when the firm is under stress, and are even willing to push the firm into bankruptcy, since their total payoffs may be larger in that event. CDS sellers anticipate this "empty creditor" problem and price it into the CDS premium, but they cannot directly intervene in the debt negotiation process. A complementary aspect of the empty creditor problem is the *ex ante* behavior of lenders to a firm, especially banks. The existence of CDS contracts may render a bank more willing to lend, due to the possibility of risk mitigation and enhanced bargaining power via CDS contracts. Further, the greater the number of lenders, the more likely it would be that some lenders are empty creditors, and the more severe would be the problems of coordination in a stressed situation, when a workout may be necessary. Therefore, CDS trading may affect lending relationships, and in particular, the number of lenders.

We test these hypotheses using a comprehensive data set on CDS trading dating back to the inception of CDS market for corporate names in 1997. It should be emphasized that it is difficult to obtain accurate data on the introduction of CDS from a single source, since

[7] "'Empty Creditors' and the Crisis," *Wall Street Journal*, April 10, 2009.

[8] There was a "squeeze" in Delphi bonds during the physical settlement of CDS contracts calling for delivery of the underlying bonds, following the default event. The New York Fed launched its first round of regulatory actions on CDS in September 2005 and required major CDS dealers to clear the backlog of unsettled contracts.

[9] Other studies such as Duffie (2007), Stulz (2010), and Jarrow (2011) also offer related discussions.

CDS trading does not take place on centralized exchanges. Indeed, even the central clearing of CDS is a relatively recent phenomenon. Our identification of the launch date relies, of necessity, on multiple data sources including GFI Inc., the largest global interdealer broker with the most extensive records of CDS trades and quotes, CreditTrade, a major intermediary especially in the early stages of the CDS market, and Markit, a data disseminator and vendor, which provides daily quotes from major institutions. Our combined data set covers 901 CDS introductions from 1997 to 2009 for North American corporate names. The list of bankruptcies for North American firms is comprehensively constructed from major data sources such as New Generation Research, the UCLA-LoPucki Bankruptcy Database, the Altman-NYU Salomon Center Bankruptcy List, Fixed Income Securities Database (FISD), and Moody's Annual Reports on Bankruptcy and Recovery. Over the same time period, we record bankruptcy filings by 1,628 firms, of which 60 had CDS trading prior to bankruptcies. We augment our bankruptcy data with credit rating downgrades. Our sample covers 3,863 rating downgrades from Standard & Poor's.

Our main empirical challenge is the potential endogeneity of CDS trading due to the possibility that firms with greater *future* credit risk deterioration are selected for CDS trading. There could also be unobserved omitted variables that drive both the selection of firms for CDS trading and bankruptcy risk. We address these concerns in several ways besides the basic fixed effects controls. In an informal check, we match firms with and without CDS traded on them by their distance-to-default calculated from Merton (1974) structural model, to examine the effect of CDS trading on this matched sample. This approach partially controls for credit risk prior to CDS trading. More formally, we construct a model to predict CDS trading for individual firms. This model allows us to undertake a difference-in-difference comparison, a propensity score matching analysis for firms with and without CDS trading, and a treatment effects model with bond turnover and analyst coverage as instrument variables.

We find that the introduction of CDS on a firm increases the likelihood of both credit downgrades and bankruptcy, after controlling for variables suggested by structural models. The effect of CDS trading is both statistically significant and economically large. For our sample firms, the credit rating declines by about half a notch, on average, in the two years after the introduction of CDS trading. In a similar vein, the probability of bankruptcy increases substantially once the CDS start trading on a firm. An average firm would have a default probability of 0.47% after CDS trading, which is 2.4 times (0.33%) higher than the average default probability of 0.14% before CDS trading. Moreover, we find that the effect of CDS trading goes beyond the influence of the rating downgrade itself. The positive relationship between CDS trading and bankruptcy risk is significant, even after controlling for the endogeneity of CDS trading. The treatment effects estimations with instrument variables show that the effect of CDS introduction is robust to the selection of a firm for CDS trading.

We present complementary analyses to highlight the specific effects of the quantum and structure of the CDS contracts outstanding. We document that the effects of CDS trading are stronger when the number of live contracts and notional amount relative to total debt outstanding are larger, and when a larger fraction of the CDS contracts containing "no restructuring" credit event clause. We stress that both these results also (indirectly) address the endogeneity concern, since they do not directly rely on the selection of firms for CDS trading. Additionally, we find that the number of lenders increases after the introduction of CDS trading and that bankruptcy risk increases with number of lenders. In sum, rather than insuring against borrower default, CDS trading can potentially lead to borrower default, as tougher creditors with CDS protection make bankruptcy the more likely outcome.

The remainder of this paper is organized as follows. Section II presents the motivation for our hypotheses in the context of the prior literature, and states them explicitly. The construction of our data set and our empirical methods are discussed in Section III. Section IV presents the baseline results for the effect of CDS trading and incorporates the selection of firms for CDS trading explicitly into our analysis of the likelihood of rating downgrades and bankruptcy filing. Section V explores the empty creditor problem by examining the quantum and structure of CDS contracts. Section VI concludes.

II. Theoretical Framework and Hypotheses

The objective of this study is to analyze the direct effect of CDS protection on a firm as a consequence of the actions of its creditors. The focus here is on the motivations of creditors following the introduction of CDS trading and their rational anticipation of the future course of events facing the firm. In particular, creditors take into account the possible future paths that the firm may take, including the possibility that the firm may become distressed. In that eventuality, the firm and its creditors would face the choice between restructuring and bankruptcy, bring to the fore the differing motivations of creditors with and without CDS protection. During the period from the introduction of CDS trading to the extreme possibility of a distressed workout (which could be short or long, depending the financial condition of the firm at the take of CDS introduction), there could be other subtle changes such as reduced monitoring by the creditors and adverse feedback effects from CDS trading to the financing and its operations.[10] We focus on the direct implications of CDS protection for creditors,

[10] Arping (2004), Morrison (2005), Thompson (2007), and Parlour and Winton (2012) model the incentives of CDS protected creditors. Beyhaghi and Massoud (2012) find that banks are more likely to hedge their loan exposures with CDS when monitoring costs are high. Ashcraft and Santos (2009) and Hirtle (2009) empirically examine how CDS affects the reference firm's cost of capital, which is modeled by Che and Sethi (2012). Saretto and Tookes (2011) find that the reference firm's leverage increases after CDS trading. Das, Kalimipalli, and Nayak (2011) find that CDS trading hurts bond market quality. Nashikkar, Subrahmanyam,

leaving considerations of monitoring and feedback effects to the background. We use a simple example to illustrate how CDS trading by creditors affects the likelihood of bankruptcy. The example is intended to convey the basic intuition of the empty creditor problem and is based on the model of Bolton and Oehmke (2011).

First consider the case where there is no CDS traded on the firm. Assume that creditors lend X to a 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 its 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.[11] In general, restructuring would dominate bankruptcy.

Suppose next that the creditors can also buy CDS protection against the firm's credit events. Clearly, bankruptcy would always be defined as a credit event. However, restructuring may or may not be defined as a credit event, 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 defined it as a "no restructuring" (NR) CDS.[12] 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 notional value of the CDS. 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 $[R \times X + (1 - R - F) \times Y]$ 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 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

and Mahanti (2011) document a liquidity spillover from CDS to bonds. Boehmer, Chava, and Tookes (2012) find that CDS trading hurts stock market efficiency. Hortacsu, Matvos, Syverson, and Venkataraman (2011) demonstrate the feedback effects from CDS to the product market. Other implications of CDS can be found in Duffee and Zhou (2001), Longstaff, Mithal, and Neis (2005), Allen and Carletti (2006), Stanton and Wallace (2011), Campello and Matta (2012).

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

[12] Other types of CDS contracts also exist, but are not relevant for purposes of this simple illustration. See Appendix C for discussion of contract clauses.

injecting more capital as long as it is less than CDS payouts) in order not to trigger CDS payments, they cannot do so unilaterally, since empty creditors who are the CDS buyers, and other creditors, mostly decide the fate of the company, since any new financing would require existing creditors' approval. 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 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 when

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

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 are 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 is more profitable in bankruptcy than restructuring without CDS protection, so long as

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

which is equivalent to saying that:[13]

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

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 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) 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

[13] The calculation for the FR CDS is the same, except that the fee is replaced by F instead of f. The precise range of values for Y relative to X would be smaller than for the NR CDS, as argued above.

contracts outstanding relative to the firm's debt, and c) the probability of bankruptcy occurring is greater for NR CDS contracts. This analysis provides the intuition for our first three hypotheses:

Hypothesis 1 (Baseline) *The credit risk of a firm and, in particular, its risk of bankruptcy increases after the introduction of trading on CDS contracts referencing its default.*

The first hypothesis highlights the incentives driving creditors to prefer bankruptcy to restructuring, due to the payoffs they receive from their holding of CDS. One could alternatively examine whether CDS trading reduces the success rate of restructuring for distressed firms.[14] Bankruptcy seems to be a better testing framework than restructuring as bankruptcy events are more unambiguously defined and observed than restructuring events. Moreover, defining distressed firms is a subjective task. Therefore, we focus on bankruptcy which could be driven by both liquidity and solvency issues.

Hypothesis 2 (Empty Creditor: CDS Exposure) *The increase in the bankruptcy risk of a firm after the introduction of trading in CDS contracts referencing its default is larger for firms with more CDS contracts relative to debt outstanding ("over-insurance").*

The second hypothesis explicitly refers to the relative benefit from the purchase of CDS contracts. The larger the holding of CDS relative to debt outstanding, the greater the benefit to the empty creditors, and hence, the incentive to tilt the firm towards bankruptcy.[15] Empty creditors do not completely determine the fate of the reference entities. In some cases, the reference firms survive without any credit events, or with straightforward debt rollover, if other creditors support the borrower and overweigh the influence of empty creditors. In such cases, empty creditors would lose the additional premium they paid to CDS sellers without any benefits. If credit events do occur, empty creditors and other CDS buyers will usually make profits. Whether the overall effect of CDS trading is significant or not depends on the incentives of the marginal creditors, and will be borne out in the data.

Hypothesis 3 (Empty Creditor: No Restructuring) *The increase in the bankruptcy risk of a firm after the introduction of trading in CDS contracts on it is larger if "no restructuring" (NR) contracts account for a larger proportion of all CDS contracts referencing its default.*

[14] In a complementary study, albeit with a much smaller sample, Danis (2012) finds that distressed firms with CDS trading are less successful in debt workouts in their sample, over the period 2006-2011. This issue is also addressed by Narayanan and Uzmanoglu (2012). Our analysis applies to the full sample of firms, both healthy and distressed.

[15] Peristiani and Savino (2011) document the higher bankruptcy risk in the presence of CDS during 2008, but insignificant overall effects. Our study uses a much more comprehensive database to provide a more powerful test than the binary CDS introduction events analyzed by them.

The third hypothesis suggests an even stronger test of the empty creditor mechanism by using a special feature of the CDS contracts. If CDS contracts cover restructuring as a credit event, then creditors will be compensated, whether the distress firm restructures or declares bankruptcy. However, if restructuring is not protected, the default event is triggered and the empty creditor will only get compensated when the firm files for bankruptcy. Therefore, we hypothesize that the empty creditor mechanism is even more effective for NR CDS.[16]

The three hypotheses above emphasize the *ex post* effect (after the loan and CDS positions are given) of CDS due to tougher lenders in debt renegotiation, although not every creditor would want to become empty creditor.[17] From an *ex ante* perspective, lenders could be strategic in their use of CDS and lending decisions.[18] Bolton and Oehmke (2011) show that more investment projects can be financed when CDS are traded on a firm, due to the possibility of risk mitigation using CDS for the lenders, and hence, their increased willingness to lend to the firm. Thus, more banks are willing to lend to the firm if CDS are available. Such an increase in the lender base and the level of lending has 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 coordination failure.[19] Therefore, the other channel for CDS trading to increase bankruptcy risk is through greater heterogeneity in creditor composition: Coordination is more difficult when there are more creditors, especially when some of them are empty creditors. Therefore we generate our last hypothesis:

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

Borrowers may also want to increase their lender base if they anticipate that some lenders could take advantage of their respective CDS positions.[20] There are other mechanisms for the exacerbation of credit risk, following the introduction of CDS trading, that go beyond our illustrative example. For instance, creditors who are not protected by CDS may demand a higher interest rate, although they are willing to lend more, and monitor the borrower

[16] Bedendo, Cathcart, and El-Jahel (2012) examine the distressed firms' decisions regarding out-of-court restructuring and bankruptcy filing during the global financial crisis. They find that CDS contracts do not significantly increase the probability of bankruptcy when the firm is already in distress, although their relatively small sample spans a short time period.

[17] Gopalan, Nanda, and Yerramilli (2011) show that the lead arranger suffers reputation damage from borrower bankruptcies.

[18] Norden, Buston, and Wagner (2011) show that banks that use credit derivatives more intensively are willing to lend at lower loan rates. The findings of Minton, Stulz, and Williamson (2009) imply that, had CDS been more liquid, banks would use CDS more extensively.

[19] Gilson, John, and Lang (1990) show that creditor coordination failure increases bankruptcies. Brunner and Krahnen (2008) show that distress workouts are less successful when there are more creditors.

[20] Acharya and Johnson (2007) suggest that bank lenders engage in insider trading in the CDS market. Hale and Santos (2009) show that if banks exploit their information advantage, firms respond by expanding their borrowing base to include lenders in the public bond market or adding more bank lenders.

less. Such effect of CDS trading on firms will be increased leverage and higher cost of debt, leading to higher debt rollover risk and bankruptcy risk. Those indirect channels generally go through the effects on firm fundamentals, as firms become riskier. In our analysis, we control for firm fundamentals. Hence, the indirect channels are not likely to drive our findings on the *direct* "tougher creditor" channels. One natural related question is: Are creditors getting tougher? The recent decline in the absolute priority deviation during bankruptcy resolution is consistent with tougher creditors and coincides with the development of the CDS market.[21]

III. Data and Empirical Methods

A. *CDS Trading and Bankruptcy Data*

We use actual transaction records to identify firms with CDS contracts written on them, and in particular, the date when CDS trading began for each firm. Unlike voluntary dealer quotes that are non-binding and may be based on hypothetical contract specifications, transaction data contain multi-dimensional information regarding the actual CDS contracts, including price, volume and contact terms. Our CDS transactions data are obtained from two separate sources: CreditTrade and GFI Group. CreditTrade was the biggest data source for CDS transactions during the initial phase of the CDS market before GFI Group took over as the market leader.[22] (GFI ranked first in the Risk Magazine ranking from 2002-2009.) Combining data from these two sources allows us to assemble a comprehensive history of North American corporate CDS trading activities. To ensure greater accuracy, we also cross-checked this list of CDS introductions with the Markit CDS database, a commonly used CDS dealer quote database, and confirmed our identification of the firms with CDS traded.[23]

The CreditTrade data cover the period from June 1997 to March 2006. GFI data cover the period from January 2002 to April 2009. Both datasets contain complete information on intra-day quotes and trades such as the time of the transaction, order type, and the CDS price. Since CDS contracts are traded over-the-counter, unlike stocks or equity options, which are mostly traded on exchanges, the first trading date for each firm's CDS is hard to pinpoint with a time stamp. However, because we have overlapping samples from these two data sources between January 2002 and March 2006, we are able to cross-check the two records to

[21]See, for example, Bharath, Panchapagesan, and Werner (2010).

[22]Many other papers have used the same data sources. For example, Acharya and Johnson (2007) and Blanco, Brennan, and Marsh (2005) utilize CreditTrade data in their analyses. CreditTrade was acquired by Creditex in 2007 and Creditex merged with the CME in 2008. The analysis in Nashikkar, Subrahmanyam, and Mahanti (2011) is also partly based on CDS data from the GFI Group.

