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

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ABSTRACT

Concerns have been raised, especially since the global financial crisis, about whether trading in credit default swaps (CDS) increases the credit risk of the reference entities. This study examines this issue by quantifying the impact of CDS trading on the credit risk of firms. 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 present evidence that the probability of a credit downgrade and of bankruptcy both increase after the inception of CDS trading. The effect is robust to controlling for the endogeneity of CDS introduction, i.e., the possibility that firms selected for CDS trading are more likely to suffer a subsequent deterioration in creditworthiness. We show that the CDS-protected lenders' reluctance to restructure is the most likely cause of the increase in credit risk. We present evidence that firms with relatively large amounts of CDS contracts outstanding, and those with "No Restructuring" contracts, are more likely to be adversely affected by CDS trading. We also document that CDS trading increases the level of participation of bank lenders to the firm. Our findings are broadly consistent with the predictions of the "empty creditor" model of Bolton and Oehmke (2011).

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

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ABSTRACT

Concerns have been raised, especially since the global financial crisis, about whether trading in credit default swaps (CDS) increases the credit risk of the reference entities. This study examines this issue by quantifying the impact of CDS trading on the credit risk of firms. 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 present evidence that the probability of a credit downgrade and of bankruptcy both increase after the inception of CDS trading. The effect is robust to controlling for the endogeneity of CDS introduction, i.e., the possibility that firms selected for CDS trading are more likely to suffer a subsequent deterioration in creditworthiness. We show that the CDS-protected lenders' reluctance to restructure is the most likely cause of the increase in credit risk. We present evidence that firms with relatively large amounts of CDS contracts outstanding, and those with "No Restructuring" contracts, are more likely to be adversely affected by CDS trading. We also document that CDS trading increases the level of participation of bank lenders to the firm. Our findings are broadly consistent with the predictions of the "empty creditor" model of Bolton and Oehmke (2011).

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I. Introduction

Credit default swaps (CDS), which are insurance-type contracts that offer investors protection against default by a debtor, are arguably the most controversial financial innovation of the past two decades. They were praised by some market observers such as former Federal Reserve Chairman Alan Greenspan, who 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] However, they also came in for strong criticism from several well-known market practitioners, particularly after the global financial crisis, which had its origins in July 2007. 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 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 investor 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 question based on theoretical arguments, the issue can only be resolved by empirical testing in specific contexts with clearly stated hypothesis that can be refuted. 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, next only to interest rate derivatives. 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 2007-2008 and the European sovereign debt crisis of 2010-2011. 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 market practitioners as well as regulators, who have built them into their assessment of credit risks at both the level of each corporate debtor, as well as the aggregate level of a sector and the overall sovereign

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

[2]Berkshire Hathaway Annual Report for 2002.

[3]Wall Street Journal, March 24, 2009.

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, and the credit risk of counter-parties. These arguments challenge the hitherto accepted notion that derivatives are redundant assets, as assumed in most pricing and hedging models, and hence have no effect, adverse or otherwise, on the price of the underlying asset or the integrity of markets.

Apart from the above concerns that apply to all derivatives, in principle, CDS contracts are somewhat different from many other derivatives for one important reason: Buyers of CDS protection can influence the financial decisions of the entities they reference, such as firms, and, indirectly, the credit risk of the claims they issue. This possibility is contrary to the "redundancy" assumption in structural models of credit risk along the lines of Merton (1974), that default risk is principally driven 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 downgrade.

In contrast to the redundancy argument, illustrative evidence from corporate restructuring and bankruptcy suggests that CDS positions play an important role in the case of distressed firms, especially just prior to bankruptcy. To cite one such instance, CIT Group attempted to work out its debt to avoid bankruptcy from late 2008 to mid-2009. In the event, however, some debt-holders, including Goldman Sachs (which had also bought CDS protection on the firm) rejected the firm's exchange offer.[4] CIT Group eventually filed for Chapter 11 bankruptcy on November 1, 2009.[5] Hu and Black (2008) call 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, in an op-ed piece, Henry Hu, one of the coauthors of Hu

[4]See, for example, "Goldman Purchase Puts CDS in Focus," Financial Times, October 4, 2009. http://www.ft.com/intl/cms/s/0/a5dcac30-b10f-11de-b06b-00144feabdc0.html#axzz1UM2DNBjJ "Goldman Sachs May Reap $1 Billion in CIT Bankruptcy", Bloomberg, October 5, 2009. http://www.bloomberg.com/apps/news?pid=newsarchive&sid=agRAQzb5M3cg

[5]Appendix A lists several other cases of a similar nature, demonstrating that the example cited is not that unique.

[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.

and Black (2008), named Goldman Sachs as AIG's empty creditor shortly before becoming the director of the SEC's Division of Risk, Strategy, and Financial Innovation.[7] In a similar vein, 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 the bonds outstanding and led to a "squeeze," when the default event called for physical delivery of the bonds. It is highly likely that many creditors had become empty creditors.[8]

The empty creditor concern highlighted by Hu and Black (2008) is formally modeled by Bolton and Oehmke (2011).[9] Their model predicts that bondholders will usually choose to "over-insure" their credit exposure by buying CDS protection, and thus, becoming empty creditors. Consequently, they have different economic interests from other bondholders and are less willing to negotiate to restructure the debt 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. A similar argument applies to events that are less extreme and more common than default such as a rating downgrade: Credit rating agencies may anticipate the potential increase in credit risk and take such action. Often, a rating downgrade is the first stage of credit deterioration towards eventual default.

An alternative channel through which creditor behavior in the presence of CDS protection may adversely affect the credit risk of a firm is through the reduction of monitoring activity by lenders who are empty creditors. Such creditors may have diminished incentives to expend resources to monitor the performance of the firm; this, in turn, may lead to lower information quality, higher risk-taking, and higher bankruptcy incidence.[10] It is important to distinguish between these two channels of increased credit risk emanating from the empty creditor phenomenon. The issue has great relevance to the current regulatory debate regarding CDS contracts and the relative importance of the two channels merits scrutiny. There are several obvious differences between the two channels. First, the increase in bankruptcy risk through the "restructuring" channel is positively related to the amount of CDS outstanding, but not necessarily through the "monitoring" 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 "restructuring" effect of CDS trading on bankruptcy risk is expected to be more severe for CDS that exclude restructuring as credit event. This

[7] http://online.wsj.com/article/SB123933166470307811.html

[8] Following this episode, the New York Fed launched its first round of regulatory actions on CDS in September 2005. It requested major CDS dealers to clear the backlog of unsettled contracts.

[9] Other studies such as Duffie (2007) also offer related analyses.

[10] See, for example, Ashcraft and Santos (2009) and Parlour and Plantin (2008), for this line of argument.

prediction is unique to the restructuring channel.[11]

An additional issue of interest is the *ex-ante* behavior of lenders to a firm, especially banks. On the one hand, the existence of CDS contracts may render a bank more willing to lend, due to the possibility of risk mitigation and enhanced bargaining power through the CDS contract. On the other hand, banks with relationships to the firm may have long-run reputation concerns about becoming empty creditors in a dynamic setting. Further, the greater the number of lenders, the more severe the problems of coordination in a stressed situation, when a workout may be necessary. To study this issue further, we explore how CDS trading affects lending relationships, and, in particular, the number of lenders, after the introduction of CDS trading. If bankruptcy risk increases with the number of lenders, this is an indirect channel for CDS trading to affect bankruptcy risk. This is also consistent with the empty creditor hypothesis as lenders tend to think they are non-pivotal in a multiple-lender structure.

We test our hypotheses using a comprehensive data set on CDS trading since the inception of CDS market for corporate names in 1997. It should be emphasized that it is difficult to retrieve accurate data on the introduction of CDS from a single source, since 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 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, Moody's Annual Reports on Bankruptcy and Recovery, and the Altman-NYU Salomon Center Bankruptcy List. Over the same time period, we record bankruptcy filings by 1,628 firms, of which 60 had CDS trading prior to bankruptcies. Since bankruptcy is a relatively rare event for firms, we also include data on credit rating downgrades, of which we find 3,863 in our data set. The data on credit ratings are from S&P.

Our main empirical challenge is the potential endogeneity of CDS trading due to the

[11]In results not reported here to conserve space, we also examined the validity of an alternative mechanism through which CDS trading may affect the credit risk of a firm. If a shock causes the CDS to become overpriced relative to the bonds issued by the firm, this overpricing may spill over to the bond market, increasing the cost of debt for the firm. This may affect the ability of the firm to refinance its debt by increasing its cost and in extreme cases, affecting its ability to pay off the bondholders.

possibility that firms with greater *future* credit risk deterioration are selected for CDS trading. In other words, there could be unobserved omitted variables that drive both selection of firms for CDS trading and bankruptcy risk. We address this concern in several ways. First, we select firms by their distance-to-default from the Merton (1974) structural model and match firms with and without CDS traded on them, to examine the effect of CDS trading on this matched sample. This partially controls for the credit risk prior to CDS trading. Second, we construct a model to predict CDS trading for individual firms. This model allows us to undertake a difference-in-difference comparison and a propensity score matching analysis for firms with and without CDS trading. Third, we use the two-stage Heckman correction for the selection of firms with CDS traded. In the first stage, we run a probit model for CDS trading. In the second stage, we estimate the probability of bankruptcy subject to the likelihood of CDS trading from the first stage.

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 next two years after the introduction of CDS trading. In a similar vein, the probability of bankruptcy more than doubles, from 0.14% to 0.33%, once the CDS starts trading. The positive relationship between CDS trading and bankruptcy risk is significant after controlling for the propensity of CDS trading. The Heckman correction results show that the effect of CDS introduction on bankruptcy risk is robust to the selection of a firm for CDS trading. Moreover, we find that the effect of CDS trading goes beyond the influence of the rating downgrade itself.

We also distinguish empirically between the different channels through which the empty creditor phenomenon manifests itself. Specifically, our analysis separates the restructuring channel from the monitoring channel. We also document that the effects of CDS trading are stronger when the the number of outstanding CDS contracts is larger, and when the CDS contract has a "No Restructuring" credit event clause. In sum, rather than insuring against borrower default, CDS can actually indirectly cause borrower default. This "tail wagging dog" effect of CDS trading is important to take into account in policy discussions of the effect of CDS trading.