[23]Markit provides end-of-day "average" indicative quotes from contributing dealers, using a proprietary algorithm. In contrast, both CreditTrade and GFI report trades as well as binding quotes.

confirm the reliability of our identification of the first CDS trading date. In the event, the dates of first appearance of a particular CDS in the two data sources are mostly within a couple of months of each other. It should be stressed that any remaining noise in identifying the precise date of introduction of a particular CDS should bias us against finding significant empirical results regarding the consequent effects on credit risk.

There are two important advantages of using transaction data in our empirical analysis of non-sovereign North American corporate CDS. First, our sample starts in 1997, which is regarded by many market observers as the inception of the CDS market.[24] Therefore, our identified first CDS trading dates will not be contaminated by censoring of the data series. Second, our CDS transaction data have the complete contractual terms such as the specification of the credit event, maturity, and security terms, at the contract level. Aggregate position or quote data obtained from broker-dealers or, more recently, clearing houses or data aggregators, would generally not have such detailed information. The credit event specification allows us to investigate the effect of restructuring clauses. The maturity information at the contract level also allows us to calculate the open CDS positions outstanding at each point in time. Our CDS introduction sample ends in April 2009. The market practice in CDS changed significantly in April 2009 due to the "Big Bang" implemented by the International Swaps and Derivatives Association (ISDA). The empty creditor concern could be even stronger thereafter, due to the removal of restructuring as standard credit event.

Based on our merged data set, there are 901 North American firms that have CDS initiated on them at some point during the 1997-2009 sample period. The industry distribution of the CDS firms in our sample is quite diverse.[25] In our initial analysis, we mainly utilize the information about the first day of CDS trading, and compare the changes in firm default risk upon the onset of CDS trading. Later on, to explore the mechanism through which CDS trading affects credit risk, we also construct measures of CDS attributes, based on the more detailed transaction information.

We assemble a comprehensive bankruptcy data set by combining data from various sources for North American corporations filing bankruptcies 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 all public companies filing for bankruptcy and also significant bankruptcies of private firms. We further augment this initial sample with additional bankruptcy filing data sources including the Altman-NYU Salomon Center Bankruptcy List, the Fixed Income Securities Database (FISD), the UCLA-LoPucki

[24]See Tett (2009), for example.

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

Bankruptcy Research Database (BRD), and Moody's Annual Reports on Bankruptcy and Recovery.[26] Unlike most other studies, we do not drop bankruptcies of small firms.

We link the bankruptcy data set with our CDS sample to identify CDS firms filing for bankruptcy protection sometime after the first day of their CDS trading. Table I presents the year-wise summary from 1997 to 2009 for all firms in the Compustat database: the number of bankrupt firms, the number of firms on which CDS are traded, and bankrupt firms with and without CDS. As the table shows, there are 1,628 bankruptcy events during this sample period. The bankruptcy filings in our sample are mostly concentrated in the time periods of 1999-2003 and 2008-2009, which account for 1,214 of the 1,628 bankruptcy events during the entire sample period (74.6%). The fourth and fifth columns of the table report the number of *New CDS* and number of *Active CDS* trading firms across the years, respectively. The introduction of CDS is most pronounced from 2000 to 2003. Among the 901 distinct CDS trading firms, 60 (6.66%) subsequently filed for bankruptcy protection. Bankruptcies among CDS firms represent a small fraction of the total number of bankruptcies, since only relatively large firms, by asset size and debt outstanding, are selected for CDS trading. However, the bankruptcy rate of 6.66% for CDS firms is close to the 4-year overall (or 11-year BBB-rated) cumulative default rate of U.S. firms (Standard & Poor's (2012)).

We obtain additional firm level data for our empirical analysis. Firm accounting and financial data are from CRSP and Compustat; credit rating data are from Compustat and FISD; bond issuance data are from FISD; and, lending relationship data are from DealScan.[27] Our bond trading data are from the Trade Reporting and Compliance Engine (TRACE) maintained by the Financial Industry Regulatory Authority (FINRA). In addition, we obtain analyst coverage data from I/B/E/S.

B. Empirical Methodology

There is a large literature on bankruptcy prediction dating back to the Z-score model of Altman (1968).[28] Bharath and Shumway (2008) and Campbell, Hilscher, and Szilagyi (2008) discuss the merits of simple bankruptcy prediction models over their more complicated counterparts. In keeping with this perspective, our baseline approach is a proportional hazard model

[26] Our combined bankruptcy sample contains 2,345 bankruptcy filings from firms reporting data to Compustat between 1978 and 2010.

[27] The construction of the data-set is detailed by Chava and Roberts (2008). We thank Michael Roberts for providing the DealScan-Compustat linking file.

[28] This model and its variants have been widely used to measure bankruptcy risk. Recent additions to the literature include Duffie, Saita, and Wang (2007), who propose a reduced form model with good out-of-sample default prediction, Das, Duffie, Kapadia, and Saita (2007) who find that defaults are more clustered than would be implied by conventional credit risk models, and Duffie, Eckner, Horel, and Saita (2009) who propose a frailty model, which solves the omitted variable bias. Follow-up studies identify other risk factors in bankruptcy risk models include Lando and Nielsen (2010) and Jorion and Zhang (2009).

for bankruptcy using our panel data. Following Shumway (2001), Chava and Jarrow (2004), and Bharath and Shumway (2008), 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}:

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

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 previous period. A higher level of $\alpha + \beta' X_{it-1}$ represents a higher probability of bankruptcy. We follow Bharath and Shumway (2008), and estimate the model with five fundamental determinants of default risk in X_{it-1}, including the logarithm of the firm's equity value (*ln(E)*), its return over the past year $(r_{it-1} - r_{mt-1})$, a measure of its equity performance in the prior period, 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 ratio of net income to total assets (*NI/TA*), a measure of its profitability.[29]

We include two CDS variables in the hazard model specifications to estimate the impact of CDS trading on bankruptcy risk, similar to Ashcraft and Santos (2009) and Saretto and Tookes (2011). *CDS Firm* is a dummy variable that equals one for firms with CDS trading at any point during our sample period. *CDS Active* is a dummy variable that equals one after the inception of the firm's CDS trading. Therefore, for a firm with CDS traded on it, *CDS Firm* always equals one, and is used to control for unobservable differences between firms with and without CDS. *CDS Active*, however, equals zero, before the CDS introduction, and one thereafter. Hence, the coefficient of interest is that of *CDS Active*, which captures the marginal impact of CDS introduction on bankruptcy risk. The analysis is conducted in a sample of firms that includes those with CDS traded on them and those without.

We also examine other indicators of changes in credit risk that can be more continuously observed. One such signal is a change in the credit rating of the firm, in particular, a downgrade. A downgrade in credit rating is a signal of deteriorating credit quality, and may be a first step towards bankruptcy. In that spirit, we use credit rating downgrades as the dependent variable in the hazard model, as an alternative specification. Since the sample size for downgrades includes many more observations, we get a more powerful test of how CDS trading affects firm credit quality. Additionally, we compare the expected default frequency (EDF) for CDS firms in a difference-in-difference analysis.

Our investigation should provide a holistic view of the changes in credit quality following the introduction of CDS trading, since a rating downgrade and bankruptcy are the first and

[29] Longstaff, Giesecke, Schaefer, and Strebulaev (2011) argue that factors suggested by structural models such as volatility and leverage predict bankruptcy better than other firm variables.

last steps, respectively, of the degradation of credit quality, with default falling just prior to bankruptcy. A middle step between a rating downgrade and bankruptcy is the restructuring negotiation. We do not investigate restructuring directly due to the more severe sample selection problem we would face. In many cases, the chances of successful restructuring are so low that no offer is publicly proposed. A few offers are made publicly because private negotiation has led to a preliminary agreement. Also, comprehensive data coverage on restructuring (and participation rates in the exchange offer) are more sparse and less reliable than those for bankruptcy. Furthermore, many "successful" restructuring negotiations ultimately end in bankruptcy.[30] We examine bankruptcy rather than default since our study of individual cases suggests that CDS buyers generally prefer the more straightforward settlements of "hard" credit events such as bankruptcy over default. Moreover, in our sample, most bankruptcies coincide with defaults. Therefore, the results on defaults will be broadly similar to our reported results on bankruptcies.[31] We do not consider other exits not directly related to credit risk, such as mergers and acquisitions, in a competing risk model framework so that we can have clear message on bankruptcy.[32] We hasten to emphasize that we do not expect any systematic bias in our setting due to our focus on bankruptcy. Future research may explore whether the introduction of CDS affects the propensity of these other exits.

We control for fixed effects in the simple panel data analysis. We take into account the potential endogeneity in the selection of firms for CDS trading. It is possible that investors anticipate the deterioration in a firm's credit quality and initiate CDS trading, where there is such potential, but with a difference of opinion among market participants as to its likelihood. If this were the case, the observed impact of CDS trading on credit risk would not be caused by the inception of CDS trading *per se*, but the realization of investor expectations. We use three methods to address the endogeneity concern: the difference-in-difference estimate, propensity score matching, and a treatment effects model with instrumental variables. In order to do conduct those analyses, we construct a prediction model for CDS trading similar to Ashcraft and Santos (2009) and Saretto and Tookes (2011).

In addition to the indicator *CDS Active* as our key independent variable, we also investigate the channel through which the impact of CDS trading manifests itself, by constructing continuous measures of both CDS contracts outstanding, as well as the nature of the CDS contracts itself. We conjecture that firms with larger proportions of CDS to debt outstanding are more likely to be affected by the empty creditor problem, and hence, potentially have higher bankruptcy risk. Moreover, we distinguish between different types of CDS contracts

[30] Altman and Kuehne (2012) document that 45.8% of distressed exchanges go bankrupt in the period subsequent to the "successsful" distressed exchange.

[31] Although, in principle, bankruptcies could occur after defaults, only in 9% of the cases in our sample do bankruptcies occur more than two months later than defaults, which is quite small. We thank Edward Altman for suggesting that we study this issue and providing the relevant data for us to do so.

[32] This is in contrast to Duffie, Saita, and Wang (2007), and Duan, Sun, and Wang (2012), for example.

by their credit event specifications as discussed in Appendix C. CDS contracts with a "no restructuring" credit event clause would be most impactful for the empty creditor concern, since they would not pay off in restructuring events.

IV. CDS Trading and Credit Risk: Empirical Results

This section presents our empirical findings on the effect of CDS trading on a firm's bankruptcy risk. We first report our baseline results regarding the effects of CDS trading on credit ratings, as well as bankruptcy in panel data regressions with fixed effects, using the full sample, and then in a sample matching CDS and non-CDS firms by distance-to-default. We next examine whether the results are robust to controlling for the endogeneity of CDS trading, whereby firms may be selected for such trading due to the potential deterioration in their credit quality. We use three different econometric methods to address the endogeneity problem: difference-in-difference estimation, propensity score matching, and treatment regressions with instruments. The key independent variable for this section is the status of CDS trading as a binary variable which equals zero, before CDS trading, and one after the first month of CDS trading. In the next section, we provide more color to our analysis in terms of the size of the CDS exposure, and the composition of the CDS contracts, to understand the precise mechanism through which CDS trading affects credit risk.

A. Rating Distributions Before and After CDS Introduction

Intuitively, a reasonable approach to a preliminary analysis of the effect of CDS trading would be an event study of credit risk changes around the date of CDS introduction. However, we cannot conduct an event study on the effect of CDS introduction on bankruptcy, as bankruptcy is a one-time event, and firms are usually dropped from databases after the event. Therefore, we choose to analyze credit ratings instead, which are observable, both before, and after, CDS introductions. As already noted, a credit rating downgrade is often the first step towards bankruptcy. Hence, the analysis of changes in credit rating is likely to have implications for bankruptcy filing as well. Furthermore, since the number of credit downgrades vastly exceeds the number of bankruptcies, we would have a much larger sample for analysis.

To motivate our empirical analysis later and provide some intuition, we compare the distribution of credit ratings in the year before (year $t-1$) CDS trading, with the rating distribution within two years after (year $t+2$) CDS trading, for all firms with such contracts traded at some point of time in our sample. The 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 by a credit rating agency at the onset of CDS trading. Only a small proportion of firms are unrated at this juncture. Compared to the general corporate rating distribution documented in Griffin and Tang (2012), our sample includes more BBB-rated firms relative to other investment grade (AAA, AA, A-rated) firms, but it also has fewer non-investment grade firms in our CDS sample. Therefore, firms tend to have relatively good credit quality at the time of CDS inception.

Figure 1 shows a discernible shift to lower credit quality after the introduction of CDS trading. While the proportion of BBB-rated firms is about the same before and after CDS trading, the proportion of AA-rated and A-rated firms decreases. At the same time, the proportion of non-investment grade and unrated firms increases. The Kolmogorov-Smirnov test statistic for distributional differences before and after CDS trading is significant at the 1% level, indicating that the credit rating distribution shifts to the right (lower rating quality) after CDS trading. These results provide preliminary evidence that, following the inception of CDS trading, the credit quality of the reference entities deteriorates.

B. Baseline Hazard Model Results (Testing H1)

We next run multivariate tests to discern systematic statistical evidence on the effect of inception of CDS trading, with appropriate control variables. We include both firms with and without CDS traded in a panel data analysis using monthly observations. In our baseline analysis, we use both credit rating downgrades and bankruptcy filing to measure credit quality deterioration.

As discussed in Section III.B, we follow Bharath and Shumway (2008) and estimate a logistic model of credit rating downgrades or bankruptcy filings.[33] Our CDS variables are: *CDS Firm*, which equals one if the firm is in the CDS sample and zero otherwise, and *CDS Active*, which equals one after the first month of CDS trading and zero otherwise. The coefficient of *CDS Firm* separates the differential likelihood of deterioration in credit risk, by a credit downgrade or bankruptcy filing, for firms with CDS traded on them. The coefficient of *CDS Active* captures the impact of CDS trading on the probabilities of credit rating downgrading or bankruptcy filing after the inception of CDS trading. Therefore, our explanatory variable of interest and important for our interpretation is *CDS Active*. Since the variables *CDS Firm* and *CDS Active* are correlated, we report results both with and without the control of *CDS Firm* in our main analysis.

The proportional hazard model estimation results are presented in Table II. Panel A shows the full-sample results using all firms. The first column lists the independent variables in the

[33]We also examined other specifications (e.g., Campbell, Hilscher, and Szilagyi (2008)), and find that our conclusions are robust to the use of different control variables.

model estimation. The dependent variable for Specifications 1 and 2 is an indicator for credit rating downgrading in the observation month. The dependent variable for Specifications 3 and 4 is an indicator for bankruptcy filing in the observation month. We include *CDS Firm* as a control to show that the effect of *CDS Active* is not driven by fundamental differences between CDS firms and non-CDS firms in Specifications 1 and 3. Specifications 2 and 4 show that the effect of *CDS Active* is significant, even without controlling for *CDS firm*; therefore, the effect of CDS introduction is not driven by the potential multicollinearity between *CDS Active* and *CDS Firm*. We include year and industry fixed effects to address concerns that unobserved attributes influencing CDS trading also affect bankruptcy risk. The coefficients of three of the five fundamental variables – market value of equity, face value of debt and equity performance – are significant in all four specifications. Equity volatility and profitability are significant in the bankruptcy specifications (3 and 4), but not in the downgrading specifications (1 and 2).

The positive coefficients of *CDS Active* in Specifications 1 and 2 indicate that firms are more likely to be downgraded after CDS trading. In both specifications, the effect of CDS trading is statistically significant at the 1% level. The economic magnitude is also large: Compared to the average downgrading probability of 0.58% in Specification 1, the marginal effect of CDS trading on downgrading is 0.39%. Specification 3 reports similar findings for bankruptcy filing. Bankruptcy risk increases after CDS trading; against an average firm bankruptcy probability of 0.14%, the marginal effect of CDS trading on the bankruptcy probability is 0.33%. The odds ratio for *CDS Active* for credit downgrades and bankruptcy predictions are 1.925 and 10.73 respectively, indicating that credit events are much more likely after CDS trading. Since firms in different industries can vary from one another on many dimensions, we control for industry fixed effects in all the results we report. Therefore, our results are not driven by industry effects.[34]

The coefficient estimate for the variable *CDS Firm* in Specification 1 is positive and statistically significant at the 1% level. That is, compared to all non-CDS firms, CDS firms are, in general, more likely to be downgraded. However, the negative and significant coefficient estimate for *CDS Firm* in Specification 3 shows that CDS firms are less likely to go bankrupt than non-CDS firms. Those findings are consistent with our conjecture that CDS firms as a group are different from non-CDS firms. Given the opposite CDS firm effects on downgrading and bankruptcy, the increase in credit risk, as evidenced by the positive coefficient of *CDS Active* in both downgrading and bankruptcy results, is indeed the CDS introduction effect, rather than purely the CDS firm effect.[35]

[34]We have also conducted other robustness checks for industry effects, especially financial firms, on these results to assure ourselves of their general validity. We find that the financial industry dummy in our baseline model is not statistically significant, indicating that the results are equally valid for financial firms. Also, when we drop financial firms from our baseline sample and re-estimate the hazard model, our results are qualitatively similar to results using the overall sample.

[35]We have also investigated time-series variation and size effects. First, we interact the *CDS Active* variable

The estimation results for the other control variables in Table II are similar to the findings in prior studies. Larger firms and firms with higher stock returns are less likely to be downgraded or to go bankrupt. Firms with more debt and greater equity volatility are more likely to be downgraded or to go bankrupt, all else being the same. As is to be expected, profitable firms are less likely to file for bankruptcy. Lastly, the pseudo-R^2's (about 15% for downgrading regressions and 24% for bankruptcy regressions) suggest that bankruptcy filings are better explained by these explanatory variables than downgrading.

In Panel A, which is our baseline estimation, we use all non-CDS firms as the control group for CDS firms. However, given that CDS firms are fundamentally different, on average, from non-CDS firms, we need to use a different control group to put CDS and non-CDS firms on the same footing. To wit, credit quality deterioration may depend on the *initial* credit quality prior to the CDS introduction as low credit quality firms are more likely to deteriorate in credit quality relative to high quality firms (Standard & Poor's (2012)). If CDS firms are, on average, riskier than non-CDS firms, the effect of *CDS Active* may be due to this effect of the initial credit quality level. To address this issue, we isolate the CDS trading effect from the initial credit quality effect by matching CDS and non-CDS firms by their initial credit quality. We use distance-to-default (DD) as a credit quality measure in matching non-CDS firms to CDS firms. DD is calculated from the Merton (1974) model, as modified by Bharath and Shumway (2008), and described in Appendix B, which is widely used in academia and industry. It is a measure of the distance between the asset value of the firm and the face value of its debt, scaled by the standard deviation of firm's asset value. By matching firms on DD, the CDS and the chosen non-CDS matched firms have a similar *ex-ante* probability of bankruptcy, at the inception of CDS trading, as indicated by their DD. The hazard model analysis of the impact of CDS trading on the probability of bankruptcy is then conducted in the sample of CDS firms and their corresponding DD matched non-CDS firms.

The estimation results for the DD-matched sample are reported in Panel B of Table II. The analysis is similar to that in Panel A, but with a smaller, albeit more homogeneous, sample (the sample size for Panel B is about one-fifth of Panel A). All four specifications in Panel B show that *CDS Active* has positive and significant coefficient estimates. The effect of CDS trading is also economically large. For example, Specification 3 shows that the marginal effect of CDS trading on probability of bankruptcy is 0.12%, compared with the sample default rate of 0.05%. Again, the effect of *CDS Active* is significant, with or without the control for *CDS Firm*. Overall, for two firms starting with similar credit quality, the one that later on has CDS

with year dummies, and find that the interaction terms are significant in 2005, 2007 and 2009. It may be that these time-series effects are related to the financial crisis, in some way. Second, we check for cross-sectional variation in the CDS effect by interacting the *CDS Active* variable with firm size. The coefficient of this interaction term is insignificant; we can conclude that there is no obvious size effect associated with the impact of CDS introduction on credit risk.

trading will, on average, be more susceptible to downgrading or bankruptcy filing, following CDS trading.

In sum, Table II of our baseline analysis shows consistent results that the credit quality of reference firms declines after CDS trading. In the next subsections, we formally address the potential endogeneity concerns, using three alternative econometric approaches.

C. Endogeneity and the Selection of Firms for CDS Trading

The main challenge to inferring a causal relationship from our baseline results in the previous subsection that CDS trading leads to deterioration in credit quality is the potential endogeneity of CDS trading. It is conceivable that CDS traders anticipate the deterioration in a firm's credit quality and then start trading its CDS. Thus, if firms of lower credit quality are more likely to be selected for CDS trading, they are inherently more likely to decline in credit quality. It should be noted that CDS firms typically have investment grade ratings, when CDS trading is initiated. Therefore, the initiation of CDS trading is not completely attributable to poor (initial) credit quality. In addition to reverse causality (the expectation of future credit quality induces the introduction of CDS trading), there could be omitted variables driving both CDS trading and credit quality deterioration, which could affect our estimation results, although this could be mitigated to some degree, due to the inclusion of industry and year fixed effects.

We now formally endogenize CDS trading and factor this endogeneity into our subsequent analysis on the effect of CDS trading on credit risk. We use three standard econometric approaches to address endogeneity issues, as suggested by Li and Prabhala (2007) and Roberts and Whited (2012): difference-in-difference estimator, propensity score matching, and a treatment effects model with instruments. All three approaches require a model to predict which firms are likely to have CDS trading initiated on them, and when the CDS trading starts. We aim to find the most appropriate model for the selection of CDS trading on firms, so that we can then adjust for this selectivity in our analysis of credit risk changes after CDS trading. The endogeneous variable is *CDS Active*. (*CDS Firm* reflects firm fundamentals and is assumed to be exogenous.) We follow Ashcraft and Santos (2009), Saretto and Tookes (2011), and other studies with similar endogeneity concerns for the specification of the CDS trading selection model. However, we need to take into account several additional considerations in choosing the explanatory variables for the CDS trading model, given that our interest is explicitly on credit risk, unlike other studies. First, we require the model to have reasonably high explanatory power so that we can find matching firms for our subsequent analysis. Second, we need to be careful about whether to include credit risk factors in the CDS trading selection model or not. Last, but not least, the instrumental variables we choose (in the first stage) should be related to CDS trading but not to credit risk. The instrumental variables will be needed for the two-stage, treatment effect regressions.

We employ two instrumental variables: bond turnover and analyst coverage. In results that are not reported here to conserve space, we find that both instrumental variables satisfy the Akaike information criterion for exclusion: bond turnover and analyst coverage are not directly related to the credit risk of the firm. However, bond turnover and analyst coverage should both be positively associated with investor interest in trading CDS, since the market for CDS is driven by the supply and demand for credit risk transfer. These variables are proxies for the liquidity of bonds that need to be hedged, as well as the availability of information about the firm in question. Besides these two instruments as explanatory variables for CDS trading, we also include firm size, as larger firms naturally attract more attention for CDS traders (also, the chance of hedging demand arising from any investor is bigger for larger firms). In addition, we include a set of firm characteristics such as sales, tangible assets, working capital, cash holdings and capital expenditure. Furthermore, we include credit risk variables such as leverage, profitability, equity volatility, and the credit rating of the firm, into one specification for predicting the inception of CDS trading. We stress that "empty creditors" contribute to only part, but not all, of CDS trading. It is conceivable that part of the CDS trading is by speculators unrelated to the firm's bondholders.

To predict the introduction of CDS trading for a firm, we use data from 1997 until the first month of CDS trading for CDS firm and all observations of non-CDS firms. The prediction model is estimated with a probit model: the dependent variable is equal to one, after the firm starts CDS trading, and zero prior to it. The probit regression results are reported in Table III. We consider four prediction models with a progressively larger number of independent variables. First, we find that larger firms are more likely to have CDS trading from Model 1 estimation results. Model 2 shows that firms with higher bond turnover are more likely to have CDS trading. CDS trading is also more likely for firms with high analyst coverage, as shown in Model 3. We add a number of credit risk factors and other firm characteristics in Model 4, which shows that CDS trading is more likely for firms with high leverage, but with investment grade ratings. Also, unrated firms are less likely to have CDS trading. Firms with high profitability, tangibility, and large working capital are more likely to have CDS trading. Overall, it appears that firms have relatively high credit quality and visibility (strong balance sheet, larger size, and high analyst coverage) at the time of CDS inception. In later analysis, we use bond turnover and analyst coverage as instrumental variables. The results in Table III show that these instruments satisfy the relevance condition as they jointly predict CDS trading, even after controlling for other variables.

Table III shows that CDS trading can be explained reasonably well by the explanatory variables. The pseudo-R^2s range from 33.54% in Model 1 to 38.37% in Model 4. In the following analysis, we will use these CDS trading prediction models to select matching firms, and re-examine the relationship between CDS trading and bankruptcy risk. To verify how good the matching can be from each prediction model when we choose the matching firm with the nearest propensity score, we report the differences in Altman's Z-scores, distance-to-default, and the propensity scores between CDS firms and their matching firms in the last three rows of Table III. There is no significant difference in Z-score between the two sets of firms, for all four prediction models. CDS firms are safer (higher a distance-to-default) than their matching firms in Models 1, 2, 3, but for model 4 CDS firms and matching firms have a similar distance-to-default. The propensity scores are not significantly different between CDS firms and matching firms in all four models. Therefore, one drawback of using the above results seems to be that CDS firms are of better credit quality than their matching firms in Models 1, 2, 3. In such cases, all else equal, it would be *less* likely for CDS firms to suffer credit quality deterioration than their matching firms.

In the following three subsections, we apply all four CDS selection models to our difference-in-difference analysis, propensity score matching, and treatment effect regressions to address endogeneity concerns. Our purpose in estimating a range of models for the prediction of CDS trading is to isolate the effect of credit factors some model specifications and examine the robustness of the results.

D. Difference-in-Difference Analysis

An intuitive approach for addressing the endogeneity concerns and identifying the treatment effect (the introduction of CDS trading) is difference-in-difference analysis. In defining firms matched by propensity score, we use all four prediction models for CDS trading, to assess the robustness of our conclusions. Moreover, we use three different propensity score matching criteria to choose matching firms: (1) the one non-CDS firm with the nearest distance, in terms of propensity score, to the CDS firm; (2) the one firm with nearest propensity score but within a difference of 1%, and (3) the two firms with propensity scores closest to the CDS trading treated firm. Additionally, we use two windows for the event analysis: year $t-1$ to year $t+2$ and year $t-1$ to year $t+3$.

We choose to first examine the expected default frequency (EDF), which is a normal transformation of the distance-to-default ($EDF = N(-DD)$). (We cannot run the difference-in-difference analysis on the bankruptcy event directly.) There are several advantages to choosing EDF as the relevant variable to track. First, EDF is a continuous measure of credit quality. Therefore, the estimation would have more power and the CDS introduction effect can be more easily identified. Second, using EDF enriches our empirical framework of credit risk measured by downgrading and bankruptcy filing. While also being a measure of credit risk, the *EDF* measure is sufficiently different from rating downgrades and bankruptcy filing, as it is implied from stock prices and balance sheet variables. Last, *EDF* is an *ex ante* measure of credit risk, while we can only observe downgrading and bankruptcy *ex post*.

Panel A of Table IV shows that the *EDF* difference-in-difference estimates are both statistically and economically significant for the $(t-1, t+3)$ event window, or using Model 4, or with two matching firms. For example, when we use Model 4 to choose the nearest-one propensity score matching firm, *EDF* is 2.9% higher after CDS introduction relative to non-CDS matching firm. Recall that the average CDS firms has a BBB rating at the time of CDS introduction. Such an increase in *EDF* is substantial given that the average BBB (BB) U.S. firm's 3-year default probability is about 1.2% (5.4%) from 1981 to 2011 according to Standard & Poor's (2012). We note that the estimates are insignificant for models 1, 2, and 3 with one matching firm. This is probably due to the higher credit quality of CDS firms compared with their matching firms as shown in Table III.

In Panel B of Table IV, we find that the leverage ratio of reference firms also increases significantly after CDS introduction. In the difference-in-difference estimation with Model 4 and event window $(t-1, t+2)$, leverage increases by 1.2% to 1.8% after CDS introduction. Our finding of the magnitude of leverage change is consistent with the conclusions of Saretto and Tookes (2011). However, this finding of increased leverage could complicate our interpretation of the CDS trading effect, because credit risk clearly increases with leverage. We have two ways to address this direct leverage effect. First, we control for firm leverage in our regressions, both before and after CDS introduction. Second, we use different CDS introduction models to test for robustness. As shown in the third row of Table IV Panel B, when we use Model 3, there is no significant difference in the increase in leverage between the CDS treatment firms and their matching firms. In such a case, our concern about the leverage complication is attenuated to some degree.

E. Propensity Score Matching

We now re-estimate our baseline model using the propensity score matched sample. Propensity score matching is a simple approach to implement and makes the "treatment effect" easy to interpret, i.e., the difference between the CDS firms and those without CDS traded is measured by the coefficient of *CDS Active*. For each CDS firm, we find one non-CDS matching firm with the nearest propensity score for CDS trading. We then run the hazard rate model on this matched sample. We choose Model 3 in Table III for CDS selection, for which CDS and the matching non-CDS firms are not statistically different in terms of changes in leverage. Panel A of Table V presents the regression results. In all specifications, the coefficient estimates for *CDS Active* are significantly positive. In other words, both the probability of a credit rating downgrade and the eventual bankruptcy increase after CDS trading. Moreover, *CDS Firm* is not significant in Specifications 1 and 3. Therefore, after matching by the propensity of CDS trading, CDS firms are no longer statistically significantly different from non-CDS firms, in terms of credit risk deterioration.

In Panel B of Table V, we use different matching methods and CDS prediction models to asses the robustness of our propensity score matching results in Panel A. To conserve space, we only present results for bankruptcy prediction and for the specification with the control, *CDS firm*. For Model 3 of CDS trading prediction in Table III, we modify the matching criterion from the nearest one to the nearest one with propensity score difference within 1%. The results are similar to those in Panel A, when we use one matching firm from Model 3, without the 1% restriction. Alternatively, we choose two matching firms with the nearest propensity scores from Model 3, and still find a significant coefficient estimate for *CDS Active*. Then, we use alternative Models 1, 2, and 4 with the nearest-one propensity score matching. These models produce different matching samples due to data availability for each prediction model to calculate propensity scores. *CDS Active* is significant in all three specifications. When we use prediction Model 4, *CDS Firm* is not significant. Besides the propensity score of CDS trading being matched, the CDS firm and non-CDS firm also have similar Z-scores in all four matching models. Moreover, CDS firms are generally safer except in Model 4, which includes credit risk variables.

Given the significant finding for rating downgrades following CDS trading, one may be concerned that the effect of CDS trading on bankruptcy risk could stem directly from the rating action. (There are 73 downgrades within one year before CDS introduction for our regression sample.) Therefore, we examine the effect of CDS trading on bankruptcy risk, while controlling for the direct effect of the rating downgrade itself. We run the hazard model of bankruptcy filings using our nearest-one propensity score matched sample, from all four CDS prediction models. The results are reported in Panel C of Table V. The dependent variable is the probability of bankruptcy. We include two rating variables: *Unrated*, which equals one, if the firm is unrated in the observation month, and the cross term between *CDS Active* and *Unrated*, which captures potential interaction effect. We also include an explanatory variable *Downgrade* to control for the direct influence of a rating downgrade. *Downgrade* is a dummy variable that equals one, if there was a credit downgrade for the firm in the one year before the observation month, and zero otherwise. This specification contrasts the predictive power of CDS trading with a credit rating downgrade, in predicting bankruptcy risk.