The remainder of this paper is organized as follows. The next section discusses related studies in the literature and places our research in context. Section III presents the motivation for our hypotheses and states them explicitly. The construction of our data-set and our empirical methods are discussed in Section IV. Section V examines closely the selection of firms for CDS trading, and incorporates this issue explicitly into our analysis of the likelihood of rating downgrades and bankruptcy filing. Section VI explores further the empty creditor problem through the restructuring and monitoring channels by which CDS trading affects bankruptcy risk. Section VII concludes.

II. Literature Review

Our study is related to three different strands of the literature. The first analyzes the implications of CDS trading, and more broadly, the introduction of credit risk transfer mechanisms for creditors and the firms themselves. The second related literature is on the wide array of models of bankruptcy prediction. The third examines the effects of CDS trading on the relationship between creditors and firms, including the role of monitoring and information asymmetry.

A. CDS Trading and Credit Risk Transfer

Duffee and Zhou (2001) provide an early discussion of the benefits of CDS contracts as risk transfer tools, but also express caution on the potential downside of CDS trading for firms. They model the impact of introduction of CDS contracts from the perspective of creditors, particularly banks. The banks' information advantage regarding borrower credit quality can cause both adverse selection and moral hazard concerns. In particular, CDS trading may reduce other types of risk-sharing, such as secondary loan sales, with ambiguous welfare consequences. Morrison (2005) argues that CDS can cause disintermediation as banks may not have incentives to monitor borrowers as closely, once their exposures are hedged with CDS.[12] Allen and Carletti (2006) show that credit risk transfer can be beneficial when banks face systematic demand for liquidity. However, when they face idiosyncratic liquidity risk and hedge this risk in the inter-bank market, credit risk transfer can be detrimental to welfare. Further, such hedging via CDS may lead to contagion between the banking and the real sectors and increase the risk of financial crises.

Several papers have investigated the impact of loan sales, an alternative tool for credit risk transfer, on the creditor's monitoring incentive. Gorton and Pennachhi (1995) focus on

[12]Arping (2004) shows that credit risk transfer alters the incentives of lenders and borrowers. With the shelter of the credit protection, lenders may be less willing to monitor the borrowers. The problem can be mitigated by setting the length of CDS protection less than the maturity of the project. Thompson (2007) extends the Duffee and Zhou (2001) formulation by allowing for informational asymmetry in the CDS market and relaxing the maturity mismatch assumption. Then, it is unclear whether the use of CDS to transfer credit risk would be beneficial, since it would depend on the nature of the moral hazard problem, the relationship between the bank and the borrower, the cost of loan sales and the cost of capital.

the moral hazard problem after loan sales. They conclude that banks can overcome the moral hazard problem by continuing to hold a fraction of the loan, and hence, have "skin in the game." Parlour and Plantin (2008) emphasize the impact of a liquid loan sale market on bank's *ex ante* incentive to monitor the debtor firm. They provide conditions under which a liquid credit risk transfer market can be socially inefficient. Parlour and Winton (2011) focus on a bank's decision to lay off credit risk through loan sales versus CDS protection. They explicitly present efficiency implications in terms of risk transfer and monitoring, and suggest that, overall, CDS as a risk transfer mechanism are more likely to undermine monitoring. Beyhaghi and Massoud (2011) find that banks are more likely to hedge with CDS when monitoring costs are high.

Notwithstanding the insightful theoretical work cited above, there is a lack of direct empirical evidence as to what extent CDS trading affects bankruptcy risk through the creditor's monitoring incentives and related channels. The only existing related evidence is somewhat indirect. Ashcraft and Santos (2009) document that CDS trading does not significantly benefit firms in terms of their cost of debt, except for safe and transparent firms. Hirtle (2009) shows that CDS trading increases bank credit supply and improves credit terms for large loans. Purnanandam (2011) discusses how the originate-to-distribute model reduces loan quality and increases bankruptcy risk. Das, Kalimipalli, and Nayak (2011) find that CDS trading hurts the bond market.[13] After the inception of CDS trading, there is greater pricing error and lower liquidity in the bond market. However, Saretto and Tookes (2011) show that CDS trading affects the corporate capital structure: Firms with CDS traded on them are able to maintain greater leverage and borrow at longer maturities.

There are several recent papers discussing the CDS-bond basis. For example, Bai and Collin-Dufresne (2010) investigate cross-sectional variation in the CDS-bond basis during the crisis period. Many other works, such as Tang and Yan (2011), focus on the determinants of the CDS spread. Giglio (2011) and Huang, Zhou, and Zhu (2009) measure the impact of systemic risk based on information contained in CDS spreads. Based on the recently developed "latent liquidity" measure for corporate bonds, Nashikkar, Subrahmanyam, and Mahanti (2011) find a liquidity spillover effect from the CDS market to the corporate bond market. They also provide empirical evidence on the impact of the limits to arbitrage on the pricing of credit risk and the CDS-bond basis.

CDS spreads can sometimes be misleading and excessively high, sending out false signals about firm performance, and thus accentuating the stress faced by the firm, and buttressing

[13]Boehmer, Chava, and Tookes (2010) document a negative impact of CDS trading on equity liquidity and prices.

the need for additional capital.[14] Stanton and Wallace (2011) find that the price levels for the AAA ABX.HE index CDS (a CDS contract based on asset-backed securities with a AAA credit rating) in 2009 are inconsistent with any reasonable forecast of the future default performance of the underlying loans. Moreover, changes in the CDS spreads are only weakly related to the credit performance of the underlying loans. Their finding casts serious doubts on the practice of using the CDS for marking-to-market purposes. However, the excessively high CDS spreads are conceivably driven by the strong demand and the limited supply of credit protection, without regard to the underlying risk itself. In such cases, if the buyers' demand is not satisfied, the CDS price spike could have feedback effects on firm value. In a related paper, Hortacsu, Matvos, Syverson, and Venkataraman (2011) find that increases in GM's CDS spreads result in a drop in the resale prices of its cars at auctions.

At a more general level, there is evidence from the equity market that derivatives trading can affect the pricing of the underlying asset.[15] However, the general conclusions drawn from the equity derivatives market may not be applicable to CDS and the underlying credit risk due to several major differences between the two types of instruments. First, CDS traders can directly influence firm operations, if they are also bond holders, especially when the firm is stressed.[16] Second, the payoff from a CDS is linked to a specific corporate event (default), while that of equity options is related to the level of stock prices. Further, bankruptcy is an irreversible event, that can occur as a "jump to default" unlike the continuous movement of stock prices. Third, CDS are also traded by credit institutions that may have other devices to attenuate the impact on bankruptcy risk, such as by bailing out the stressed firm with additional junior debt. Lastly, CDS contracts are traded over-the-counter, where price transparency and discovery are less clear-cut than exchange traded markets where most equity derivatives are traded.

B. Bankruptcy Risk

The literature on bankruptcy prediction, which can be dated back to the Z-score model of Altman (1968) is too vast to survey here. This model and its variants have been widely used to measure of bankruptcy risk.[17] Bharath and Shumway (2008) and Campbell, Hilscher, and

[14]The Department of Justice investigated Markit, the data aggregator and vendor for price manipulation in July 2009. http://www.bloomberg.com/apps/news?pid=newsarchive&sid=a3mU4TmtYCww

[15]See, for example, an early survey by Damodaran and Subrahmanyam (1992), and Sorescu (2000), an example of such studies.

[16]Although bond holders can also buy equity derivatives, CDS provide a direct protection on their exposure. Moreover, given the maturity of equity derivatives, it is harder for bond holders to hedge their exposure with equity derivatives.

[17]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

Szilagyi (2008) discuss the merits of simple bankruptcy prediction models over their more complicated counter-parts. On the other hand, 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. Chava, Stefanescu, and Turnbull (2011) argue that the specification of the default model has a major impact on the predicted loss distribution. The literature suggests that the merits of using a large number of independent variables in bankruptcy prediction models are debatable. Hence, we use a same simple hazard specification, in the spirit of structural models, throughout our analysis.

Another aspect of the bankruptcy problem has received extensive attention in the literature is the coordination problem between creditors that increases the likelihood of bankruptcy. In an early paper, Gilson, John, and Lang (1990) show that creditor coordination failure increases bankruptcies. More recently, Brunner and Krahnen (2008) show that distress workout is less successful when there are more creditors.

C. CDS and the Lending Relationship

Several papers examine the effect of CDS trading on the incentives and behavior of lenders to firms, in general, and banks, in particular. Acharya and Johnson (2007, 2010) demonstrate evidence of insider trading activity in the CDS market. Further, they show that the intensity of insider trading is related to the number of lenders.[18] Their evidence indicates that creditors often choose to become empty creditors and engage in insider trading in the CDS market. However, Minton, Stulz, and Williamson (2009) find that bank use of CDS is limited, possibly due to the lack of liquidity in CDS contracts. Moreover, Hilscher, Pollet, and Wilson (2011) provide evidence that equity returns lead returns from credit protection at daily and weekly frequencies, casting doubt on the possibility of insider trading in the CDS market.

CDS could affect bankruptcy risk through two channels associated with the empty creditor problem. The first and direct channel is the effect on the willingness to restructure the debt, whereby creditors (over)insured with CDS break the link between cash flow rights and control

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. Other follow-up studies to identify and include important risk factors in bankruptcy risk models include Lando and Nielsen (2010) and Jorion and Zhang (2009).

[18] Several other studies also find that lenders exploit their information advantage. 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. Massoud, Nandy, Saunders, and Song (2011) and Ivashina and Sun (2011) find that institutional investors trade on their private information from syndicated loan lending relationships. Gormley, Gupta, and Jha (2011) show that creditor incentives to monitor borrowers and recover loans affect bankruptcy outcomes.

rights. Empty creditors are unwilling to restructure the firm even if doing so is efficient for debt value as they can profit significantly from their CDS positions. Several theoretical papers model the empty creditor issue. Bolton and Oehmke (2010) emphasize the *ex-ante* commitment benefit of CDS trading, which relaxes the borrower's debt constraint and decreases the probability of strategic default. However, the optimal level of CDS protection depends on the tradeoff between the *ex-ante* commitment benefit and the resulting intransigent over-insured creditors, who may push the firm into an inefficient bankruptcy filing. Campello and Matta (2011) show that the empty creditor problem is a pro-cyclical phenomenon. Based on their model, CDS over-insurance can minimize the moral hazard problem and maximize the probability that the firm's investments are profitable.