Panel C of Table V shows that, in all four specifications with different propensity score matching models, the effect of *CDS Active* is robust to controlling for rating status. The significant coefficient estimates for *Unrated* suggest that unrated firms are more likely to go bankrupt. Also, firms are more likely to go bankrupt if they were downgraded just prior to the introduction of CDS trading. However, the interaction term *Unrated*CDS Active* is not significant. More importantly, CDS trading significantly increases the firm's probability of bankruptcy, even after controlling for the influence of downgrading. Against an average sample probability of bankruptcy 0.09% using Model 1 for the matching, the marginal effect of CDS trading is 0.15%. The odds ratio for *CDS Active* is 6.606. This finding suggests that the *direct* influence of CDS trading on bankruptcy risk is not fully absorbed by the rating agencies' credit analysis, at least during our sample period.

Our propensity score matching analysis assumes that unobservable variables are irrelevant to the outcomes of CDS trading. Such an assumption is difficult to refute or confirm, although it may be too strong. To alleviate this concern about relying on such a strong assumption, we use an alternative approach, the treatment effects model with instrument variables in the spirit of the Heckman two-stage model, to further address the endogeneity issue.

F. Treatment Effects Model with Instrumental Variables

The fundamental issue of endogeneity is that we do not observe the counterfactual outcome (CDS active firms without CDS trading). This is analogous to the missing data problem in the spirit of Heckman (1979). Therefore, correcting for self-selection can be viewed as including an omitted variable which is proxied by the *Inverse Mills Ratio* from the first stage of the Heckman procedure to produce a consistent estimate. The Heckman treatment effects model is methodologically different from the propensity score matching approach in addressing the endogeneity issue.[36]

Instrumental variables in the first step, the selection model, are often employed for the two-stage treatment effects model. Undoubtedly, the quality of the instruments in relation to other variables is important for the consistency of such treatment effect regressions. In particular, the instruments need to satisfy the relevance and exclusion restrictions. In our case, we use two instruments: bond turnover and analyst coverage. The relevance condition is met as Table III shows that CDS trading is significantly associated with bond turnover and analyst coverage. The exclusion restriction is impossible to test formally, as argued by Roberts and Whited (2012). However, in unreported results, we find that bond turnover and analyst coverage cannot predict bankruptcy filing or downgrading by the candidate firms. Therefore, they seem to satisfy the exclusion restriction.[37] We have also examined some

[36] An important note is that the Heckman model assumes a bivariate normal distribution for the error terms of the first stage and second stage regressions. Thus far, there is no theory regarding alternative distributional assumptions.

[37] Strictly speaking, the exclusion restriction is not necessary in our application of the Heckman selection model, because our model is identified due to its non-linearity. But in practice, it is safe to impose the exclusion restriction as the selection can be approximately linear in the relevant region. Hence, having multiple instruments can be helpful, although it will not solve the problem entirely.

other variables that are significant in determining CDS trading but they do not satisfy the exclusion condition. We acknowledge that, even though we have two instruments but only one endogenous variable, the test of the overidentifying restrictions may lack power, and not be useful as an alternative way to validate our instruments. Bond turnover and analyst coverage are economically sound instruments, because they are associated with the hedging interest in, and the information on, the reference entities. Beyhaghi and Massoud (2012) suggest that the selection of a firm for CDS trading may be contingent on monitoring costs. Thus, firms with more active bond trading and analyst coverage (which is also associated with equity trading) are more likely to trigger CDS trading. On the other hand, bond trading and analyst coverage cannot influence bankruptcy risk in a direct manner.

The selection models for CDS trading are the same probit models that underlie Table III. Based on the estimated model parameters from the first stage, we calculate the *Inverse Mills Ratio*, which is a transformation of these predicted individual probabilities of CDS trading. Then, the second stage of the hazard model analysis includes the *Inverse Mills Ratio* as an additional explanatory variable. We include all firm observations in the second-stage analysis. Testing the significance of the *Inverse Mills Ratio* is a test of whether the private information possessed by CDS traders explains the outcome (i.e., bankruptcy filing).

The results of the Heckman correction with instrument variables are presented in Table VI. We present here the second-stage results (and refer to those in the first-stage in Table III). We use all four CDS prediction models for the first stage estimation to generate the *Inverse Mills Ratio*. The first CDS prediction model includes only firm size which is not included in the second stage. We do not term firm size as an instrumental variable as it does not satisfy the exclusion condition. Model 2 uses bond turnover as the instrumental variable. Models 3 and 4 use bond turnover and analyst coverage as instrument variables. We find that *CDS Active* has a positive and significant coefficient estimate in all four specifications. In other words, firms are more likely to go bankrupt after the introduction of CDS trading. The economic magnitude of the coefficient is also large. For example from the Model 3 in the first stage, the marginal effect of CDS trading on bankruptcy filing is 0.39%, compared with the average bankruptcy probability of 0.14%. In contrast, the coefficient of *Inverse Mills Ratio* is insignificant, suggesting that the selection of a firm for CDS trading in itself does not predict an increase in bankruptcy risk. These results show that the positive relationship between CDS trading and bankruptcy risk is robust to the selection of firms for CDS trading.

G. *Other Robustness Checks*

We believe that our analysis of the endogeneity issue here is comprehensive. We have considered all the appropriate approaches to addressing endogeneity concerns suggested by the literature (see Roberts and Whited (2012), for a detailed survey). The difference-in-difference analysis, propensity score matching method, and the treatment effects using instrument variables via the Heckman correction procedure, each have their respective merits (and demerits). However, in our case, all approaches yield consistent results that bankruptcy risk increases after CDS trading, providing robust supporting evidence for Hypothesis 1.

The econometric methods employed in previous subsections to address endogeneity concerns mainly handle omitted variables and simultaneity. We have also conducted other untabulated robustness checks that help alleviate other potential concerns. First, we split our sample by analyst coverage, and find a significant CDS effect for firms with both high and low analyst coverage. The effect is not statistically different between those sub-samples, suggesting that the CDS effect is not related to the information environment in which a firm operates. Second, when we shift the CDS introduction by one year, the effect of *CDS Active* is insignificant. This finding supports the correct identification of the timing of CDS introduction, as well as the effect of CDS trading. Since CDS are traded over-the-counter, there could be measurement error resulting from the unobservable exact date of CDS introduction.[38] Such a measurement error may lead to an attenuation bias, although this may not always be the case. Our falsification test of shifting the year of CDS introduction suggests that measurement error would indeed attenuate our results. Third, we consider the BBB/BB boundary for the separation between investment and speculative grades for a regression discontinuity design. Although we do not present a detailed economic model for how this boundary, and its clientele effects among investors, affects CDS trading, we find that the effect of CDS trading is more pronounced for speculative grade firms.

Self-selection in our case hinges on the selection of a firm for CDS trading by creditors, not third parties or speculators. Since CDS can be traded by *any* pair of buyer and seller, and not just by current creditors, it should be emphasized that the extent of the problem is somewhat narrower in our setting. CDS trading by parties unrelated to the reference firms would weaken empty creditor concerns and makes it more unlikely to find significant CDS trading effects. We acknowledge that, absent a controlled experiment, no statistical technique can completely eliminate endogeneity concerns. We next consider additional economic variables based on the characteristics of CDS contracts to further corroborate our primary findings.

[38] We considered using two-stage least squares (2SLS) for this estimation, to address the errors-in-variables problem. Unfortunately, we face a technical challenge in implementing this estimation when the first stage of the 2SLS is a logit regression estimated with maximum likelihood, instead of least squares.

V. The "Empty Creditor" Mechanism

A unique advantage of our CDS transactions database is that it includes details about the notional amount of the CDS contracts outstanding and the contractual specifications of each contract. Such detailed information is useful to form other measures of CDS trading to uncover the precise mechanism by which CDS trading increases bankruptcy risk. As pointed out by Li and Prabhala (2007), the magnitude of the selection variable (i.e., CDS trading) introduces an independent source of variation and helps the identification of the treatment effect, while ameliorating the self-selection concern. Also, analyzing the specifics of CDS contracts adds more color to the discussion of the treatment effect of CDS introduction, which was treated as a binary variable in Section IV. In this section we present direct evidence for the empty creditor mechanism, using these additional variables. We also analyze how CDS trading may affect the size and composition of the creditor group, which may accentuate coordination failures during distress workouts and increase the probability of bankruptcy.

A. Effect of Outstanding CDS Exposures (Testing H2)

The driver of the empty creditor mechanism is the extent of over-insurance by lenders using CDS contracts. This over-insurance with CDS directly drives the lenders' incentive to force borrowers into bankruptcy by rejecting restructuring proposals (the channel through which the empty creditor mechanism works), and consequently, receiving payments from CDS sellers by precipitating a default event. The greater the degree of over-insurance by the empty creditor, the larger the benefit from rejecting restructuring and potentially causing bankruptcy.

Our data does not reveal the identity of individual CDS traders. Hence, we cannot directly observe the presence of empty creditors. The indirect, and imperfect, proxies we can construct is through the trading records in our data which can provide a measure of outstanding CDS contracts (similar to cumulative trading volume) in our sample. We measure the severity of the empty creditor problem – the level of over-insurance – in two ways. First, we use the *Number of Live CDS Contracts*, measured by the number of CDS contracts initiated, but yet to mature, as of the observation month.[39] This variable measures the breadth and consistency of CDS trading activity and should be positively correlated with the extent of empty creditor activity. Second, we calculate the ratio of the notional dollar amount of CDS contracts outstanding to the total dollar amount debt outstanding at the same time, *CDS Notional Outstanding/Total Debt*. We scale the CDS position by total debt to relate the dollar amount of CDS outstanding to creditors' demand. We conjecture that firms with

[39] Since CDS contracts are defined by their maturity, rather than their maturity date, new contracts are created potentially each trading day, depending on the level of trading activity.

greater relative proportions of CDS outstanding are more exposed to empty creditors.

We estimate the hazard model of bankruptcy filing with these two CDS exposure measures instead of the indicator variable *CDS Active*. Recall that *CDS Active* is a regime variable; hence, once a firm starts CDS trading, it cannot go back to being a non-CDS firm. However, the continuous measures of CDS exposure, *Number of Live CDS Contracts* and *CDS Notional Outstanding/Total Debt* are not static or permanent. The continuous measures of CDS exposure may go up or down, as and when new CDS contracts are created or old contracts mature. Therefore, these continuous measures are not as affected by the selection issue analyzed at length in Section IV. The maximum value for *CDS Notional Outstanding/Total Debt* is 4.14, strongly suggestive of over-insurance for such firms and the potential presence of "empty creditors". (The mean is 0.10 and median is 0.02.)

Table VII reports our estimation results with the two continuous variables. Specification 1 shows that bankruptcy risk increases with the number of live CDS contracts, evidenced by the significant positive coefficient estimate. (We also find that CDS trading is relatively more active, shortly before the bankruptcy filing.) Specification 2 of Table VII shows a significant positive coefficient of *CDS Notional Outstanding/Total Debt*. The marginal effect of an increase in this variable on the probability of bankruptcy is 0.01%, compared with the overall sample probability of 0.14%. This finding is direct evidence supporting the prediction of the empty creditor model. That is, a larger dollar amount of CDS contracts outstanding relative to firm's debt outstanding is associated with a higher probability of firm bankruptcy.

Comparing the pseudo-R^2s in Table VII and the tables discussed in Section IV suggests that an empirically preferable specification is to use the indicator variable *CDS Active*, rather than the continuous variables measuring CDS exposure to predict bankruptcy. (We do not put *CDS Active*, *Number of Live CDS Contracts* and *CDS Notional Outstanding/Total Debt* in the same regression due to multi-collinearity concerns.) On the one hand, it is likely that the aggregate continuous variables, *Number of Live CDS Contracts* and *CDS Notional Outstanding/Total Debt*, are noisy measures of the incentives of individual creditors, who may be "over-insured." After all, for the empty creditor mechanism to manifest itself, we do not need all creditors to become empty creditors; it may just take a few or even just one large empty creditor to holdout a restructuring proposal. On the other hand, the potential empty creditor problem is the main issue, and the concern about accentuating this problem is perhaps of secondary importance: Once some creditors have reasonably large stakes in CDS, their incentive to push the borrowers into bankruptcy will be strong enough, and additional positions may not accentuate the effects much.

B. *The Restructuring Clause in CDS Contracts (Testing H3)*

Empty creditors would clearly prefer firms to declare bankruptcy rather than have the firm's debt restructured *only if* bankruptcy, but not restructuring, triggers a credit event for CDS contracts and generates payments to CDS buyers. Empty creditors would not have this incentive to the same degree if their CDS contracts also cover restructuring as a credit event, as argued in our analysis in Section II. Thus, the strength of the empty creditor mechanism depends crucially on the definition of the restructuring clause in the CDS contracts.

In this subsection, we investigate the effect of differences in the contractual terms for the credit risk consequences of CDS trading. Appendix C describes the restructuring clauses in CDS contracts and their historical evolution. Essentially, there are four types of CDS contracts based on the definition of credit events: full restructuring (FR), modified restructuring (MR), modified-modified restructuring (MMR), and no restructuring (NR). For FR contracts, any type of restructuring qualifies as a trigger event, and any debt obligations with a maturity of up to 30 years can be delivered in that event. Under MR also, any restructuring is included as credit event; however, the 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. Under NR, restructuring is excluded as a credit event. Firms with more NR contracts are more subject to the empty creditor threat than other types of CDS. FR contracts would not be as strongly influenced by the empty creditor incentives, as illustrated by the analysis in Section II.[40]

Figure 2 plots the number of contracts in each year with different contractual terms observed in our CDS transactions records. The majority of firms in our sample have MR type of clauses in their CDS contracts. The other two types (FR and MMR) are negligible in our sample, which is quite representative of the market as whole. The figure shows that there were hardly any NR CDS contracts prior to 2002. Packer and Zhu (2005) show that, in their sample period, the MR contracts were just slightly more expensive than NR contracts. In such case, CDS buyers would probably buy MR contracts rather than NR contracts. The proportion of CDS contracts with NR specifications increased dramatically in recent years, especially in 2007. The median (mean) fraction of NR contracts out of all CDS contracts for a reference entity is 0.61 (0.55). We also find that there is wide variation across firms in the proportion of NR type of contracts.

[40] Another related issue is the type of settlement. Earlier, most CDS contracts were settled by physical delivery (CDS buyers deliver bonds to sellers to receive the face value), while more recently, cash settlement is the norm (CDS sellers pay the difference between the face value its recovery value directly to CDS buyers). Contracts settled by physical delivery may have an additional influence from the empty creditor problem. Unfortunately, we do not have data on the delivery option. Therefore, we do not consider the delivery specification as a variable in our analysis.

We account for the differences in contractual specifications in the estimations reported in Table VIII, which include variables measuring the type of CDS contracts. *No Restructuring CDS Proportion* is the fraction of CDS contracts with NR clauses out of all CDS contracts on the same reference entity. (This measure would be zero for firms without CDS.) Similarly, *Modified Restructuring CDS Proportion* is the fraction of CDS with MR clauses out of all contracts on the same reference entity. Since there are very few contracts with the FR or MMR specification in our sample, we focus only on the MR and NR types. We run separate regressions with the two CDS-type variables (reported in Specification 1 and Specification 2), and also a combined one with both of them (Specification 3). The results in Table VIII show that only for NR contracts do we find a significant positive relationship of CDS trading with bankruptcy risk, while the coefficient of the MR type is not statistically significant. The marginal effect of an increase in the *No Restructuring CDS Proportion* variable in the combined regression on the probability of bankruptcy is 0.22% in Specification 3, which is large in comparison to the overall sample default probability of 0.14%. We include year dummies in our regressions to control for potential time series patterns in the composition of CDS contract types.[41]

The results in this subsection strongly support the empty creditor model prediction. We find that Table VIII has higher pseudo-R^2 than Table VII, suggesting that the specification with restructuring information relating to the contracts (also continuous measures) fits the data better. Therefore, the effect of *CDS Active* seems to be driven by the CDS contracts with NR clauses. This finding will likely be relevant to many more reference names in the future as more and more corporate CDS contracts use NR as the credit event specification (e.g., all CDS index constituents of the North America investment grade index CDX.NA.IG).