The second and indirect channel of the empty creditor mechanism is reduced monitoring by creditors who are insured by CDS, and hence, less concerned about the credit risk of the borrower. Absent monitoring activity by creditors, managers can shift risk from shareholders to creditors, since this improves shareholder value, and thereby increases the probability of bankruptcy. Parlour and Plantin (2008) show that if CDS market is liquid, lenders may initiate too many loans and reduce monitoring, *ex post*.[19] Ashcraft and Santos (2009) also argue that such reduced monitoring may ultimately lead to a higher cost of debt. Hirtle (2009) shows that the presence of CDS does not lead to greater credit supply. Norden, Buston, and Wagner (2011) document lower loan rates for banks that use credit derivatives more intensively. The recent decline in the absolute priority deviation (APD) during bankruptcy resolution (see, for example, Bharath, Panchapagesan, and Werner (2010)) is consistent with tougher creditors and coincides with the development of the CDS market.

Another aspect of the empty creditor mechanism is the reputation effect on a bank. Relationship banks may choose not to become empty creditors. While Bolton and Oehmke (2011) use a one-period model that cannot incorporate relationship lending, Gopalan, Nanda, and Yerramilli (2011) show in a different setting that the lead arranger suffers reputation damage from borrower bankruptcies due to inadequate screening or monitoring. But since CDS encourage lending, more banks are willing to lend after introduction of CDS trading. New banks can become empty creditors. Then empty creditor problem exists even when there are relationship banks.

In contrast to the restructuring and monitoring channels that derive from the empty creditor problem associated with covered CDS positions, Che and Sethi (2011) model an alternative mechanism for the impact of "naked" CDS on economic fundamentals. They argue that CDS can crowd out debt investors, reduce the firm's debt capacity and increase

[19]DeMarzo and Duffie (1999) model security design with risk transfer in a similar setting.

its costs of debt. They find that the permitting naked CDS positions may increase the borrower's bankruptcy risk due to its impact on the cost of debt. Naked CDS trading induces the most optimistic investors to sell CDS protection, which channels their capital away from purchasing bonds to investing in collateral to back their naked CDS positions. The remaining less optimistic bond investors require higher returns. This increase in the cost of debt, in turn, can increase the borrowing firms' default risk.

The changed incentives of the borrowers with regard to restructuring and monitoring as a consequence of the empty creditor problem play a critical role in the discussion in the literature on the impact of CDS trading. However, there is lack of *direct* empirical evidence in this regard. Even when information on the proportion of CDS insured debt for a firm is available, it is hard to distinguish between covered and naked CDS positions. Some recent research investigates the empty creditor hypothesis from an indirect perspective. Bedendo, Cathcart, and El-Jahel (2011) 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. Similarly, Peristiani and Savino (2011) document the higher bankruptcy risk in the presence of CDS during 2008.

III. Theoretical Framework and Hypotheses

In this section, we present the key insights from the theoretical literature that we use to motivate the specific hypotheses for our empirical tests. The prior literature has discussed both direct and indirect mechanisms through which CDS trading affects bankruptcy risk. The direct mechanism acts to lower the success of debt restructuring due to increased coordination failures among creditors. The coordination failure can result from the creation of empty creditors or, simply a larger, more diverse group of creditors. The indirect mechanism causes an increase in firm risk due to a higher leverage ratio and higher borrowing cost, as a result of catering to a more heterogeneous group of creditors, some of whom are hedged against the credit risk of the firm. The higher leverage can result either because of more efficient risk transfer or lower monitoring by some of the creditors.[20] Higher borrowing costs may arise because of potential feedback effects from the CDS market to the firm's financing decisions: a shock to the CDS market as a whole can be transmitted to the firm's bonds by arbitrageurs

[20]Another channel through which the empty creditor problem may manifest itself is through a reduction in monitoring by the empty creditors, who no longer derive any benefit from such activity. Thus, reduced monitoring is the attenuated case of the empty creditor problem, and contributes to an increase in the credit risk of the firm, and in turn, leads to a higher probability of bankruptcy.

who take advantage of mispricing between the bonds and the CDS.

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 agree to pay them say $R \times X$, with $R > r$. Clearly, the creditors would consider such a restructuring and try to avoid bankruptcy.[21] 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 define the contract to be a Full Restructuring (FR) CDS. If it is not, we defined it as a No Restructuring (NR) CDS.[22]

We first consider the case of FR CDS. Assume that the CDS premium (price) is F in present value terms at the time of default. Suppose the creditors buy CDS against Y of face 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 $[R \times X + (1 - R - F) \times Y]$ if the debt is restructured. Again, 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, for FR CDS, bankruptcy dominates restructuring as a choice for empty creditors for whom the amount of CDS purchased exceeds the bonds held.

Now consider the case of NR CDS. Assume that the CDS premium (price) in this case is f in present value terms, where $f < F$. Suppose again that the creditors buy CDS against Y

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

[22] Other types of contracts also exist, but are not relevant for purposes of this simple illustration. See Appendix C for details.

of face 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 is 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 alternative for a larger range of holdings of CDS by the creditors.

It is also easy to see that buying CDS protection, with NR CDS contracts is a better choice in bankruptcy than restructuring without CDS protection, so long as either

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

which is equivalent to saying that:[23]

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

This condition is met when $Y > X$ as long as $R < 1 - f$ which is almost always true as the cost of CDS protection should not be higher than the loss in the event of restructuring. As before, it is likely to be true, even if Y<X, for reasonable values of R and f. Further, the greater the difference between Y and X, the greater the incentive to push the firm into bankruptcy. Hence, our example shows that a) creditors have an incentive to over-insure and push the firm into bankruptcy, b) this incentive increases with the difference between Y and X, i.e., the amount of CDS contracts outstanding relative to the firm's debt, and c) the probability of bankruptcy occurring is greater for NR CDS contracts. 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*

[23] 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.

increases after the introduction of trading on CDS contracts referenced to 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.

Hypothesis 2 (Empty Creditor: CDS Trading) *The increase in the bankruptcy risk of a firm after the introduction of trading in CDS contracts referencing it 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.

Hypothesis 3 (Empty Creditor: No Restructuring) *The increase in the bankruptcy risk of a firm after the introduction of trading in CDS contracts referencing it is larger for No Restructuring (NR) contracts than for Full Restructuring (FR) contracts.*

The third hypothesis suggests an even stronger test of the empty creditor channel 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, then 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 channel is even more effective for NR CDS.

Besides the empty creditor problem, another channel for CDS trading to affect bankruptcy is through greater heterogeneity in creditor composition: coordination is more difficult when there are more creditors. These coordination problems may be exacerbated due to potential gaming activity by different groups of creditors.[24]

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 more willing to lend to the firm if CDS are traded and an increased number of lenders after CDS trading is consistent with the empty creditor model. Therefore, we hypothesize that the number of lenders increases after CDS trading:

[24]This coordination problem has been linked with an accentuation of the bankruptcy risk by Gilson, John, and Lang (1990). Brunner and Krahnen (2008) show that distress workouts are less successful when there are more creditors.

Hypothesis 4 (Number of Lenders) *The number of (bank) lenders increases after the introduction of CDS trading.*

There are other mechanisms for the exacerbation of credit risk, following the introduction of CDS trading, that go beyond our illustrative example. More lenders are willing to participate after the introduction of CDS contracts, as their downside risk can be better managed and used to earn a spread; if the loan performs well, the lending generates profits, if, on the other hand, the loan quality deteriorates, the lender is protected by the CDS. Workouts are less likely to be successful as more lenders see themselves as non-pivotal. Moreover, the CDS market creates a venue for "insider trading" on credit information, as shown by Acharya and Johnson (2007). Ultimately the net cost of insider trading is born by the borrower. (Lenders may also bear a cost, but they will be repaid from the insider trading profits they generate.) As the information asymmetry is likely to be priced in CDS spreads, this would be fed back to the cost of debt, leading to greater bankruptcy risk. Thus, the overall effect of CDS trading on firms will be increased leverage and higher cost of debt, leading to higher bankruptcy risk.

As discussed earlier, there are other indirect channels for CDS trading to affect bankruptcy risk, such as increased debt capacity resulting from better risk sharing, reduced monitoring, and feedback to firm borrowing costs. Such indirect channels generally go through the effects on firm fundamentals, as firms become riskier. However, in our analysis, we control for firm fundamentals, and hence, the indirect channels are not likely to drive our findings on the *direct* channels.

IV. 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 which 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 transaction data are derived 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.[25] (GFI ranked first in the Risk Magazine ranking from 2002-2009). Combining data from these two sources allows us to assemble a comprehensive record of virtually the entire 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.[26]

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. In our empirical analysis, we focus on CDS contracts written on non-sovereign North American corporate issuers. Since CDS contracts are traded over-the-counter, unlike stocks or equity options, which are mostly listed 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 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. First, our sample starts in 1997, which is regarded by many market observers as the inception of the CDS market.[27] 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 delivery 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 information. The credit event specification allows us to investigate the effect of restructuring clauses, as we do in this paper. The maturity information at the contract level also allows us to calculate the open CDS positions outstanding at each point in time.

Based on our merged data set, there are 901 North American firms that have CDS initiated

[25]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.

[26]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.

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

on them at some point during the 1997-2009 sample period. In the initial part of our 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 distinguish between the alternative channels through which CDS trading affects credit risk, we also construct measures of CDS attributes, based on the more detailed transaction information that we assemble.

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.[28] This database includes all public companies filing for bankruptcy and also significant bankruptcies of private firms. We further augment this preliminary sample with additional bankruptcy filing data sources including the Altman-NYU Salomon Center Bankruptcy List, the Fixed Income Securities Database (FISD), the UCLA-LoPucki Bankruptcy Research Database (BRD), and Moody's Annual Reports on Bankruptcy and Recovery.[29] Unlike other studies on bankruptcy, 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 Acive 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 subsequently filed for bankruptcy protection. The number of bankruptcies among CDS firms is 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.

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.[30] Our bond trading data are from the Trade Reporting and Compliance Engine (TRACE) maintained by the Financial Industry Regulatory Authority (FINRA) over the period from

[28]The data are available at the website Bankruptcydata.com

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

[30]We thank Michael Roberts for providing the DealScan-Compustat linking file.

2002-2009. In addition, we obtain analyst coverage data from I/B/E/S.