C. Change in the Number of Lenders (Testing H4)

Another unique, albeit implicit, prediction of the empty creditor theory is that firms will have a more diversified lender base, following CDS trading. This is related to strategic actions by creditors and a potential coordination failure. Lead banks probably would not want to appear to drive their borrowers into bankruptcy, as the long-run reputational damage may overweigh the short-run gains from empty creditor trading profits. However, other lenders, who are not similarly constrained may take advantage of CDS trading more intensively. Therefore, CDS trading may affect the size and composition of the loan syndicate to a firm.

We investigate the impact of CDS introduction on the creditor relationships of a firm. The

[41] We also segmented the sample by time, to test for the secular evolution of contract terms. We expect that the restructuring concern should be less material in influencing credit risk prior to 2000, when restructuring was normally included as credit event in CDS contracts. In results not reported here, we find that the CDS trading effect is indeed significant only in more recent years.

overall creditor relationship is represented in our analysis by the bank relationships available from Dealscan LPC data. For each firm in a given month, we examine the prior five-year period for any syndicated loan facilities for this firm. Summing over all such active facilities, we compute the number of unique banks. $\triangle$*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 the inception of CDS trading. First, from 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 relative to matching firms using CDS trading prediction Model 4 in Table III. Second, we regress $\triangle$*Number of Banks* from the year before CDS trading to two years after CDS trading on a set of firm characteristics and the *CDS Active* variable for CDS firms only. These event study results are reported in Panel A of Table IX. We find that CDS trading significantly increases the number of banking relationships that a firm has. On average, firms have 2.4 more lenders two years after CDS introduction, controlling for other factors which may affect the number of lenders such as firm size and leverage.

The relationship between the number of lenders and bankruptcy risk has been previously documented by, among others, Gilson, John, and Lang (1990) and Brunner and Krahnen (2008). We present similar evidence from our sample, also 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 probability of bankruptcy. The results indicate that a firm's bankruptcy risk increases with the number of banking relationships, even after controlling for direct impact of CDS trading. Therefore, the results in this table support Hypothesis 4 that CDS trading increases the number of creditors which affects bankruptcy risk.

D. *Discussion of Alternative Mechanisms*

Our primary focus in the empirical analysis is on the "empty creditor" mechanism; i.e., creditors insured with CDS protection will be tougher in the renegotiation of existing debt obligations, and restructuring would be less successful.[42] We note two caveats. First, not all creditors will become empty creditors. Second, not all empty creditors can successfully force the borrower into bankruptcy. There could be other alternative channels by which CDS trading may affect credit risk.

Creditors whose exposures are protected by CDS may have diminished incentives to expend resources to monitor the performance of the firm; this, in turn, may lead to lower information

[42] The Trust Indenture Act of 1939 prohibits public debt restructuring without unanimous consent. Hence, public debt restructuring usually takes the form of exchange offers. As a consequence, there could be a potential holdout problem, since some bondholders may not participate in the offer. In this context, James (1996) shows that bank debt forgiveness is important for the success of public debt exchange offers.

quality, higher risk-taking, and higher bankruptcy incidence.[43] There are several obvious differences between the "anti-restructuring" channel and the "monitoring reduction" channel. First, the increase in bankruptcy risk through the "anti-restructuring" channel is positively related to the amount of CDS exposure, but not necessarily so for the "monitoring reduction" channel. In the former case, the greater the amount of CDS outstanding, the greater is the potential for the standoff regarding restructuring, whereas in the latter case, zero monitoring is the worst possible scenario and lenders cannot do any damage below that level. Second, the "anti-restructuring' effect of CDS trading on bankruptcy risk is expected to be more severe for CDS contracts that exclude restructuring as credit event. This prediction is unique to the restructuring channel and has been verified in the prior sub-section.

Another potential channel of CDS trading effect is via the feedback of CDS pricing. On the one hand, if CDS spreads are too high relative to the corresponding bond yield spreads, this may feed back to the firm's bond market through arbitrage between the two markets, making it more costly and difficult for the firm to refinance its obligations. This may cause the operating environment to worsen, leading to a deterioration of the firm's credit quality.[44] High CDS spreads also increase the cost of buying CDS protection, and hence, reduce the incentive of creditors to become empty creditors. If, on the other hand, CDS spreads are underpriced or too low, then informed traders have a greater incentive to buy CDS contracts and expect to make profits from the subsequent increase in CDS spreads. In untabulated results, we find that the effect of CDS trading on bankruptcy risk is significant for both firms with likely overpriced and underpriced CDS (as predicted by the basis between the CDS and bond yield spreads). Moreover, there is no statistically significant difference between these two groups.

In summary, we do not find supportive evidence for the monitoring reduction and CDS feedback channels for the impact of CDS trading on credit risk. In contrast, we find unambiguous support for the anti-restructuring channel of the empty creditor mechanism.

VI. Concluding Remarks

We find strong evidence that the bankruptcy risk of reference firms increases after CDS trading using a comprehensive data set of North American corporate CDS introductions over the period of 1997-2009. The marginal effect of CDS trading on the probability of bankruptcy is 0.33% in our baseline estimation, which is a substantial increase from the average default probability of 0.14% before CDS trading. Our conclusion is robust to controlling for the endo-

[43]See, for example, Ashcraft and Santos (2009) and Parlour and Plantin (2008), for this line of argument.
[44]See, "A Market Backfires and Investors Pay," by Henry Sender, *Wall Street Journal*, December 5, 2002.

geneity in CDS trading using difference-in-difference analysis, propensity score matching, and treatment model with instrument variables. Not only does trading in CDS on a firm increase the credit risk of the firm, but the effects are accentuated by the size of the CDS contracts outstanding, and when more contracts exclude restructuring as a credit event. Our results support the "empty creditor" hypothesis proposed by Hu and Black (2008) and modeled by Bolton and Oehmke (2011). That is, lenders holding CDS protection can push borrowers into bankruptcy in order to trigger CDS payments (outweighing potential counter force, if any, from CDS sellers), even though restructuring may be a better choice for the firm from the conventional lenders' perspective. To our knowledge, our study is the first comprehensive empirical work with a complete data set, to formally examine the empty creditor concern, which has attracted a lot of attention among academics, practitioners and regulators.

Our research uncovers one real consequence of CDS trading and contributes to the ongoing debate on this important derivative market. We emphasize that, although firms become more vulnerable to bankruptcy once CDS start trading on them according to our findings, this does *not* imply that CDS trading necessarily reduces social welfare. Indeed, CDS can increase debt capacity, many previously unqualified projects may get funded due to the possibility of credit risk mitigation afforded by the CDS. Therefore, the increase in bankruptcy risk could be offset by an increased borrower base, which increases the overall supply of credit in the economy. Future work may examine the tradeoff between the increased debt capacity and bankruptcy vulnerability caused by CDS, shedding light on the overall impact of CDS trading on allocative efficiency.

This study has implications for investors, corporate executives, and regulators. Investors can incorporate the impact of CDS trading on the likelihood of bankruptcy in their pricing of corporate debt. Creditors and corporates should take the incentives of CDS protected "empty creditors" into consideration when tendering for a restructuring exchange offer. Corporate executives, as well as investment bankers, should factor the CDS market into their decision making regarding capital structure and leverage choices. Consequently, CDS trading may affect managerial risk-taking, which is a conjecture worth investigating in the future. Financial regulators and policy makers can take the increase in credit risk following CDS trading into account in their regulatory actions. In particular, banking regulators need to incorporate this effect in their risk weighting formulae, while securities regulators may require further disclosures of CDS positions, so that investors are made more aware of the extent of the empty creditor problem for individual firms.

Appendices

A Bankrupt CDS Trading Firms

Company Name	CDS Date	Bankruptcy Date	Summary	Potential Empty Creditor
ABITIBI CONSOLIDATED	200005	200904	Newsprint company; Canadian units of AbitibiBowater Inc; Filed for bankruptcy protection in the U.S. after lenders refused to accept a proposed debt restructuring.	Yes
ABITIBIBOWATER	200104	200904	North Americas biggest newsprint maker; Faced with cash flow problems; Filed for bankruptcy protection after lenders refused to accept a proposed debt restructuring.	Yes
ADELPHIA COMMUN	200102	200206	The fifth largest cable company in the US; Filed for bankruptcy after financial fraud scandal.	
BEARINGPOINT INC	200504	200902	Management and technology consulting firm; Filed for bankruptcy under a heavy debt load to carry out a prearranged restructuring plan.	
BETHLEHEM STEEL	199909	200110	Steel producer; Cost-cutting effort; Filed for bankruptcy due to the competition from cheap imports and a slowing U.S. economy.	
CALPINE CORP	200105	200512	Power company; Took steps to reduce debt.	
CHARTER COMMUNICATIONS	200003	200903	Cable operator; Filed for pre-arranged bankruptcy with the support of major bondholders.	
CHEMTURA CORPORATION	200102	200903	Specialty chemicals and polymer maker; Filed for bankruptcy due to the reduced liquidity position caused by the impact of the global economic recession on their customers and the industries, and an anticipated expiration of a bank waiver.	
CIT GROUP INC	199909	200911	Commercial lender; Funding dried up; Debt holders rejected the exchange offer, with 90 percent of holders who voted opting for the company's prepackaged bankruptcy plan; Bank of America was the largest unsecured claim holders.	Yes
COMDISCO HOLDING	199912	200107	Technology services; The technology stock crash; Debt ratings were downgraded below investment grade; Lost access to the commercial paper market.	
CONSECO INC	200002	200212	Insurance, investment and lending company; Unsustainable insurance acquisition strategy; Epic stock-slide; Filed for bankruptcy after reaching a tentative pact with major creditors.	
CONSOL ENERGY INC	200502	200707	Energy company.	
DANA HOLDING CORP	199909	200603	Auto parts maker; Filed for bankruptcy after struggling with declining revenues amid a troubled U.S. auto market.	

(Continued)

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Company Name	CDS Date	Bankruptcy Date	Summary	Potential Empty Creditor
DELPHI CORP	200001	200510	Auto parts maker and one of General Motors' largest suppliers; Auto industry decline; Had sought deals with both the UAW and former parent GM to stave off a bankruptcy filing.	
DELTA AIR LINES INC	199803	200509	Filed for bankruptcy due to a spike in jet fuel costs.	
DURA AUTOMOTIVE SYS	200507	200610	Designer and manufacturer of driver control systems; Financial and industry pressures.	
ENRON CORP	199802	200112	Energy company; Mismanagement, poor business and accounting procedures.	
EQUISTAR CHEMICALS LP	200006	200901	Wholly owned subsidiary of LyondellBasell Industries; Filed for Chapter 11 bankruptcy protection in January 2009, after failing to reach a deal with its creditors.	Yes
EXIDE TECHNOLOGIES	200002	200204	Battery maker; Accumulated more than $2.5 billion in debt, much of it from acquisitions.	
EXODUS COMMUNICATIONS	200102	200109	Internet service provider; Filed for bankruptcy during the bursting of the dot-com bubble.	
FINOVA GROUP INC	200003	200103	Commercial finance company; Struggled to overcome the liquidity squeeze; Bank and bondholder creditors objected to the investment of up to $350 million in new equity by the Leucadia National Corp.	
FLEMING COMPANIES INC	200201	200304	Supermarket supplier; Investigation by the SEC; Lawsuit from its shareholders over the validity of its public statements; Ended its relationship with its largest customer, Kmart; Stock price dropped to less than one dollar per share etc.	
GENERAL GROWTH PPTYS INC	200805	200904	Property investor; Filed for bankruptcy after failing to reach a deal with its creditors.	Yes
GM	200102	200906	Filed for bankruptcy after failing to reach a deal with its creditors.	Yes
GLOBAL CROSSING LTD	200002	200201	Telecommunications company; Slower-than-forecasted growth in demand; Obtained a waiver from its leading lenders.	
GREAT LAKES CHEMICAL	200005	200903	Chemical company; Part of Chemtura Corp; Hit by falling demand; Filed for bankruptcy protection after it failed to sell enough assets to raise cash for its debt obligations.	
JPM CO	199805	200203	Manufacturer of cable assemblies; Before bankruptcy, there was a substantial demands on JPM's limited cash flow.	
LAIDLAW INTERNATIONAL	199912	200106	Bus services; Before the bankruptcy filing, faced heavy investment losses and struggled under a $3.5 billion of debt.	
LEAR CORP	200202	200907	Seat maker; Failed to make bond payment; Had a 30-day grace period to meet the payment; Two years before the bankruptcy, shareholders rejected buyout offer from billionaire investor Carl Icahn.	
LEHMAN BROTHERS	199707	200809	Huge losses in the mortgage market and a loss of investor confidence.	
LYONDELL CHEMICAL	200008	200901	US subsidiary of LyondellBasell Industries; Filed for Chapter 11 bankruptcy protection after failing to reach a deal with its creditors.	Yes
MILLENNIUM CHEMICALS	200201	200901	Acquired by Lyondell Chemical in November 2004, with which it had a joint venture Equistar Chemicals in December 1997; Lyondell Chemical filed for Chapter 11 bankruptcy protection in January 2009 after failing to reach a deal with its creditors.	Yes

(Continued)

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Company Name	CDS Date	Bankruptcy Date	Summary	Potential Empty Creditor
MIRANT CORP	200110	200307	Energy company; Unable to work out a deal with its creditors.	Yes
NORTEL NETWORKS	200102	200901	Losses and financing dried up; Bankruptcy filing would trigger about $1.5 billion of derivatives protecting against a default on the bond; Banks, hedge funds, insurers and other investors had bought or sold CDS protection.	Yes
NORTHWEST AIRLINES	199709	200509	Hit by a spike in jet fuel prices; unable to win wage concessions from its unions.	
NORTHWESTERN	200212	200309	Electricity and natural gas provider; Filed for bankruptcy after failing to refinance or sell stock.	
NRG ENERGY INC	200110	200305	Leading power producer; Filed for bankruptcy under a prearranged settlement with unsecured creditors; Prior to bankruptcy, NRG was hit by the declining power prices and the collapse of Enron; Bonds were downgraded to junk.	
OWENS CORNING	199809	200010	U.S. insulation maker; Filed for bankrutpcy after being swamped by asbestos lawsuits.	
QUEBECOR WORLD	200203	200801	Commercial and industrial printing; Rescue financing proposal from Quebecor Inc. and Tricap Partners was rejected by Quebecor World's lenders.	
READERS DIGEST ASSN	200502	200908	Publisher of the magazine; Decreased consumer and advertising spending; Highly leveraged debt structure; Withdrawal of foreign credit lines, and pressure from trade creditors hurt the company's liquidity.	
ROUSE CO	200401	200904	Subsidiary of General Growth; General Growth filed for Chapter 11 bankruptcy protection after failing to reach a deal with its creditors.	Yes
KMART CORP	199709	200201	Retailer; Prior to bankruptcy filing, there were weeks of speculation about the company's financial health; Filed for bankruptcy after Fleming Companies Inc., Kmart's biggest food distributor, halted shipments to Kmart after the retailer failed to make its regular weekly payments; Fleming said Kmart's filing would have no impact on its business.	
SIX FLAGS INC	200508	200906	American theme-park operator; Filed for bankruptcy after failing to reach a deal with its creditors.	Yes
SMURFIT-STONE	200210	200901	Paper-based packaging manufacturer; Decline in demand, drop in price and recent changes in the capital markets reduced the company's prospects for refinancing its debt outside of bankruptcy; Filed critical vendor motion in its bankruptcy.	
SOLUTIA INC	200109	200312	Chemical business; Significant effort to come to an out-of-court resolution with Monsanto Corporation regarding the legacy liabilities; However, these negotiations had not been successful.	
SPECTRASITE INC	200103	200211	Cell phone tower operators; Filed for bankruptcy protection after announcing a prepackaged reorganization plan.	
SPECTRUM BRANDS	200604	200902	Battery Maker; Filed for bankruptcy with a pre-negotiated bankruptcy plan; Most of its bondholders agreed to trim debt.	
STATION CASINOS	200404	200907	Filed for a standard Chapter 11 bankruptcy reorganization after Station was unable to reach agreement with creditors on a prepackaged bankruptcy deal.	
TELEGLOBE INC	200010	200205	Hit by telecom meltdown; Filed for bankruptcy a month after its parent company, Canadian telephone giant BCE Inc., withdrew financial backing.	

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Company Name	CDS Date	Bankruptcy Date	Summary	Potential Empty Creditor
TRIBUNE CO	199908	200812	Media conglomerate; Taken private a year before bankruptcy; Before filing, Tribune worked with its creditors to renegotiate its debt; Revenue decline, terrible economy and banks unwilling to negotiate a deal pushed the firm into bankruptcy.	
UAL CORP	199801	200212	Parent company of United Airlines; Tried hard to avoid bankruptcy; Sought wage cuts from employees and applied for a U.S. government loan guarantee; But the loan application was rejected.	
USG CORP	200011	200106	Manufacturer and distributor of building materials; USG cited the growing costs of asbestos litigation as the main reason for the bankruptcy.	
VISTEON CORP	200009	200905	Global automotive supplier; Aggressive restructuring before bankruptcy; But still suffered considerable losses due to the global recession.	
WASHINGTON MUTUAL INC	200201	200809	Savings bank holding company and the former owner of Washington Mutual Bank; Subprime losses.	
WILTEL COMMUNICATIONS	200010	200204	Optical-network provider; Telecom sector downturn; Prior to the bankruptcy filing, CFO announced any reorganization plan would not include bankruptcy.	
WINN-DIXIE STORES INC	200402	200502	American supermarket chain; Widening losses and deteriorated liquidity position.	
WINSTAR COMMUNICATIONS	200004	200104	Telecommunications company; Vinstar blamed Lucent Technologies for violating a vendor financing agreement and forcing the filing.	
WORLDCOM INC-MCI	199801	200207	Long-distance and data services company; Prior the filing, Worldcom was hoping to get $3 billion from lenders such as J.P. Morgan Chase & Co., Citigroup Inc., Bank of America Corp. to avoid bankruptcy; Rapid erosion of its profits and an accounting scandal were cited as the reason for bankruptcy.	
XO HOLDINGS INC	200004	200206	Broadband provider; Prior filing, the company was seeking rescue by investor who hold $1 billion in XO debt.	
YOUNG BROADCASTING	200212	200902	Massive debt load incurred from its purchase and ownership of KRON.	

B The Estimation of Distance-to-Default

The Merton (1974) model provides a framework to measure the Distance-to-Default (Merton DD), a measure of a firm's default probability at any given point in time. Under the Merton framework, the firm is assumed to default when its asset value is less than the face value of debt at the forecasting horizon. Based on Merton (1974), the model assumes that the firm's asset value follows a geometric Brownian motion:

$$dV = \mu V dt + \sigma_V V dW, \tag{2}$$

where V is the asset value of the firm, μ is the expected continuously compounded return on asset, σ_V is the asset value volatility and dW is a standard Wiener process. Then, the equity value of the firm is a call option on the firm's assets, with a strike price equal to the face value of the firm's debt:

$$E = VN(d_1) - e^{-rT} FN(d_2), \tag{3}$$

$$d_1 = \frac{ln(V/F) + (r + 0.5\sigma_V^2)\sqrt{T}}{\sigma_V T}, d_2 = d_1 - \sigma_V \sqrt{T} \tag{4}$$

where E is the market value of the firm's equity, F is the face value of debt, r is the risk-free rate, $N(.)$ is the cumulative standard normal distribution. By Ito's lemma, the volatilities of the asset value and the equity are related by:

$$\sigma_E = (\frac{V}{E})N(d_1)\sigma_V \tag{5}$$

Based on this framework, Merton DD utilizes equations above to estimate the unobservable value and volatility of a firm's assets, i.e., V and σ_V respectively, using the observed E and the estimated σ_E. Following an iterative procedure along the lines of Vassalou and Xing (2004) and Bharath and Shumway (2008), the Merton DD can be calculated as

$$DD = \frac{ln(V/F) + (\mu - 0.5\sigma_V^2)T}{\sigma_V \sqrt{T}} \tag{6}$$

Hence, the Expected Default Frequency (EDF), or the implied default probability, is calculated as

$$EDF = N(-(\frac{ln(V/F) + (\mu - 0.5\sigma_V^2)T}{\sigma_V \sqrt{T}})) = N(-DD). \tag{7}$$

This approach to calculating DD and EDF is parsimonious, but does not consider several nuances, such as the impact of jumps in the asset value, fat tails, the liquidity of the assets, etc. However, Bharath and Shumway (2008) show that this simple approach performs well against the popular Moody's KMV model's EDF, which is computed with a proprietary database and methodology. Moody's KMV has a special treatment for financial firms, due to their unusual use of leverage, and the distinctive characteristics of the liabilities they employ, particularly government guarantees, implicit or explicit. Our calculations adjust the leverage for financial firms, in the spirit of our understanding of Moody's KMV proprietary methodology. Specifically, for financial firms, we set the leverage to a level of 0.7, and the risk premium to 6%.[45] Moreover, as we find in our empirical work, the regression results are not driven by financial firms: we obtain similar results when we control for financial firms, using a dummy variable or drop financial firms entirely from the sample.

C 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 payment 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 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 the 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 for calling 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* obligations with a maturity up to 30 years can be delivered. This creates a "cheapest to deliver" option for protection buyers who would 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 22 September 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

[45]We thank Shisheng Qu for helpful advice on implementing this approach.

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 credit event. However, the 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 deliverable obligations were relaxed to those with maturities within 60 months of the CDS contract's maturity for restructured debt, and 30 months for other obligations. Thus, following 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 the failure to pay. To further standardize the CDS market, since April 2009, ISDA does not include 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 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.

References

Acharya, Viral V., and Timothy C. Johnson, 2007, Insider trading in credit derivatives, *Journal of Financial Economics* 84, 110-141.

Altman, Edward I., 1968, Financial ratios, discriminant analysis and the prediction of corporate bankruptcy, *Journal of Finance* 23, 589-609.

Altman, Edward I., and Brenda J. Kuehne, 2012, Defaults and returns in the high-yield bond and distressed debt market: The year 2011 in review and outlook, Working paper, New York University.

Allen, Franklin, and Elena Carletti, 2006, Credit risk transfer and contagion, *Journal of Monetary Economics* 53, 89-111.

Ashcraft, Adam B., and João A.C. Santos, 2009, Has the CDS market lowered the cost of corporate debt?, *Journal of Monetary Economics* 56, 514-523.

Arping, Stefan, 2004, Credit protection and lending relationships, Working paper, University of Amsterdam.

Bedendo, Mascia, Lara Cathcart, and Lina El-Jahel, 2012, In- and out-of-court debt restructuring in the presence of credit default swaps, Working paper, Universita's Bocconi and Empirical College Business School.

Beyhaghi, Mehdi, and Nadia Massoud, 2012, Why and how do banks lay off credit risk? The choice between loan sales and credit default swaps, Working paper, York University.

Bharath, Sreedhar T., and Tyler Shumway, 2008, Forecasting default with the Merton distance to default model, *Review of Financial Studies* 21, 1339-1369.

Bharath, Sreedhar T., Venky Panchapegesan, and Ingrid M. Werner, 2010, The changing nature of chapter 11, Working paper, Arizona State University, The Goldman Sachs Group, Inc. and The Ohio State University.

Blanco, Roberto, Simon Brennan, and Ian W. Marsh, 2005, An empirical analysis of the dynamic relationship between investment grade bonds and credit default swaps, *Journal of Finance* 60, 2255-2281.

Boehmer, Ekkehart, Sudheer Chava, and Heather Tookes, 2012, Capital structure, derivatives and equity market quality, Working paper, EDHEC Business School, Georgia Institute of Technology and Yale University.

Bolton, Patrick, and Martin Oehmke, 2011, Credit default swaps and the empty creditor problem, *Review of Financial Studies* 24, 2617-2655.

Brunner, Antje, and Jan Pieter Krahnen, 2008, Multiple lenders and corporate distress: Evidence on debt restucturing, *Review of Economic Studies* 75, 415-442.

Campbell, John Y., Jens Hilscher, and Jan Szilagyi, 2008, In search of distress risk, *Journal of Finance* 63, 2899-2939.

Campello, Murillo, and Rafael A. Matta, 2012, Credit default swaps, firm financing and the economy, Working paper, Cornell University and University of Illinois.

Chava, Sudheer, and Robert A. Jarrow, 2004, Bankruptcy prediction with industry effects, *Review of Finance* 8, 537-569.

Chava, Sudheer, and Michael Roberts, 2008, How does financing impact investment? The role of debt covenants, *Journal of Finance* 63, 2085-2121.

Che, Yeon-Koo, and Rajiv Sethi, 2012, Credit derivatives and the cost of capital, Working paper, Columbia University.

Damodaran, Aswath, and Marti G. Subrahmanyam, 1992, The effects of derivative securities on the markets for the underlying assets in the United States: A survey, *Financial Markets, Institutions and Instruments* 1, 1-22.

Danis, Andras, 2012, Do empty creditors matter? Evidence from distressed exchange offers, Working paper, Vienna Graduate School of Finance.

Das, Sanjiv R., Darrell Duffie, Nikunj Kapadia, and Leandro Saita, 2007, Common failings: how corporate defaults are correlated, *Journal of Finance* 62, 93-117.

Das, Sanjiv, Madhu Kalimipalli, and Subhankar Nayak, 2011, Did CDS trading improve the market for corporate bonds, Working paper, Santa Clara University and Wilfrid Laurier University.

Duan, Jin-chuan, Jie Sun, and Tao Wang, 2012, Multiperiod corporate default prediction – A forward intensity approach, Working paper, National University of Singapore.

Duffie, Darrell, 2007, Innovations in credit risk transfer: Implications for financial stability, Working paper, Stanford University.

Duffie, Darrell, Andreas Eckner, Guillaume Horel, and Leandro Saita, 2009, Frailty correlated default, *Journal of Finance* 64, 2089-2123.

Duffie, Darrell, Leandro Saita, and Ke Wang, 2007, Multi-period corporate default prediction with stochastic covariates, *Journal of Financial Economics* 83, 635-665.

Duffee, Gregory R., and Chunsheng Zhou, 2001, Credit derivatives in banking: Useful tools for managing risk?, *Journal of Monetary Economics* 48, 25-54.

Gilson, Stuart C., Kose John, and Larry H. P. Lang, 1990, Troubled debt restructurings: An empirical study of private reorganization of firms in default, *Journal of Financial Economics* 27, 315-354.

Gopalan, Radhakrishnan, Vikram Nanda, and Vijay Yerramilli, 2011, Does poor performance damage the reputation of financial intermediaries? Evidence from the loan syndication market, *Journal of Finance* 66, 2083-2120.

Griffin, John, and Dragon Yongjun Tang, 2012, Did subjectivity play a role in CDO credit ratings?, *Journal of Finance* 67, 1293-1328.

Hale, Galina, and João A.C. Santos, 2009, Do banks price their informational monopoly?, *Journal of Financial Economics* 93, 185-206.

Heckman, James, 1979, Sample selection bias as a specification error, *Econometrica* 47, 153-161.

Hirtle, Beverly, 2009, Credit derivatives and bank credit supply, *Journal of Financial Intermediation* 18, 125-150.

Hortaçsu, Ali, Gregor Matvos, Chad Syverson, and Sriram Venkataraman, 2011, Are consumers affected by durable goods makers' financial distress? the case of auto manufacturers, Working paper, University of Chicago and Emory University.

Hu, Henry T.C., and Bernard S. Black, 2008, Debt, equity, and hybrid decoupling: Governance and systemic risk implications, *European Financial Management* 14, 663-709.

James, Christopher, 1996, Bank debt restructurings and the composition of exchange offers in financial distress, *Journal of Finance* 51, 711-727.

Jarrow, Robert A., 2011, The Economics of Credit Default Swaps, *Annual Review of Financial Economics* 3, 235-257.

Jorion, Philippe, and Gaiyan Zhang, 2009, Credit contagion from counterparty risk, *Journal of Finance* 64, 2053-2087.

Lando, David, and Mads Stenbo Nielsen, 2010, Correlation in corporate defaults: Contagion or conditional independence?, *Journal of Financial Intermediation* 19, 355-372.

Li, Kai, and Nagpurnanand R. Prabhala, 2007, Self-selection models in corporate finance, in B. Espen Eckbo ed., *Handbook of Corporate Finance: Empirical Corporate Finance I*, Elsevier, Chapter 2, 37-86.

Longstaff, Francis A., Kay Giesecke, Stephen Schaefer, and Ilya Strebulaev, 2011, Corporate bond default risk: A 150-year perspective, *Journal of Financial Economics* 102, 233-250.

Longstaff, Francis A., Sanjay Mithal, and Eric Neis, 2005, Corporate yield spreads: Default risk or liquidity? New evidence from the credit default swap market, *Journal of Finance* 60, 2213-2253.

Merton, Robert C., 1974, On the pricing of corporate debt: the risk structure of interest rates, *Journal of Finance* 29, 449-470.

Minton, Bernadette A., Rene M. Stulz, and Rohan Williamson, 2009, How much do banks use credit derivatives to hedge loans?, *Journal of Financial Services Research* 35, 1-31.

Morrison, Alan D., 2005, Credit derivatives, disintermediation, and investment decisions, *Journal of Business* 78, 621-47.

Narayanan, Rajesh, Cihan Uzmanoglu, 2012, Empty creditors and distressed debt restructuring, Working paper, Louisiana State University.

Nashikkar, Amrut, Marti G. Subrahmanyam, and Sriketan Mahanti, 2011, Liquidity and arbitrage in the market for credit risk, *Journal of Financial and Quantitative Analysis* 46, 627-656.

Norden, Lars, Consuelo Silva Buston, and Wolf Wagner, 2011, Banks' use of credit derivatives and the pricing of loans: What is the channel and does it persist under adverse economic conditions?, Working paper, Erasmus University Rotterdam and Tilburg University.

Packer, Frank, and Haibin Zhu, 2005, Contractual terms and CDS pricing, *BIS Quarterly Review*, 89-100.

Parlour, Christine A., and Guillaume Plantin, 2008, Loan sales and relationship banking, *Journal of Finance* 63, 1291-314.

Parlour, Christine A., and Andrew Winton, 2012, Laying off credit risk: Loan sales versus credit default swaps, *Journal of Financial Economics*, forthcoming.

Peristiani, Stavros, and Vanessa Savino, 2011, Are credit default swaps associated with higher corporate defaults?, Working paper, Federal Reserve Bank of New York.

Roberts, Michael R., and Toni M. Whited, 2012, Endogeneity in empirical corporate finance, in George Constantinides, Milton Harris, and Rene Stulz, eds., *Handbook of the Economics of Finance 2*, Elsevier, forthcoming.

Saretto, Alessio, and Heather Tookes, 2011, Corporate leverage, debt maturity and credit default swaps: The role of credit supply, Working paper, University of Texas at Austin and Yale University.

Shumway, Tyler, 2001, Forecasting bankruptcy more accurately: A simple hazard model, *Journal of Business* 74, 101-124.

Sorescu, Sorin M., 2000, The effect of options on stock prices: 1973-1995, *Journal of Finance* 55, 487-514.

Standard & Poor's, 2012, 2011 Annual U.S. corporate default study and rating transitions.