B. *Empirical Methodology*

The main objective of our analysis is to assess the impact of CDS inception on a firm's bankruptcy risk. We employ three approaches in our analysis. The first is based on univariate difference-in-difference analysis. For each firm with CDS traded on it, we identify a corresponding firm with similar characteristics, based on a matched propensity score, that does not have CDS traded. The criterion for the propensity score matching is that firms in the matched sample do not have CDS traded on them, but have a similar probability of CDS trading to those with which they are matched. In our analysis, we focus on firms around the date when CDS were first traded on them (year t) to measure changes in credit risk from the year $t-1$ through the end of year $t+1$, or year $t+2$.[31]

Our second approach is a proportional hazard model 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 log of the firm's equity value (*ln(E)*), its return over the past year $(r_{it-1} - r_{mt-1})$, the log of 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*).[32]

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 firm started 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

[31] We also examine other windows in our analysis, as a robustness check.

[32] Longstaff, Giesecke, Schaefer, and Strebulaev (2011) find that the variables suggested by such structural models outperform others in bankruptcy prediction.

without CDS. *CDS Active*, however, equals zero before the CDS introduction and one after the CDS introduction. 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.[33]

Since filing for bankruptcy is relatively uncommon for firms, we also examine other indicators of changes in credit risk that occur more frequently. One such signal is a change in the credit rating of the firm, in particular a downgrade that signals deterioration in credit quality. 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.

Our third and main approach takes into account the endogeneity effect 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 there is 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.

In case of an endogeneity problem, the estimation of the treatment effect (i.e., the effect of CDS trading) may suffer from errors due to a selection bias (*sample-selection bias* or *self-selection bias*). *Sample-selection bias* originates from the availability of observable data; for example, we observe CDS data only when there are actual trades that are reported in the databases. On the other hand, *self-selection or endogeneity bias* refers to the possibility that some of the predictors in the estimation equations may actually be choice variables. In our empirical estimation, if the *CDS Active* variable is used as a primary predictor of bankruptcy risk, and the non-random nature of the *CDS Active* is ignored, biased estimates of the coefficient of *CDS Active* may result. Both propensity score matching and the Heckman two-stage approach could be used to partially correct for this selection bias.

With propensity score matching, we first create a control group of firms that do not have CDS traded on them, which can be compared with the treatment group of firms with CDS traded. The control group is constructed based on observed predictors, obtained from a probit regression to create a reference group. The model is then estimated with the two groups of firms to determine whether the *CDS Active* variable has predictive power in the equation for

[33]We also analyze the coefficient of the *CDS Active* variable in an alternative specification with firm fixed effects.

the probability of credit downgrades or bankruptcy.

In the Heckman two-stage approach (or the Heckman correction), the sample selection problem is regarded as an omitted variable bias. There might be an unobserved variable that affects both the response variable (e.g., the probability of bankruptcy) and the individuals' choice for the treatment group (e.g., the introduction of CDS trading) for the sample firms. If the variable was observable, the problem can be solved by adding it as a covariate in the response equation. However, since it is not observable, the Heckman correction approach solves the problem by constructing a proxy variable (i.e., the *Inverse Mills Ratio*) for the unobservable variable. In the first step, a selection model is estimated via probit or logit regressions. Then, the *Inverse Mills Ratio* can be calculated based on the residuals (i.e., the unobservable variables) of the selection model. In the second step, the original response equation is estimated with the *Inverse Mills Ratio* as an additional explanatory variable. Conditional on the original independent variables and the additional *Inverse Mills Ratio*, the sample can be viewed as being randomly selected.[34]

The self-selection model of CDS trading that we use is based on Ashcraft and Santos (2009):

$$\Pr(CDSActive = 1) = f(Z_{it-1}), \tag{2}$$

where Z includes a set of explanatory variables for CDS trading such as volatility, firm size, leverage, profitability, credit rating status, and so on. From the previous probit regression, we can calculate the propensity scores at each date, for each firm, for CDS trading, and use them to find matching firms. We can then estimate the probability of credit downgrades or bankruptcy after controlling for possible selection bias. Alternatively, we could use the above model to run a two-stage Heckman correction analysis.

In addition to *CDS Active* as our key indicator variable, we also investigate the channel through which the impact of CDS trading manifests itself by constructing measures of both CDS contracts outstanding, as well as the nature of the CDS contract itself. To measure the extent of the empty creditor problem, we calculate the ratio of logarithm of the total active CDS outstanding for the firm during month t scaled by the total debt outstanding at the end of the month (*Active CDS Outstanding/Debt*). We conjecture that firms with larger proportions of CDS to debt outstanding are more likely to be affected by the empty credi-

[34]It should be emphasized, however, that the Heckman correction approach relies on the strong distributional assumptions about the error terms - that is the error terms from the first step selection equation and from the second step response equation are jointly normally distributed. This limitation partially explains the continued popularity of the propensity score matching approach.

tor problem, and hence, potentially have higher bankruptcy risk. Moreover, we distinguish between different types of CDS contracts by their credit event specifications. CDS contracts with a "No Restructuring" credit event clause would be most susceptible to the empty creditor concern, since they would not pay off in restructuring events. A detailed discussion on the definition of credit events in the different types of CDS contracts is provided in Appendix C.

V. CDS Trading and Credit Risk: Empirical Results

This section presents our empirical findings on how the introduction of CDS trading on a firm affects its bankruptcy risk. We first report our baseline results regarding the effects on credit ratings as well as bankruptcy. We then show that 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.

A. Rating Changes Before and After CDS Introduction

Since bankruptcy is often an absorbing state, many bankrupt firms disappear from public databases. Hence, we cannot conduct event studies on the effect of CDS introduction on bankruptcy, as bankruptcy is a one-time event. Therefore, we choose to first analyze credit ratings, which are observable both before and after CDS introductions. As already noted, a credit downgrade is often the first step towards bankruptcy. Hence, the analysis of changes in credit rating is likely to shed light on the likelihood of bankruptcy as well. Furthermore, the number of credit downgrades in our sample vastly exceeds the number of bankruptcies.

We compare the distribution of credit ratings in the year before CDS trading to the rating distribution within two years after CDS trading for firms with such contracts traded at some point of time in our sample. The distributions are reported 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.

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 investment grade firms decreases. At the same time, the proportion of non-investment grade and unrated firms increases (the increase in non-rated firms is likely to be partly due to their withdrawals from the rating process). The results provide some preliminary evidence that following the inception of CDS trading on a firm, its credit quality deteriorates: the Kolmogorov-Smirnov test statistic on distributional differences, which is significant at the 1% level, shows that the credit rating distribution shifts to the right (deteriorates) after CDS trading.

B. *CDS Trading and Credit Risk: Baseline Hazard Model Results (H1)*

After the preliminary analysis showing credit quality deterioration in a simple comparison of ratings, we run multivariate tests to discern more systematic 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, to study whether the introduction of CDS trading increases credit risk. In our baseline analysis, we use both credit rating downgrades and bankruptcy filing to measure bankruptcy risk.

We follow Bharath and Shumway (2008) and estimate the logistic model of credit rating downgrade or bankruptcy outlined in Section IV.B.[35] Our main CDS variables are: *CDS Firm* which equals one if the firm is in the CDS sample and zero otherwise, *CDS Active* which equals one if the firm has CDS trading one year before the observation month. The coefficient of *CDS Firm* separates the differential likelihood of deterioration in credit risk, by a credit downgrade or eventually 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. The analysis is conducted with monthly observations.

The proportional hazard model estimation results are presented in Table II. Panel A shows results using all firms. The first column lists the independent variables in the model estimation. The second and third columns show the results for credit rating downgrades. The fourth and fifth columns show the results for bankruptcy prediction. The third and fifth columns 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.

Credit ratings are more likely to be downgraded after CDS trading as evidenced by the positive coefficient estimate for *CDS Active*. In both the second and the third columns, 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 the third column, the marginal effect of CDS trading on downgrading is 0.39%. The fifth column of reports

[35] We also examined other specifications (e.g., Campbell, Hilscher, and Szilagyi (2008)) and our conclusions are not affected by the use of different control variables.

similar findings for bankruptcy filing. Firms are more likely to go bankrupt after CDS trading. Against an average firm bankruptcy probability of 0.14%, the marginal effect of CDS trading on bankruptcy probability is 0.33%. The odds ratio for *CDS Active* for credit downgrades and bankruptcy predictions are 1.925 and 10.73 respectively.

The estimation results for the variable *CDS Firm* in the third and fifth columns, which are statistically significant at the 1% level, for both downgrades and bankruptcy analysis, are worth noting. Compared to non-CDS firms, CDS firms are more likely to be downgraded but less likely to go bankrupt, which is consistent with our conjecture that CDS firms are fundamentally different from non-CDS firms as a group. Moreover, we find that *CDS Active* is significant, whether we include *CDS Firm* in the regressions or not.

The estimation results for the control variables 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 more volatile firms are more likely to be downgraded or to go bankrupt. Profitable firms are, obviously, less likely to file for bankruptcy.

Since our main focus here is on credit risk, and, in particular, the probability of bankruptcy, an alternative approach in isolating the CDS trading effect is to match firms based on their initial credit quality, rather than using all non-CDS firms as control group. We use distance-to-default (DD) as a credit risk control to identify matching firms for our CDS firms. DD is calculated from the Merton (1974) model and modified by Bharath and Shumway (2008) as described in Appendix B. It is a measure of the difference 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 on DD, the CDS and non-CDS matched firms have a similar probability of bankruptcy, at the inception of CDS trading. Then, the hazard model analysis of the impact of CDS trading on the probability of bankruptcy is conducted in the sample of CDS firms and their corresponding non-CDS DD matched firms.

The estimation results for the DD-matched sample are reported in Table II Panel B. The analysis is the same as in Panel A except with a smaller, but more comparable sample (the sample size for Panel B is about one-fifth of Panel A). All columns show that *CDS Active* has a positive and significant effect on credit risk. For example, the fifth column shows that the marginal effect of CDS trading on probability of bankruptcy is 0.12% relative to the sample default rate of 0.05%. Compared to Panel A, we find that, as expected, the effect of the control variable *CDS Firm* appears to be less significant for bankruptcy prediction, since the firms have already been matched based on DD.