Stanton, Richard, and Nancy Wallace, 2011, The bear's lair: Index credit default swaps and the subprime mortgage crisis, *Review of Financial Studies* 24, 3250-3280.

Stulz, Rene M., 2010, Credit default swaps and the credit crisis, *Journal of Economic Perspectives* 24, 73-92.

Tett, Gillian, 2009, *Fool's Gold: How the Bold Dream of a Small Tribe at J.P. Morgan Was Corrupted by Wall Street Greed and Unleashed a Catastrophe*, The Free Press, New York, NY.

Thompson, James R., 2007, Credit risk transfer: To sell or to insure, Working Paper, University of Waterloo.

Vassalou, Maria, and Yuhang Xing, 2004, Default risk in equity returns, *Journal of Finance* 59, 831-868.

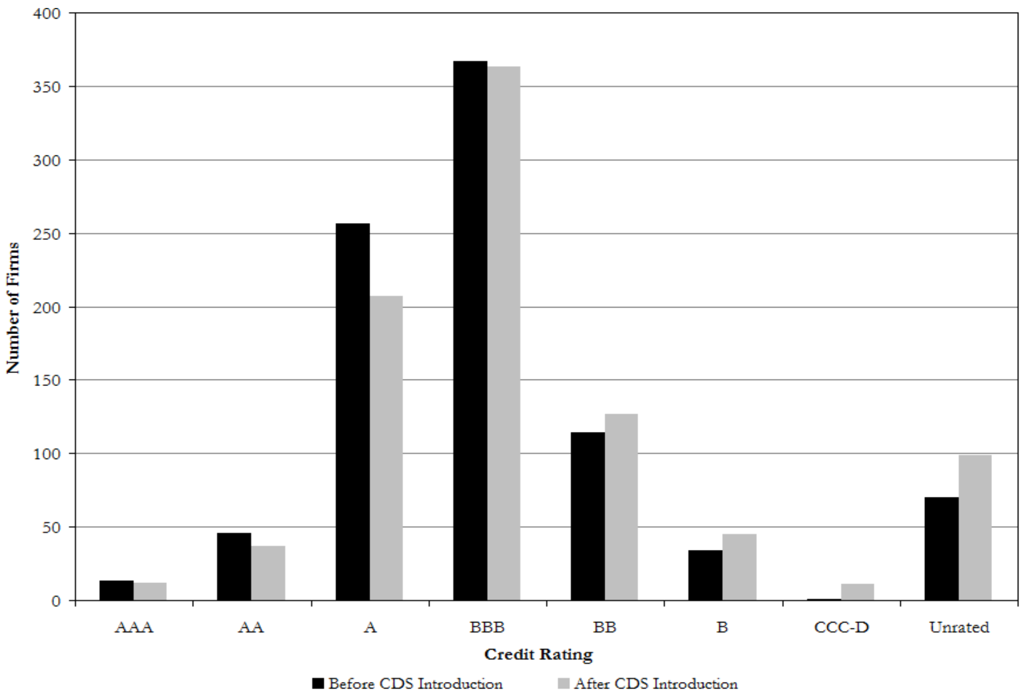

Figure 1: Rating Distribution Around the Introduction of Credit Default Swaps. This figure plots the credit rating distributions for firms with credit default swaps (CDS) before the inception of CDS trading and two years after the inception of CDS trading. The credit ratings are from S&P Credit Ratings.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

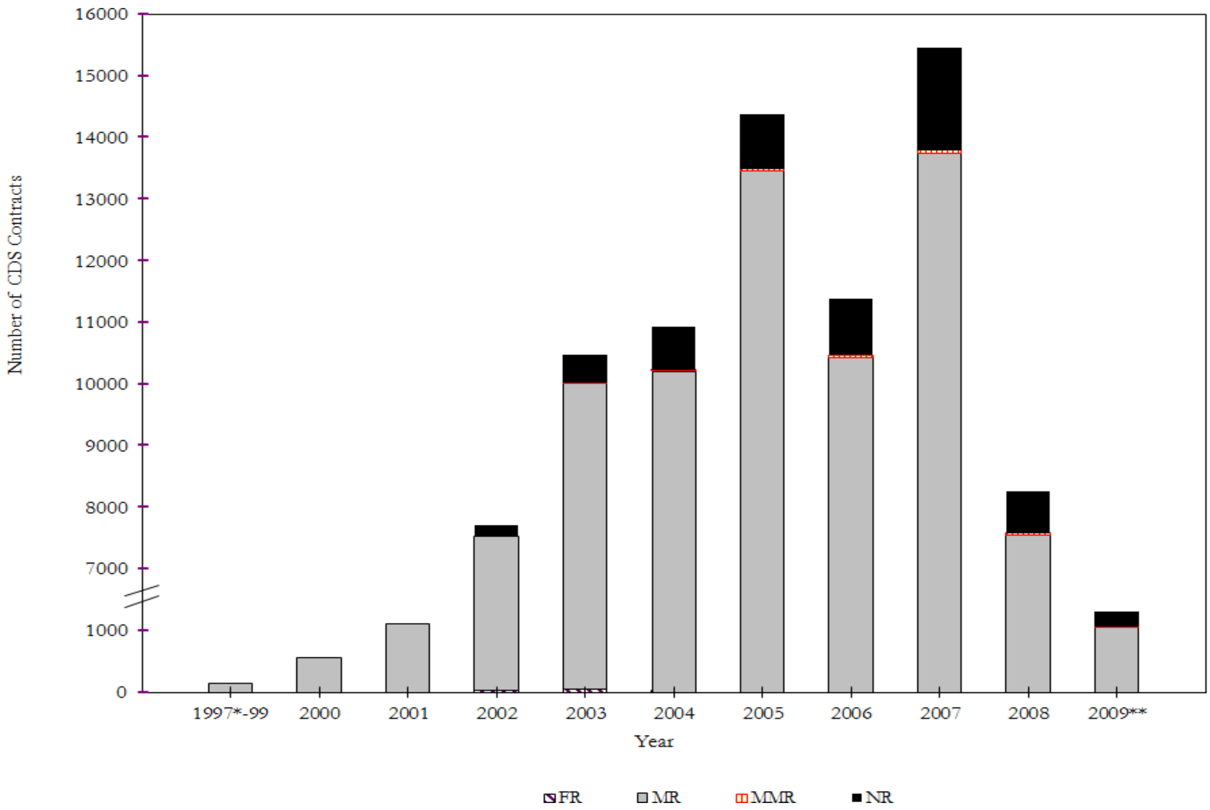

Figure 2: Credit Default Swaps Restructuring Clauses by Year. This figure plots the distribution of credit default swaps (CDS) restructuring clauses, by year, in our sample between 1997 and 2009. The CDS data are from CreditTrade and GFI Group. There are four types of contract terms related to restructuring: full restructuring (FR), modified restructuring (MR), modified-modified restructuring (MMR), and no restructuring (NR). For firms with NR as 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 from the Compustat, which includes all companies in the database during 1997-2009. The CDS data are from CreditTrade and GFI Group. There are 901 firms in our sample that have CDS traded at some point during the June 1997-April 2009 sample period. The bankruptcy data are from New Generation Research's "Public and Major Company Database", the UCLA-LoPucki Bankruptcy Research Database (BRD), the Altman-NYU Salomon Center Bankruptcy List, 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. The fifth column presents firms with active CDS trading during each year. The last two columns report the number of CDS firms filed for bankruptcy and the number of non-CDS firms filed for bankruptcy respectively. († 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

Table II
Impact of Credit Default Swaps Trading on Credit Quality

This table presents the estimates of the probability of credit downgrades and bankruptcy using a logistic model. Panel A shows the estimates in a sample including firms with credit default swaps (CDS) and all non-CDS firms. Panel B presents the estimates in a sample including firms with CDS and non-CDS distance-to-default (DD) matched firms. The matched firms are selected as the one with the closest DD. DD is calculated from the Merton (1974) model described in Appendix B. *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 credit downgrades or bankruptcy, we include credit default swaps 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 which 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 credit downgrades or bankruptcy after the inception of CDS trading. The sample period is from 1997-2009, based on monthly observations. (*** Significant at 1% level, ** significant at 5% level, and * significant at 10% level. The numbers in parentheses are standard errors.)

Panel A: Baseline Model

	Probability of Downgrades		Probability of Bankruptcy	
	(1)	(2)	(3)	(4)
ln(E)	-0.735^{***}	-0.736^{***}	-0.713^{***}	-0.710^{***}
	(0.014)	(0.014)	(0.024)	(0.024)
ln(F)	0.507^{***}	0.503^{***}	0.711^{***}	0.713^{***}
	(0.015)	(0.015)	(0.023)	(0.023)
$1/\sigma_E$	-0.062^{**}	-0.017	-1.626^{***}	-1.675^{***}
	(0.027)	(0.026)	(0.131)	(0.131)
$r_{it-1} - r_{mt-1}$	-0.281^{***}	-0.252^{***}	-1.320^{***}	-1.331^{***}
	(0.035)	(0.035)	(0.111)	(0.111)
NI/TA	-0.003	-0.000	-0.038^{***}	-0.038^{***}
	(0.025)	(0.024)	(0.013)	(0.013)
CDS Firm	0.755^{***}		-2.009^{***}	
	(0.057)		(0.711)	
CDS Active	0.691^{***}	1.371^{***}	2.373^{***}	0.400^{**}
	(0.067)	(0.045)	(0.729)	(0.177)
Time Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Pseudo R^2	15.08%	14.75%	24.18%	24.06%
N	658966	658966	658966	658966
# of Downgrades (Bankruptcy)	3863	3863	940	940
CDS Active Odds Ratio	1.925	3.939	10.730	1.492
CDS Active Marginal Effect	0.39%	0.78%	0.33%	0.06%
Sample Probability of a Downgrade (Bankruptcy)	0.58%	0.59%	0.14%	0.14%

Panel B: Distance-to-Default Matching

	Distance-to-Default Matching			
	Probability of Downgrades		Probability of Bankruptcy	
	(1)	(2)	(3)	(4)
ln(E)	-0.462^{***}	-0.447^{***}	-0.923^{***}	-0.891^{***}
	(0.027)	(0.028)	(0.114)	(0.113)
ln(F)	0.318^{***}	0.270^{***}	0.853^{***}	0.865^{***}
	(0.030)	(0.031)	(0.116)	(0.118)
$1/\sigma_E$	-0.155^{***}	-0.008	-1.905^{***}	-1.971^{***}
	(0.042)	(0.038)	(0.315)	(0.317)
$r_{it-1} - r_{mt-1}$	-0.614^{***}	-0.09	-0.076	-0.101
	(0.073)	(0.056)	(0.191)	(0.196)
NI/TA	-0.845^{***}	-0.700^{***}	-0.331	-0.994^{***}
	(0.133)	(0.221)	(0.221)	(0.259)
CDS Firm	1.307^{***}		-1.809^{**}	
	(0.100)		(0.759)	
CDS Active	0.586^{***}	1.313^{***}	2.196^{***}	0.773^{***}
	(0.083)	(0.069)	(0.759)	(0.299)
Time Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Pseudo R^2	12.02%	8.03%	23.16%	23.05%
N	119143	119143	119143	119143
# of Downgrades (Bankruptcy)	1469	1469	67	67
CDS Active Odds Ratio	1.797	3.717	8.989	2.166
CDS Active Marginal Effect	0.64%	1.46%	0.12%	0.04%
Sample Probability of a Downgrade (Bankruptcy)	1.13%	1.14%	0.05%	0.05%

Table III
Probability of Credit Default Swaps Trading

This table presents the estimates of the probability of credit default swaps (CDS) trading using a probit model. Propensity scores are estimated based on the model parameters. *ln(Asset)* is logarithm of the firm's total assets value. *Bond Turnover* is defined as the ratio of bond trading volume to amount outstanding. *Analyst Coverage* is the number of analyst following the firm. *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 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 expenditures to total assets. *Investment Grade* is a dummy variable that equals one if the firm has investment grade (BBB- and above) rating. *Rated* is a dummy variable that equals one if the firm is rated. *Difference in Z-Score* is the difference in Z-score calculated from Altman (1968) between CDS firm and propensity score matched firm. *Difference in Distance-to-Default* is the difference in the firms' distance-to-default estimated from the Merton (1974) model described in Appendix B between CDS firm and propensity score matched firm. *Difference in Propensity Score* is the difference in the firms' propensity scores between CDS firm and propensity score matched firm. The sample period is from 1997-2009, based on monthly observations. (*** Significant at 1% level, ** significant at 5% level, and * significant at 10% level. The numbers in parentheses are standard errors.)

	CDS Prediction Model 1	CDS Prediction Model 2	CDS Prediction Model 3	CDS Prediction Model 4
ln(Asset)	0.436***	0.433***	0.426***	0.320***
	(0.012)	(0.012)	(0.012)	(0.017)
Bond Turnover		0.116***	0.111***	0.090***
		(0.016)	(0.016)	(0.018)
Analyst Coverage			0.080***	0.058***
			(0.015)	(0.017)
Leverage				0.328***
				(0.106)
ROA				0.036**
				(0.017)
$r_{it-1} - r_{mt-1}$				0.032
				(0.022)
Equity Volatility				−0.042
				(0.058)
PPENT/Total Asset				0.290***
				(0.105)
Sales/Total Asset				−0.102
				(0.117)
EBIT/Total Asset				−0.039
				(0.047)
WCAP/Total Asset				0.270***
				(0.056)
RE/Total Asset				0.012
				(0.027)
Cash/Total Asset				0.065
				(0.056)
CAPX/Total Asset				−0.499
				(0.394)
Investment Grade				0.658***
				(0.051)
Rated				0.440***
				(0.093)
Time Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Pseudo R^2	33.54%	34.08%	34.38%	38.37%
N	834251	802016	802016	690111
# of CDS Event	552	552	552	511
Difference in Z-Score	−1.027	−0.095	−0.462	−0.153
Difference in Distance-to-Default	0.552**	0.646***	0.658***	0.119
Difference in Propensity Score	0.003	0.002	0.002	0.004

Table IV
Changes in EDF and Leverage Around the Introduction of Credit Default Swaps: Difference-in-Difference Analysis

This table presents a univariate analysis of changes in EDF and leverage from one year before to two years or three years after after the introduction of credit default swaps (CDS) trading. The changes in EDF and leverage of CDS trading firms are compared with those of the matching firms. Matching firms are selected based on propensity scores estimated from the model of probability of CDS trading presented in Table III. The change in *EDF* is the change in firm's expected default frequency. *EDF* is calculated based on the Merton (1974) model, as explained in Appendix B. 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 stock price. (*** Significant at 1% level, ** significant at 5% level, and * significant at 10% level.)

Panel A: Change in EDF

	Year t-1 to t+2			Year t-1 to t+3		
	Nearest One	Nearest One PS Diff <1%	Nearest Two	Nearest One	Nearest One PS Diff <1%	Nearest Two
CDS Prediction Model 1	0.025	0.022*	0.041***	0.073***	0.064***	0.074***
CDS Prediction Model 2	0.025	0.024*	0.036***	0.073***	0.074***	0.071***
CDS Prediction Model 3	0.015	0.009	0.025**	0.043***	0.042**	0.064***
CDS Prediction Model 4	0.029***	0.022***	0.027***	0.043***	0.036***	0.045***

Panel B: Change in Leverage

	Year t-1 to t+2			Year t-1 to t+3		
	Nearest One	Nearest One PS Diff <1%	Nearest Two	Nearest One	Nearest One PS Diff <1%	Nearest Two
CDS Prediction Model 1	0.013	0.001	0.008	0.029***	0.005	0.015*
CDS Prediction Model 2	0.013	0.013	0.018**	0.029***	0.029**	0.036***
CDS Prediction Model 3	−0.011	−0.005	−0.005	0.007	0.011	0.012
CDS Prediction Model 4	0.012**	0.016**	0.018***	0.022***	0.028***	0.026***

Table V
Credit Default Swaps Trading and Credit Quality: Propensity Score Matching

This table presents the estimates of the probability of credit downgrades or 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 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 credit downgrades or bankruptcy, we include credit default swaps 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 which 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 credit downgrades or bankruptcy after the inception of CDS trading. Panel A conducts the analysis in the baseline matching sample, i.e. the closest one propensity score matching firms selected based on CDS prediction model 3 in Table III. Panel B presents the results in alternative matching samples. Panel C investigates the CDS effect after controlling for the direct effect of credit rating downgrades. *Unrated* equals one if the firm is not rated. *Downgrade* equals one if the firm's rating is downgraded one year before the observation month. The sample period is from 1997-2009, based on monthly observations. (*** Significant at 1% level, ** significant at 5% level, and * significant at 10% level. The numbers in parentheses are standard errors.)

Panel A: Baseline with CDS Prediction Model 3 in Table III

	Probability of Downgrades		Probability of Bankruptcy	
	(1)	(2)	(3)	(4)
ln(E)	−0.272***	−0.272***	−1.190***	−1.205***
	(0.020)	(0.020)	(0.114)	(0.114)
ln(F)	0.258***	0.259***	1.057***	1.074***
	(0.022)	(0.022)	(0.107)	(0.107)
$1/\sigma_E$	−0.344***	−0.345***	−0.493*	−0.457
	(0.037)	(0.037)	(0.298)	(0.300)
$r_{it-1} - r_{mt-1}$	−0.611***	−0.611***	−1.898***	−1.967***
	(0.055)	(0.055)	(0.526)	(0.529)
NI/TA	−0.459***	−0.460***	−0.931**	−0.949**
	(0.124)	(0.124)	(0.433)	(0.431)
CDS Firm	−0.019		−1.031	
	(0.066)		(0.751)	
CDS Active	0.619***	0.604***	1.837**	0.912***
	(0.075)	(0.056)	(0.756)	(0.282)
Time Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Pseudo R^2	6.21%	6.21%	37.96%	37.77%
N	118675	118675	118675	118675
# of Downgrades (Bankruptcy)	2065	2065	77	77
CDS Active Odds Ratio	1.857	1.829	6.278	2.489
CDS Active Marginal Effect	1.04%	1.02%	0.11%	0.05%
Sample Probability of a Downgrade (Bankruptcy)	1.74%	1.74%	0.06%	0.06%

Panel B: Alternative Matching

	Probability of Bankruptcy				
	CDS Prediction Model 3		CDS Prediction Model 1	CDS Prediction Model 2	CDS Prediction Model 4
	Nearest One PS Diff<1%	Nearest Two Matching	Nearest One Matching	Nearest One Matching	Nearest One Matching
ln(E)	-1.205^{***}	-1.021^{***}	-0.989^{***}	-0.964^{***}	-1.202^{***}
	(0.117)	(0.082)	(0.098)	(0.098)	(0.148)
ln(F)	1.071^{***}	0.915^{***}	0.984^{***}	0.860^{***}	1.186^{***}
	(0.110)	(0.073)	(0.088)	(0.087)	(0.137)
$1/\sigma_E$	-0.480	-0.811^{***}	-0.396	-0.756^{**}	0.064
	(0.300)	(0.269)	(0.286)	(0.302)	(0.282)
$r_{it-1} - r_{mt-1}$	-1.894^{***}	-1.918^{***}	-3.275^{***}	-2.630^{***}	-2.107^{***}
	(0.529)	(0.402)	(0.567)	(0.522)	(0.646)
NI/TA	-0.865^{*}	-0.781^{***}	-2.181^{***}	-1.599^{***}	0.064
	(0.472)	(0.255)	(0.384)	(0.353)	(0.194)
CDS Firm	-1.053	-1.402^{*}	-1.866^{**}	-1.727^{**}	-0.618
	(0.751)	(0.729)	(0.734)	(0.740)	(0.799)
CDS Active	1.841^{**}	1.991^{***}	1.983^{***}	2.218^{***}	2.029^{**}
	(0.756)	(0.749)	(0.752)	(0.759)	(0.801)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	38.16%	38.00%	41.37%	37.26%	34.17%
N	113803	170013	118720	116726	114127
# of Bankruptcy	76	126	103	93	45
CDS Odds Ratio	6.303	7.323	7.265	9.189	7.606
CDS Marginal Effect	0.11%	0.14%	0.16%	0.20%	0.07%
Sample Probability of a Bankruptcy	0.07%	0.07%	0.09%	0.08%	0.04%

Panel C: Probability of Bankruptcy Controlling for Direct Effect of Downgrade

	Probability of Bankruptcy			
	CDS Prediction Model 1	CDS Prediction Model 2	CDS Prediction Model 3	CDS Prediction Model 4
ln(E)	-1.005^{***}	-1.034^{***}	-1.263^{***}	-1.167^{***}
	(0.098)	(0.101)	(0.119)	(0.150)
ln(F)	0.964^{***}	0.882^{***}	1.078^{***}	1.135^{***}
	(0.087)	(0.086)	(0.107)	(0.136)
$1/\sigma_E$	-0.244	-0.449	-0.254	0.102
	(0.281)	(0.295)	(0.289)	(0.163)
$r_{it-1} - r_{mt-1}$	-3.230^{***}	-2.571^{***}	-1.858^{***}	-1.697^{***}
	(0.565)	(0.525)	(0.524)	(0.613)
NI/TA	-2.115^{***}	-1.441^{***}	-0.888^{**}	0.091
	(0.376)	(0.344)	(0.412)	(0.194)
CDS Firm	-1.878^{**}	-1.737^{**}	-1.084	-0.583
	(0.734)	(0.746)	(0.755)	(0.799)
CDS Active	1.888^{**}	2.524^{***}	1.910^{**}	1.807^{**}
	(0.773)	(0.798)	(0.802)	(0.859)
Unrated	0.919^{***}	1.667^{***}	1.165^{***}	1.108^{**}
	(0.335)	(0.330)	(0.404)	(0.554)
*Unrated*CDS Active*	0.420	-0.415	0.290	0.946
	(0.568)	(0.574)	(0.629)	(0.753)
Downgrade	0.772^{**}	0.859^{***}	0.638^{*}	1.268^{***}
	(0.311)	(0.332)	(0.372)	(0.427)
Time Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Pseudo R^2	42.51%	39.60%	39.35%	37.12%
N	118720	116726	118675	114127
# of Bankruptcy	103	93	77	45
CDS Active Odds Ratio	6.606	12.478	6.753	6.092
Downgrade Odds Ratio	2.164	2.361	1.893	3.554
CDS Active Marginal Effect	0.15%	0.18%	0.11%	0.07%
Downgrade Marginal Effect	0.06%	0.06%	0.04%	0.04%
Sample Probability of a Bankruptcy	0.09%	0.08%	0.06%	0.04%

Table VI
Credit Default Swaps Trading and Probability of Bankruptcy:
Treatment Effects Model with Instrument Variables

This table presents the second-stage estimation results of two-stage treatment effects model. The second stage analysis is on 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. *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 credit downgrades or bankruptcy, we include credit default swaps 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 which 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 credit downgrades or bankruptcy after the inception of CDS trading. The sample period is from 1997-2009, based on monthly observations. (*** Significant at 1% level, ** significant at 5% level, and * significant at 10% level. The numbers in parentheses are standard errors.)

	Probability of Bankruptcy			
	CDS Prediction Model 1	CDS Prediction Model 2	CDS Prediction Model 3	CDS Prediction Model 4
ln(E)	-0.638^{***}	-0.637^{***}	-0.637^{***}	-0.639^{***}
	(0.022)	(0.022)	(0.022)	(0.022)
ln(F)	0.646^{***}	0.645^{***}	0.646^{***}	0.645^{***}
	(0.022)	(0.022)	(0.022)	(0.022)
$1/\sigma_E$	-1.407^{***}	-1.413^{***}	-1.412^{***}	-1.399^{***}
	(0.125)	(0.125)	(0.125)	(0.126)
$r_{it-1} - r_{mt-1}$	-1.330^{***}	-1.331^{***}	-1.331^{***}	-1.330^{***}
	(0.109)	(0.109)	(0.109)	(0.109)
NI/TA	-0.032^{**}	-0.032^{**}	-0.032^{**}	-0.032^{**}
	(0.013)	(0.013)	(0.013)	(0.013)
CDS Firm	-2.286^{***}	-2.300^{***}	-2.296^{***}	-2.270^{***}
	(0.711)	(0.711)	(0.711)	(0.710)
CDS Active	2.742^{***}	2.826^{***}	2.811^{***}	2.624^{***}
	(0.751)	(0.749)	(0.750)	(0.750)
Inverse Mills Ratio	−0.053	−0.126	−0.112	0.038
	(0.147)	(0.153)	(0.153)	(0.130)
Time Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Pseudo R^2	22.42%	22.42%	22.42%	22.42%
N	657440	657440	657440	657438
# of Bankruptcy	940	940	940	940
CDS Active Odds Ratio	15.518	16.878	16.627	13.791
CDS Active Marginal Effect	0.38%	0.39%	0.39%	0.37%
Sample Probability of a Bankruptcy	0.14%	0.14%	0.14%	0.14%

Table VII
CDS Exposure and Probability of Bankruptcy

This table investigates the impact of credit default swaps (CDS) induced empty creditor problem on firm's probability of bankruptcy in a sample including firms with CDS and all non-CDS firms. The empty creditor problem is approximated by the logarithm of the number of live CDS contracts (*Number of Live CDS Contracts*), and the total notional CDS outstanding scaled by the book value of the total debt (*CDS Notional Outstanding/Total Debt*). *CDS Firm* equals one if the firm has CDS trading at any point of time and zero otherwise. The coefficient of interest is that of *Number of Live CDS Contracts* and *CDS Notional Outstanding/Total Debt*, which capture the impact of CDS induced empty creditor problem. *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 from 1997-2009, based on monthly observations. (*** Significant at 1% level, ** significant at 5% level, and * significant at 10% level. The numbers in parentheses are standard errors.)

	Probability of Bankruptcy	
	(1)	(2)
ln(E)	-0.689^{***}	-0.689^{***}
	(0.026)	(0.026)
ln(F)	0.651^{***}	0.652^{***}
	(0.026)	(0.026)
$1/\sigma_E$	-1.535^{***}	-1.533^{***}
	(0.103)	(0.104)
$r_{it-1} - r_{mt-1}$	-0.622^{***}	-0.620^{***}
	(0.075)	(0.075)
NI/TA	-0.076^{***}	-0.076^{***}
	(0.023)	(0.023)
CDS Firm	-0.644^{***}	-0.582^{***}
	(0.210)	(0.211)
Number of Live CDS Contracts	0.240^{***}	
	(0.077)	
CDS Notional Outstanding/Total Debt		0.071^{**}
		(0.032)
Time Fixed Effects	Yes	Yes
Industry Fixed Effects	Yes	Yes
Pseudo R^2	15.84%	15.82%
N	658966	658966
# of Bankruptcy	940	940
Number of Live CDS Contracts Odds Ratio	1.271	
CDS Notional Outstanding/Total Debt Odds Ratio		1.074
Number of Live CDS Contracts Marginal Effect	0.03%	
CDS Notional Outstanding/Total Debt Marginal Effect		0.01%
Sample Probability of a Bankruptcy	0.14%	0.14%

Table VIII
Restructuring Clauses of CDS Contracts and Probability of Bankruptcy

This table investigates the impact of the restructuring clauses of credit default swaps (CDS) on the probability of bankruptcy of firms in a sample including firms with and without CDS traded. The empty creditor problem is expected to be more significant for firms with more contracts with "no restructuring" as the restructuring clause. In Model 1, for each CDS firm, we include a variable for the *No Restructuring CDS Proportion*, which is the total amount of active CDS contracts with "no restructuring" as the restructuring clause, scaled by total number of CDS contracts trading on it. In Model 2, for each CDS firm, we also calculate the *Modified Restructuring CDS Proportion*, which is the total amount of active CDS contracts with "modified restructuring" as the restructuring clause, scaled by total number of CDS contracts trading on it. *CDS Firm* equals one if the firm has CDS trading at any point of time and zero otherwise. The coefficient of interest is that of *No Restructuring CDS Proportion* which captures the impact of the CDS induced empty creditor problem. *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 from 1997-2009, based on monthly observations. (*** Significant at 1% level, ** significant at 5% level, and * significant at 10% level. The numbers in parentheses are standard errors.)

	Probability of Bankruptcy		
	(1)	(2)	(3)
ln(E)	-0.716^{***}	-0.717^{***}	-0.716^{***}
	(0.024)	(0.024)	(0.024)
ln(F)	0.715^{***}	0.716^{***}	0.715^{***}
	(0.023)	(0.023)	(0.023)
$1/\sigma_E$	-1.636^{***}	-1.645^{***}	-1.641^{***}
	(0.132)	(0.131)	(0.132)
$r_{it-1} - r_{mt-1}$	-1.327^{***}	-1.327^{***}	-1.325^{***}
	(0.111)	(0.111)	(0.111)
NI/TA	-0.037^{***}	-0.037^{***}	-0.037^{***}
	(0.013)	(0.013)	(0.013)
CDS Firm	-0.206	-0.163	-0.432^{*}
	(0.195)	(0.210)	(0.255)
No Restructuring CDS Proportion	1.315^{**}		1.557^{***}
	(0.565)		(0.599)
Modified Restructuring CDS Proportion		0.572	0.858
		(0.492)	(0.528)
Time Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
Pseudo R^2	24.06%	24.04%	24.08%
N	658966	658966	658966
# of Bankruptcy	940	940	940
NR CDS Odds Ratio	3.725		4.745
MR CDS Odds Ratio		1.772	2.358
NR CDS Marginal Effect	0.18%		0.22%
MR CDS Marginal Effect		0.01%	0.12%
Sample Probability of a Bankruptcy	0.14%	0.14%	0.14%

Table IX
CDS Trading, Bank Relationships and Probability of Bankruptcy

This table conducts an analysis of the impact of credit default swaps (CDS) on firm-creditor relationships. The creditor relationships are measured by bank relationships 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. △ *Number of Banks* is the change in the number of bank relationships from one year before the inception of CDS trading to two year after the inception of CDS trading. △ *ln(Asset)* is the change in logarithm of the firm's total assets value. △ *ROA* is the change in firm's return on asset. △ *Leverage* is the change in leverage. △ *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 CDS trading and zero before 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 at any point of time and zero otherwise. *Number of Banks* is the number of existing bank relationships. The coefficient of interest is that of *CDS Active* and *Number of Banks*. (*** Significant at 1% level, ** significant at 5% level, and * significant at 10% level. The numbers in parentheses are standard errors.)

Panel A: CDS and Bank Relationships

	△ Number of Banks
△ *ln(Asset)*	6.291***
	(1.849)
△ *ROA*	−0.396
	(2.76)
△ *Leverage*	8.581*
	(5.201)
△ *PPENT/Total Asset*	−1.586
	(10.84)
CDS Active	2.432**
	(1.069)
Time Fixed Effects	Yes
Industry Fixed Effects	Yes
R^2	9.75%
N	496

Panel B: Bank Relationships and Bankruptcy Risk

	Probability of Bankruptcy
ln(E)	−0.669***
	(0.026)
ln(F)	0.683***
	(0.024)
$1/\sigma_E$	−1.763***
	(0.136)
$r_{it-1} - r_{mt-1}$	−1.339***
	(0.111)
NI/TA	−0.040***
	(0.013)
CDS Firm	−2.210***
	(0.712)
CDS Active	2.378***
	(0.728)
Number of Banks	0.153***
	(0.035)
Time Fixed Effects	Yes
Industry Fixed Effects	Yes
Pseudo R^2	24.32%
N	658966
# of Bankruptcy	940
CDS Active Odds Ratio	10.783
Number of Banks Odds Ratio	1.165
CDS Active Marginal Effect	0.33%
Number of Banks Marginal Effect	0.02%
Sample Probability of Bankruptcy	0.14%