C. The Selection of Firms for CDS Trading

The main challenge to inferring a causal relationship from our baseline results in the previous sub-section that CDS trading is positively related to deterioration in credit quality is the potential endogeneity of CDS trading. It is conceivable that investors anticipate the deterioration in a firm's credit quality and initiate CDS trading on it. Thus, there could be a selection bias for firms on which CDS trading is initiated, in that they are inherently more likely to decline in credit quality. In this section, we attempt to endogenize CDS trading and factor this endogeneity into our bankruptcy risk analysis. Our CDS trading selection model is generalized from Ashcraft and Santos (2009), as discussed in Section IV.B. [36] Our objective is to use the best model to explain the presence of CDS trading on firms, and then estimate the probabilities of credit deterioration, after adjusting for such potential selection bias.

The endogeneous variable is *CDS Active*. (*CDS Firm* is used to measure firm fundamentals and assumed to be exogenous.) The market for CDS is driven by the supply and demand for credit risk transfer. The concern for bankruptcy is more pronounced for firms with inherently higher credit risk. Therefore, we include credit risk variables such as profitability, equity volatility, leverage, and distance-to-default (DD), and whether the firm is rated, into the model for predicting the inception of CDS trading. In addition, we also include a set of firm characteristics such as firm size, revenues, working capital, cash holdings and capital expenditure. Lastly, we also include the reference firm's bond trading turnover which measures potential demand for hedging with CDS contracts.

We start with firms with CDS traded on them, but keep data for firm-months from 1997 until the first month of inception of CDS trading. Then, we add all non-CDS firms. Thus, the probit model analysis of the probability of CDS trading is conducted in a sample including both firms with CDS traded and all non-CDS firms. The dependent variable is equal to one after the firm starts CDS trading, and it equals zero before CDS trading. The probit regression results are reported in Table III. They show that CDS trading is more likely for larger firms, firms with credit ratings, and firms with higher leverage. However, CDS trading is less likely for firms with higher equity volatility and DD. CDS trading is also more likely for firms with higher profit margin and cash holding. As expected, firms with higher bond trading turnover are more likely to have CDS trading. The pseudo-R^2 of the prediction model is 37.12%.

In the following analysis, we will use this CDS trading prediction model to select matching firms and re-examine the relationship between CDS trading and bankruptcy risk. Our first

[36] A similar approach is used by Saretto and Tookes (2011).

approach relies on propensity score matching. Based on the estimated model parameters, propensity scores can be calculated for each firm. For each CDS firm, the matched non-CDS trading firm is selected as the one with closest match in propensity score.

D. Difference-in-Difference Analysis

We compare the changes in firm characteristics relevant to credit quality before and after CDS introduction, relative to matching firms with similar propensity scores for CDS trading. In the sample of CDS and non-CDS propensity score matched firms, we first conduct a univariate difference-in-difference analysis of the change in firm credit quality around the date of introduction of CDS trading. The treatment we examine here is the introduction of CDS trading on a firm, which captures an increase in the availability of credit risk transfer instruments to suppliers of capital. The difference-in-difference results are reported in Table IV. The left panel shows the changes from year $t-1$ to year $t+1$. The right panel shows the changes from year $t-1$ to year $t+2$.[37]

The results show that the credit quality of firms deteriorates significantly after the introduction of CDS trading, compared to their matched firms. The popular default probability measure, expected default frequency (EDF), which is a transformation of DD, increases by 0.4% more than matched firms from year $t-1$ to year $t+1$, and by 4.2% from year $t-1$ to year $t+2$, with greater statistical significance. The Z-score decreases after CDS introduction as well, although this is only marginally significant. Credit ratings are marginally lower for year $t+1$ compared to year $t-1$, although the changes are not statistically significant in all cases. In addition, firm leverage significantly increases by 0.016 from year $t-1$ to year $t+1$, and by 0.023 from year $t-1$ to $t+2$, around the introduction of CDS trading. These indicators suggest that the credit condition of firms is negatively affected by CDS trading. This finding, as well as the magnitude of leverage change, is consistent with the conclusions of Saretto and Tookes (2011).

The advantage of the difference-in-difference analysis is that it controls for firm characteristics before CDS trading, relative to firms matched by CDS trading propensity score. The findings from the difference-in-difference analysis suggest that the credit quality of CDS firms drops significantly after CDS introduction. Such a comparison is akin to a "short-window" event analysis. However, the univariate difference-in-difference analysis of the change in firm performance may raise concerns of omitted variables. We address these concerns in the following section, where we use hazard models in a "long-window" analysis with controls for

[37]We also examined other neighboring windows and find similar results. However, the effects are muted beyond year $t+3$.

matching firms.

E. CDS Trading and Bankruptcy Risk: Propensity Score Matching

Table V presents the results from re-estimation of the model used in Table II, with a restricted sample. The full sample, including firms with CDS and without CDS traded on them, is used for the analysis in Table II, Panel A. For Table V, we only include firms with CDS traded and their propensity score-matched firms, dropping firms that either have no CDS traded or are not chosen from the propensity score matching. Therefore, the firms in the restricted sample are more comparable to each other, but the sample size is also much smaller in Table V. Since DD is included in the CDS selection model, the analysis for Table V further improves upon Panel B of Table II.

Table V shows that the positive relation between CDS trading and bankruptcy risk is still significant, when we use the propensity score matching to control for CDS trading endogeneity. CDS firms are, on average, less likely to go bankrupt compared to non-CDS firms, which are equally likely to have CDS trading. This could be due to the increased financing channels for CDS firms.[38] The coefficient for *CDS Active* continues to be positive and significant in both the downgrading and the bankruptcy specifications. The economic magnitude is also large, as seen in the second column: Compared to the average downgrading probability of 1.90%, the marginal effect of CDS trading on downgrading is 1.33%. The third column of Table V reports similar findings for bankruptcy. Firms are more likely to go bankrupt after CDS trading. Against an average firm probability of bankruptcy in the universe of firms of 0.07%, the marginal effect of CDS trading is 0.13%. The odds ratios for *CDS active* for credit downgrades and bankruptcy prediction are 2.051 and 6.456 respectively.

Propensity score matching is useful when there is no systematic bias in the calculation of the propensity scores. However, it does suffer from potential mis-specification of the hazard model itself. To alleviate this potential deficiency, we next use the two-stage Heckman correction model as an alternative approach to take into account the endogeneity of CDS trading.

[38]We note that, in Table II, firms with CDS traded are more likely to be downgraded. After controlling for the endogeneity in CDS trading in Table V, firms with CDS traded on them are still more likely to be downgraded compared to firms without CDS.

F. CDS Trading and Bankruptcy Risk: Heckman Correction

The CDS sample selection issue can be viewed as a form of omitted-variables bias in the sense of Heckman (1979). In the first step, we model the probability of CDS trading using a probit model similar to the model underlying 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, in the second stage, the hazard model analysis of the probability of credit downgrades/bankruptcy is conducted by including the *Inverse Mills ratio* as an additional explanatory variable. Unlike the propensity score matching approach with only matched firms, we include all firm observations in the second-stage analysis.

The results are presented in Table VI. The effect of *CDS Firm* on downgrading is again positive, but negative for bankruptcy filing. The coefficient of the *Inverse Mills Ratio* is insignificant for the bankruptcy regression, but significantly negative for the downgrading regression. Therefore, selection bias does not seem to affect the bankruptcy results, but may influence the inference of the downgrading results. More importantly, the coefficients of *CDS Active* are positive and significant at the 1% level in both the downgrading and bankruptcy analysis. The economic magnitude is also large as seen in the second column: Compared to the average downgrading probability of 0.58%, the marginal effect of CDS trading on downgrading is 0.80%. The third column of Table VI reports similar findings for bankruptcy filings. Firms are more likely to go bankrupt after CDS trading. Against an average sample probability of bankruptcy is 0.14%, the marginal effect of CDS trading is 0.37%. The odds ratios for *CDS Active* for credit downgrades and bankruptcy prediction are 4.187 and 14.585 respectively. These results shows that the positive relationship between CDS trading and bankruptcy risk is robust to the selection of firms for CDS trading.

The propensity score matching method and the Heckman correction procedure each have their respective merits (and demerits). However, in our case, both approaches yield consistent results that suggest that the finding that bankruptcy risk increases with CDS trading is robust.[39]

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

G. Imperfect Matching and Identification

One part of the endogeneity concern is that unobservable factors may drive the introduction of CDS trading. It is possible that CDS introduction is based on private information that our matching variables cannot pick up either directly or by proxy. In such a case, our matching approach cannot effectively address the concern on CDS trading endogeneity. We hypothesize that private information is more likely to be important when the information environment is poor. Therefore, if our results are driven by imperfect matching, our findings should be stronger for firms with poor information quality.

We examine the issue of information quality by segmenting firms based on the extent of their analyst coverage, high versus low, to examine if the effects of CDS trading differ between the two groups. We then re-estimate our baseline hazard model for bankruptcy prediction for the two sub-samples. (The downgrading results are not reported to preserve space.) The results of these estimations are reported in Table VII. The second column presents results for firms with low analyst coverage and third column presents results for firms with high analyst coverage. These regressions show that the effect of CDS trading, as measured by the coefficient of the *CDS Active* variable, is positive and significant for firms with high analyst coverage, but only marginally significant for firms with low analyst coverage, contrary to the private information hypothesis. We check this further by running the estimation for the full sample with a dummy variable for low analyst coverage, *Low Coverage*, including a cross term for this variable with *CDS Active*. The last column reports the results, which show that the CDS trading effects for the low analyst coverage firms are not statistically significantly different from firms with the high analyst coverage, as shown by the coefficient estimate for *CDS Active * Low Coverage*. These findings suggest that private information is not driving our finding. It is noteworthy that in the third and fourth columns, the coefficients of the *CDS Active* variable remain remarkably stable and statistically significant. The marginal effect of an increase in the *CDS Active* variable in the full sample regression on the probability of bankruptcy is 0.32%, compared to the overall sample probability of 0.14%.

Our finding on analyst coverage has implications for the channel through which CDS trading affects bankruptcy risk. Bank monitoring is arguably less critical for firms with high analyst coverage, which essentially serves as public monitoring tool. Given that there is no cross-sectional variation in the CDS effect with respect to analyst coverage, we can infer that the CDS effect is not fully driven by its impact on bank monitoring. This evidence motivates our focus on the empty creditor channel in the next section.

In additional analysis to check for the robustness of our results (not presented here, to conserve space), we find that if we shift the CDS introduction by one year, the effect of *CDS Active* is insignificant. This finding is consistent with the correct identification of timing of CDS introduction, as well as the the effect of CDS trading. These results indirectly suggest that our findings are not affected by private information, which may be driving the introduction of new CDS contracts.

H. CDS Trading or Downgrading? Controlling for the Credit Rating Effect

We examine the effect of CDS trading on bankruptcy risk relative to the direct effect of rating downgrading itself.[40] A rating downgrade is a potential omitted variable for the bankruptcy analysis, as we find that the introduction of CDS trading directly affects credit rating. Therefore, we investigate bankruptcy risk changes while controlling for changes in the credit rating status. We conduct a logistic regression of bankruptcy filings in two different ways using our propensity score matched sample. The results are reported in Table VIII. We retain the baseline results in the second column, titled Model 1, for comparison.

The dependent variable is the probability of bankruptcy. In Model 2, reported in the third column, we use a dummy variable *Unrated* which equals one if the firm is unrated in the observation month. We also include the cross term between *CDS Active* and *Unrated* to capture the interaction effect. We find that the effect of *CDS Active* is robust to controlling for rating status. Furthermore, the effect of *CDS Active* is stronger (although only marginally significant) for unrated firms, since such firms may be more likely to go bankrupt to begin with. In the fourth column, Model 3, we add the 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, one year before the current month. This specification contrasts the predictive power of CDS trading with credit rating downgrading in predicting bankruptcy risk. Against an average sample probability of bankruptcy is 0.07%, the marginal effects of CDS trading are 0.12% and 0.11% in Model 2 and Model 3 respectively. The odds ratio for *CDS Active* for the Models 2 and 3 are 5.635 and 6.773 respectively. The results show that firms are more likely to go bankrupt if they were unrated, or were downgraded, just prior to the introduction of CDS trading. More importantly, CDS trading significantly increases the firm's probability of bankruptcy, even after controlling for the influence of downgrading.

Given that rating agencies make downgrade decisions based on their own judgements, the impact of CDS trading on rating downgrading and bankruptcy may be driven by different mechanisms. The finding that the CDS trading effect is consistent, but beyond the effect of

[40] In our regression sample, there are 73 downgrades within one year before CDS introduction.

rating downgrading, suggests that rating agencies may overlook the *direct* influence of CDS trading on bankruptcy risk when conducting credit analysis.

VI. The Mechanisms: "Empty Creditor", Restructuring, and Lender Composition

In the previous section, we presented consistent, robust evidence that CDS trading increases corporate credit risk. As argued in the introduction, the primary mechanism through which this occurs is through the creation of empty creditors of the firm (who hedge their credit risk partially, completely or even more than completely). This mechanism manifests itself through two different channels (*restructuring* and *monitoring*): The first channel through which the empty creditor mechanism works is by creating different incentives regarding restructuring of the firm's liabilities for empty creditors compared with other creditors - empty creditors are less willing to restructure the firm's debt; this, in turn, increases the probability of a credit downgrade and bankruptcy.[41] The second channel arises because empty creditors have reduced incentives to monitor the borrower, since they gain little from such activity. Consequently, if some creditors reduce their monitoring, borrowers may take on riskier projects, thus exacerbating the firm's bankruptcy risk.[42] Moreover, the selection of of a firm for CDS trading may be contingent on monitoring costs, as suggested by Beyhaghi and Massoud (2011).

This section explores the restructuring channel in greater depth. We present direct evidence for the restructuring channel of the empty creditor mechanism. Moreover, we analyze how CDS trading may affect the lender composition, which may induce coordination failures during distress workouts.

[41]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.

[42]An alternative channel through which CDS trading affects the credit risk of the firm is through mispricing of the CDS. If CDS spreads are pushed up due to an external shock, in relation 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 causes the operating environment to worsen, leading to a worsening of the firm's credit quality. On the other hand, high CDS spreads also increase the cost of buying CDS protection, and hence, reduce the incentive of creditors to become empty creditors. If 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.

A. *Testing the Empty Creditor Hypothesis: Outstanding CDS Positions (H2)*

The unique aspect of the restructuring channel of the empty creditor mechanism is the prevalence of over-insurance with CDS contracts by lenders. The monitoring channel will not have such an implication, as the minimum level of monitoring is no monitoring at all (lenders cannot "negatively" monitor). Hence, over-insurance should have little or no incremental effect for the monitoring channel. In contrast, this over-insurance is directly linked to the lenders' incentive to force borrowers into bankruptcy by rejecting restructuring (the channel through which the empty creditor mechanism works), and consequently, receiving payments from CDS sellers. The greater the degree of over-insurance by the empty creditor, the larger her benefit from rejecting restructuring.

Unfortunately, we do not have data on individual investors' CDS positions. The only indirect proxy we can observe is CDS trading volume which provides a measure of outstanding CDS contracts in our sample. We measure the severity of the empty creditor problem - the level of over-insurance - by the ratio of total CDS contracts outstanding during month t scaled by total debt outstanding at the same time (*Active CDS Outstanding/Debt*). We conjecture that firms with greater relative proportions of CDS outstanding are more exposed to the empty creditor problem, and consequently, will have higher bankruptcy risk.

Table IX reports our estimation results. This table re-estimates the baseline hazard model, where instead of using the indictor variable for *CDS Active*, we use a continuous measure for CDS exposure. *CDS Active* is a regime variable, since once a firm starts CDS trading, it cannot go back to be a non-CDS firm. However, the continuous measure of CDS exposure, (*Active CDS Outstanding/Debt*) is not static or permanent. The continuous measure of CDS exposure goes up/down, as and when CDS contracts are created/matured. Therefore, this continuous measure is not as affected by the selection issue analyzed at length in Section V of the paper. The average CDS exposure relative to total debt is 0.10 and median is 0.02. The maximum exposure in our sample is 4.14, strongly suggestive of over-insurance for such firms.

Table IX shows a significant positive coefficient of *Active CDS Outstanding/Debt*. The marginal effect of an increase in this variable on the probability of bankruptcy is 0.01%, compared to the overall sample probability of 0.14%. This finding is direct evidence supporting the prediction of the empty creditor model. That is, a larger amount of CDS contracts outstanding relative to firm's debt outstanding is associated with a higher probability of firm bankruptcy.

While it is comforting to find that outstanding amount of CDS contracts also affects bankruptcy risk, comparing the results in Table IX and results in Section V suggests that a better specification is to treat *CDS Active* as a regime variable. (We do not include both *CDS Active* and *Active CDS Outstanding/Debt* in the analysis of Table IX due to multi-collinearity concern.) An explanation for this finding could be that the aggregate variable, *Active CDS Outstanding/Debt*, capture the incentives of individual creditors, who may be "overinsured" with noise. However, there seem to be fundamental changes in firms after the introduction of CDS trading. The potential empty creditor problem is the main issue, but the concern about accentuating this problem is perhaps of secondary importance: Once the creditors have substantial stakes from CDS, their incentive to push the borrowers into bankruptcy will be strong.

B. Testing the Empty Creditor Hypothesis: The Restructuring Clause in CDS Contracts (H3)

Empty creditors would clearly prefer firms to declare bankruptcy rather than have the 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 include restructuring as a credit event, as argued in Section III. Thus, the strength of the restructuring channel of the empty creditor problem depends crucially on the definition of the restructuring clause in the CDS contracts.

In this section, we investigate the effect of differences in contractual terms on the credit risk consequences of CDS trading. Appendix C provides a detailed discussion of the restructuring clause in CDS contracts and its historical evolution. Essentially, there are four types of CDS contracts, based on their definition of credit events: full restructuring (FR), modified restructuring (MR), modified-modified restructuring (MMR), no restructuring (NR). For FR contracts, *any* restructuring qualifies as a trigger event, and *any* obligations with a maturity up to 30 years can be delivered in the event that the event is triggered. Under MR also, *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. 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 credit event.

As argued in Section III, firms with more NR contracts are more subject to the empty creditor threat than other types of CDS. FR contracts would not as strongly influenced by the empty creditor incentives. Another related issue is the type of settlement. Earlier, most CDS contracts were settled by physical delivery, while more recently, cash settlement is the norm. Contracts settled by physical delivery, such as MR and MMR, should have an additional influence from the empty creditor problem. The actual CDS spreads in the market reflect the differences in the contract structure, as shown by Packer and Zhu (2005).[43]

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 is hardly any NR CDS prior to year 2002. This is reasonable as the MR contracts were only just slightly more expensive than NR contracts (as documented by Packer and Zhu (2005)); therefore, CDS buyers prefered to buy MR contracts. The proportion of CDS contracts with NR specifications increased considerably in recent years, especially in 2007. The median fraction of NR contracts out of all CDS contracts for a reference entity is 0.61, and mean is 0.55. We also find that there is wide variation across firms in the proportion of NR type of contracts.

We account for the differences in contractual specifications in the revised estimations reported in Table X, which include variables measuring the type of CDS contracts. *No Restructuring CDS* is the fraction of CDS contracts with NR clauses. *Modified Restructuring CDS* is the fraction of CDS with MR clauses. 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 dummy variables (reported in the second and third columns), and also a combined one with both of them (reported in the last column). The results in Table X show that indeed only for NR contracts do we find a positive relationship of CDS trading to bankruptcy risk, while the coefficient of the MR dummy is not statistically significant. The marginal effect of an increase in the *No Restucturing CDS* variable in the combined regression on the probability of bankruptcy is 0.22%, compared to the overall sample probability of 0.14%.[44]

The results in this subsection strongly support the empty creditor model prediction. Com-

[43] However, the magnitude of this contractual effect appears to be modest. FR contracts command 7.7 bps higher spreads, on average, compared with NR contracts. The MR-MMR spread difference is only 1.4 bps. It is unclear whether the latter difference in contractual terms would have a material influence on bankruptcy prediction. It should be noted that these results use data from the earlier period of the CDS market and may not reflect the changes that occurred later on, especially after the global financial crisis, and should be interpreted with caution.

[44] 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 significant only in more recent years.

paring Table IX and Table X, we can see that Table X fits the data better. The effect of *CDS Active* seems to be driven by those CDS contracts with NR clauses. Given that more and more CDS contracts use NR as the credit event specification (e.g., all index constituents of the CDX.NA.IG index), our findings will likely to be applicable to many more reference names in the future.

C. Testing the Implications of the Empty Creditor Hypothesis: Change in Number of Lenders (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, as discussed earlier. It is reasonable to expect that the lead bank may not choose to become an empty creditor for short-run profits, due to long-run reputation concerns. Therefore, CDS trading may affect the size and composition of the loan syndicate to a firm. Indeed, 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.

We investigate the impact of CDS introduction on the creditor relationships of a firm. The overall creditor relationship is represented in our analysis by the bank relationships available from Dealscan LPC. 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. We regress the change in *Number of Banks* on a set of firm specific variables and the *CDS Active* variable. The results are reported in Panel A of Table XI. We find that CDS trading significantly increases the number of banking relationships a firm has. On average, firms have 2.4 more lenders 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. We present similar evidence for our sample, also including the effect of CDS trading, in Panel B of Table XI. 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 are consistent with the prediction of the empty creditor model in Bolton and Oehmke (2011) i.e., CDS trading increases the number of creditors as well as bankruptcy risk.

VII. Concluding Remarks

We show that CDS trading increases the bankruptcy risk of firms by analyzing a comprehensive data set of North American CDS introductions over the period of 1997-2009. On average, firms with CDS traded on them see a decline in their credit rating by half a notch, while their probability of bankruptcy more than doubles from 0.14% to 0.33%. Our conclusion is robust to controlling for the endogeneity in CDS trading, i.e., the possibility that firms that are vulnerable to exacerbated credit risk are selected for CDS trading in the first place. Our results support the “empty creditor” hypothesis originally proposed by Hu and Black (2008) and modeled by Bolton and Oehmke (2011). Lenders who insure themselves by buying CDS protection help push borrowers into bankruptcy, even though restructuring may be a better choice for the firm from the conventional (without CDS protection) lenders’ perspective. This is because the empty creditors are better off in default due to the payment from the CDS being triggered following the bankruptcy event.

Our study is the first empirical work, to our knowledge, to formally address the empty creditor concern, which has attracted a lot of attention among academics, practitioners and regulators. The robustness checks we employ range from alternative controls for the effects of endogeneity, the quantum of CDS contracts outstanding and the definition of credit events in the CDS contracts. Our main conclusion remains valid even after taking these factors into account: 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 the contracts do not include restructuring as a credit event.

We hope that our study will improve our understanding of the implications of CDS trading and contribute to the ongoing debate on this important market. We emphasize that although we show that firms become more vulnerable to bankruptcy once CDS starts trading, our study does *not* imply that CDS trading necessarily reduces social welfare. Indeed, as Bolton and Oehmke (2011) argue, CDS may actually increase debt capacity, since many previously unqualified projects may get funded due to the possibility of mitigation of credit risk afforded by the CDS. Therefore, the increase in bankruptcy risk may result from 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 impact of CDS trading on bankruptcy efficiency.

Our 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, particularly when the risk is already high. Credit rating agencies ought to take CDS trading into account in their rating decisions. Corporate executives as well as investment bankers should factor in the CDS market into their decision making regarding capital structure and leverage choices. Financial regulators and policy makers need to consider 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 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 bankruptcy after struggling with declining revenues amid a troubled U.S. auto market.	

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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 Lyondell Basell 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; 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 drop 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
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	Chemicalcompany; 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 bankruptcy, 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 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 in December 1997, Equistar Chemicals; 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
GM	200102	200906	Filed for bankruptcy after failing to reach 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 and an inability 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 companys liquidity.	
ROUSE CO	200401	200904	Subsidiary of General Growth; General Growth files for Chapter 11 bankruptcy protection after failing to reach a deal with its creditors.	Yes
KMART CORP	199709	200201	Retailer; Prior to bankruptcy 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.	

(Continued)

-Continued

Company Name	CDS Date	Bankruptcy Date	Summary	Potential empty creditor
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.	
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 driven 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 bankruptcy, 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 Merton Model and the 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:

$$dV = \mu V dt + \sigma_V V dW, \tag{3}$$

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:

$$E = VN(d_1) - e^{-rT}FN(d_2), \tag{4}$$

$$d_1 = \frac{ln(V/F) + (r + 0.5\sigma_V^2)\sqrt{T}}{\sigma_V T}, d_2 = d_1 - \sigma_V \sqrt{T} \tag{5}$$

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:

$$\sigma_E = (\frac{V}{E})N(d_1)\sigma_V \tag{6}$$

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

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

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

$$EDF = N(-(\frac{ln(V/F) + (\mu - 0.5\sigma_V^2)T}{\sigma_V \sqrt{T}})) = N(-DD). \tag{8}$$

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 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 and MMR. By 2009, the rules essentially excluded restructure as a credit event for all North American corporate CDS contracts.

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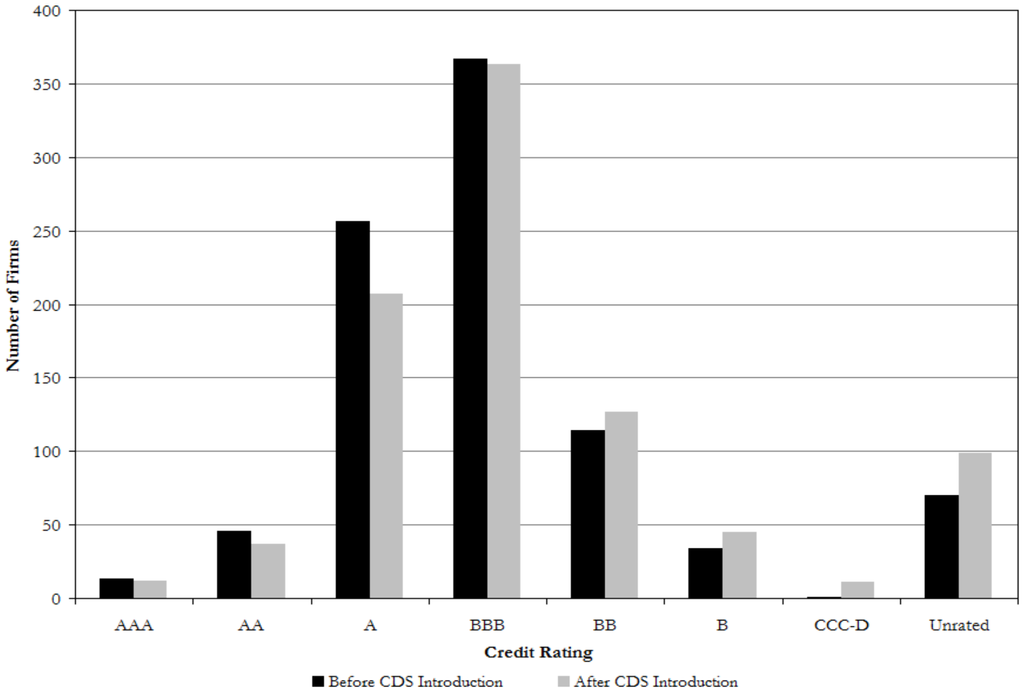

Figure 1: Rating Distribution Around the Introduction of Credit Default Swaps This figure plots the credit rating distributions for firms with credit default swaps (CDS) before the inception of CDS trading and two years after the inception of CDS trading. The credit ratings are from S&P Credit Ratings. 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.

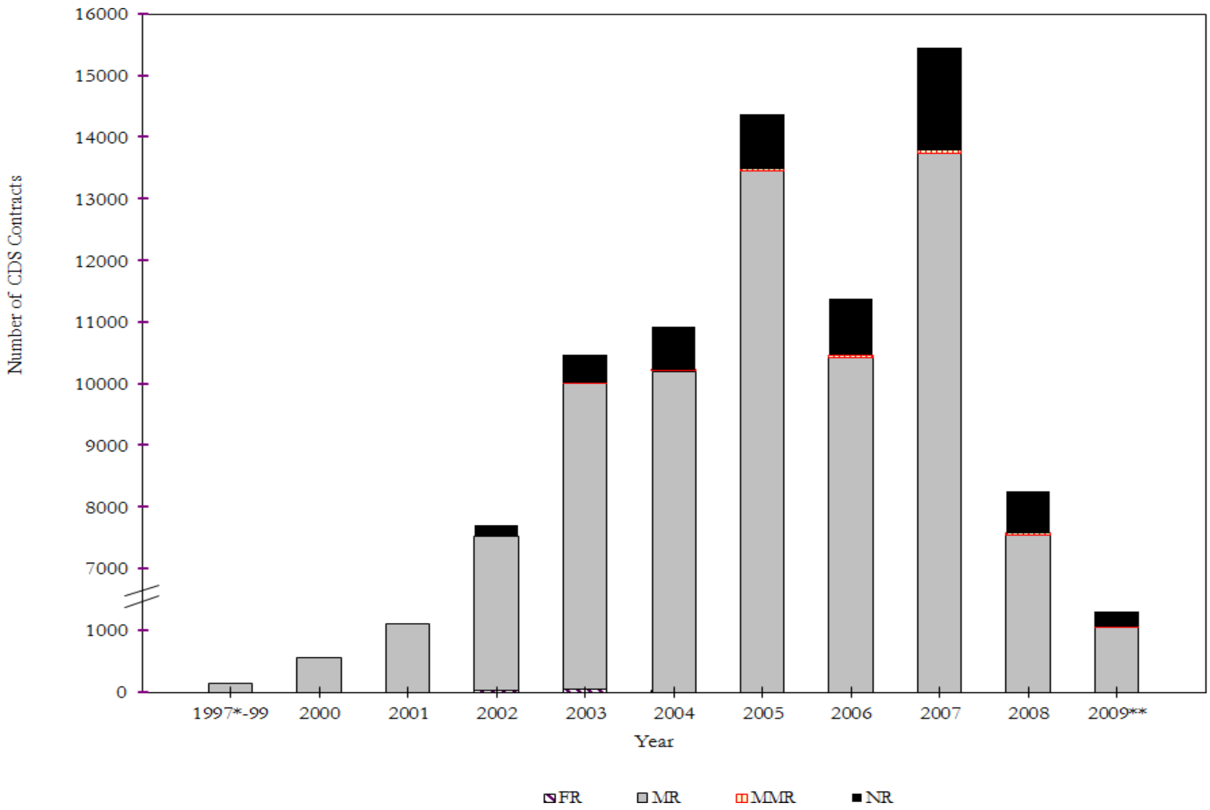

Figure 2: Credit Default Swaps and Restructuring Clause by Year This figure plots the distribution of credit default swaps (CDS) restructuring clauses, by year, in our sample between 1997 and 2009. The CDS data are from CreditTrade and GFI Group. There are four types of contract terms related to restructuring: 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 bankruptcies and the number of Non-CDS firms filed for bankruptcies respectively. (* from June 2007, ** 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 equity value. *ln(F)* is the logarithm of the firm's debt. $1/\sigma_E$ is the inverse of the firm's annualized equity volatility. $r_{it-1} - r_{mt-1}$ is the firm's excess return over the past year, and *NI/TA* is the firm's ratio of net income to total assets. To estimate the impact of CDS trading on the probability of credit downgrades/bankruptcy, we include credit default swap variables in the model specification. *CDS Firm* equals one, if the firm is in the CDS sample and zero otherwise. *CDS Active* is a dummy variable that equals one if the firm has CDS traded on its debt, one year before month t. The coefficient of interest is that of *CDS Active*, which captures the impact of CDS trading on the probability of credit downgrades/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	
ln(E)	−0.736***	−0.735***	−0.710***	−0.713***
	(0.014)	(0.014)	(0.024)	(0.024)
ln(F)	0.503***	0.507***	0.713***	0.711***
	(0.015)	(0.015)	(0.023)	(0.023)
$1/\sigma_E$	−0.017	−0.062**	−1.675***	−1.626***
	(0.026)	(0.027)	(0.131)	(0.131)
$r_{it-1} - r_{mt-1}$	−0.252***	−0.281***	−1.331***	−1.320***
	(0.035)	(0.035)	(0.111)	(0.111)
NI/TA	−0.000	−0.003	−0.038***	−0.038***
	(0.024)	(0.025)	(0.013)	(0.013)
CDS Firm		0.755***		−2.009***
		(0.057)		(0.711)
CDS Active	1.371***	0.691***	0.400**	2.373***
	(0.045)	(0.067)	(0.177)	(0.729)
Time Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
R-Square	14.75%	15.08%	24.06%	24.18%
N	658966	658966	658966	658966
# of Downgrades(Bankruptcy)	3863	3863	940	940
CDS Active Odds Ratio	3.939	1.925	1.492	10.73
CDS Active Marginal Effect	0.78%	0.39%	0.06%	0.33%
Sample Probability of a Downgrade(Bankruptcy)	0.59%	0.58%	0.14%	0.14%

Panel B: Distance-to-Default Matching

	Distance-to-Default Matching			
	Probability of Downgrades		Probability of Bankruptcy	
ln(E)	$-0.447***$	$-0.462***$	$-0.891***$	$-0.923***$
	(0.028)	(0.027)	(0.113)	(0.114)
ln(F)	$0.270***$	$0.318***$	$0.865***$	$0.853***$
	(0.031)	(0.030)	(0.118)	(0.116)
$1/\sigma_E$	-0.008	$-0.155***$	$-1.971***$	$-1.905***$
	(0.038)	(0.042)	(0.317)	(0.315)
$r_{it-1} - r_{mt-1}$	-0.090	$-0.614***$	-0.101	-0.076
	(0.056)	(0.073)	(0.196)	(0.191)
NI/TA	$-0.700***$	$-0.845***$	$-0.994***$	-0.331
	(0.221)	(0.133)	(0.259)	(0.221)
CDS Firm		$1.307***$		$-1.809**$
		(0.100)		(0.759)
CDS Active	$1.313***$	$0.586***$	$0.773***$	$2.196***$
	(0.069)	(0.083)	(0.299)	(0.759)
Time Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
R-Square	8.03%	12.02%	23.05%	23.16%
N	119143	119143	119143	119143
# of Downgrades(Bankruptcy)	1469	1469	67	67
CDS Active Odds Ratio	3.717	1.797	2.166	8.989
CDS Active Marginal Effect	1.46%	0.64%	0.04%	0.12%
Sample Probability of a Downgrade(Bankruptcy)	1.14%	1.13%	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. *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. Market Equity is the measure of the Number of Common Shares Outstanding multiplied by 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. *Ln(Asset)* is logarithm of the firm's Total Assets value. *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. *DD* is the firm's distance-to-default estimated from the Merton(1974) model described in Appendix B. *Rated* is a dummy variable that equals one, if there is credit rating on the firm in month t. *Bond turnover* is defined as the ratio of bond trading volume to amount outstanding. 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 CDS Trading
Leverage	$0.146***$
	(0.041)
ROA	0.021
	(0.030)
$r_{it-1} - r_{mt-1}$	$0.049**$
	(0.023)
Equity Volatility	$-0.427***$
	(0.079)
Ln(Asset)	$0.403***$
	(0.015)
PPENT/Total Asset	0.109
	(0.097)
Sales/Total Asset	0.018
	(0.015)
EBIT/Total Asset	0.169
	(0.143)
WCAP/Total Asset	$0.132***$
	(0.035)
RE/Total Asset	-0.007
	(0.005)
Cash/Total Asset	-0.228
	(0.192)
CAPX/Total Asset	-0.001
	(0.355)
DD	$-0.046***$
	(0.014)
Rated	$0.647***$
	(0.089)
Bond Turnover	$0.087***$
	(0.018)
Time Fixed Effects	Yes
Industry Fixed Effects	Yes
R-Square	37.12%
N	520565
# of CDS Events	477

Table IV
Changes in Performance Around the Introduction of Credit Default Swaps: Difference-in-Difference Analysis

This table presents a univariate analysis of changes in firm performance before and after the induction of credit default swaps (CDS) trading, i.e., from one year before the inception of CDS trading to one year (-1,1) or two year (-1,2) after the inception of CDS trading. The changes in the performance measures 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. $\triangle$ *Leverage* is the change in leverage, defined as the change in the ratio of Book Debt to the sum of Book Debt and Market Equity. $\triangle$ *EDF* is the change in firm's expected default frequency. EDF is calculated based on the Merton (1974) model, as explained in Appendix B. $\triangle$ Z-score is the change in firm's Z-score calculated from Altman(1968). $\triangle$ *Rating* is the change in firm's credit rating. The number of observations is 477. In the case of missing data, the number of observations is smaller. (*** Significant at 1% level, ** significant at 5% level, and * significant at 10% level.)

	(-1,1)			(-1,2)		
Variables	CDS Firm	Matched	Difference	CDS Firm	Matched	Difference
$\triangle$ *Leverage*	0.006	−0.010	0.016 **	0.003	−0.020	0.023 **
$\triangle$ *EDF*	0.022	0.018	0.004*	−0.012	−0.054	0.042 ***
$\triangle$ *Z-Score*	−0.405	−0.373	−0.032*	−0.424	−0.266	−0.158*
$\triangle$ *Rating*	0.385	0.260	0.126*	0.717	0.642	0.075

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

This table presents the estimates of the probability of credit downgrades/bankruptcy using a logistic model in a sample including firms with credit default swaps (CDS) and non-CDS 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 equity value. *ln(F)* is the logarithm of the firm's debt. $1/\sigma_E$ is the inverse of the firm's annualized equity volatility. $r_{it-1} - r_{mt-1}$ is the firm's excess return over the past year, and *NI/TA* is the firm's ratio of net income to total assets. To estimate the impact of CDS trading on the probability of credit downgrades/bankruptcy, we include credit default swap variables in the model specification. *CDS Firm* equals one, if the firm is in the CDS sample, and zero otherwise. *CDS Active* is a dummy variable that equals one, if the firm has CDS traded on its debt, one year before month t. The coefficient of interest is that of *CDS Active*, which captures the impact of CDS trading on the probability of credit downgrades/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 Downgrades	Probability of Bankruptcy
ln(E)	$-0.121***$	$-0.492***$
	(0.021)	(0.091)
ln(F)	$0.111***$	$0.593***$
	(0.023)	(0.09)
$1/\sigma_E$	$-0.251***$	$-1.883***$
	(0.035)	(0.269)
$r_{it-1} - r_{mt-1}$	$-0.344***$	$-0.799***$
	(0.045)	(0.262)
NI/TA	0.054	1.869
	(0.096)	(1.139)
CDS Firm	$-0.320***$	$-1.819**$
	(0.065)	(0.732)
CDS Active	$0.718***$	$1.865**$
	(0.076)	(0.76)
Time Fixed Effects	Yes	Yes
Industry Fixed Effects	Yes	Yes
R-Square	8.72%	27.64%
N	113731	113731
# of Downgrades(Bankruptcy)	2157	82
CDS Active Odds Ratio	2.051	6.456
CDS Active Marginal Effect	1.33%	0.13%
Sample Probability of a Downgrade(Bankruptcy)	1.90%	0.07%

Table VI
Credit Default Swaps Trading and Credit Quality: Heckman Correction

This table presents the estimates of the probability of credit downgrades/bankruptcy using a logistic model in a sample including firms with credit default swaps (CDS) and all non-CDS firms. The model used is similar to that in Table II, but adjusts for the selection bias using the Heckman correction method. The *Inverse Mills Ratio* is calculated from a probit regression modeling the probability of CDS trading. *ln(E)* is the logarithm of the firm's equity value. *ln(F)* is the logarithm of the firm's debt. $1/\sigma_E$ is the inverse of the firm's annualized equity volatility. $r_{it-1} - r_{mt-1}$ is the firm's excess return over the past year, and *NI/TA* is the firm's ratio of net income to total assets. To estimate the impact of CDS trading on the probability of credit downgrades/bankruptcy, we include credit default swap variables in the model specification. *CDS Firm* equals one, if the firm is in the CDS sample and zero otherwise. *CDS Active* is a dummy variable that equals one, if the firm has CDS traded on its debt, one year before month t. The coefficient of interest is that of *CDS Active*, which captures the impact of CDS trading on the probability of credit downgrades/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 Downgrades	Probability of Bankruptcy
ln(E)	$-0.662***$	$-0.639***$
	(0.015)	(0.022)
ln(F)	$0.415***$	$0.646***$
	(0.015)	(0.022)
$1/\sigma_E$	$-0.134***$	$-1.403***$
	(0.029)	(0.126)
$r_{it-1} - r_{mt-1}$	$-0.345***$	$-1.330***$
	(0.038)	(0.109)
NI/TA	0.003	$-0.032**$
	(0.021)	(0.013)
CDS Firm	$0.649***$	$-2.277***$
	(0.059)	(0.71)
CDS Active	$1.432***$	$2.680***$
	(0.086)	(0.744)
Inverse Mills Ratio	$-0.706***$	-0.003
	(0.051)	(0.115)
Time Fixed Effects	Yes	Yes
Industry Fixed Effects	Yes	Yes
R-Square	14.64%	22.42%
N	657438	657438
# of Downgrades(Bankruptcy)	3723	940
CDS Active Odds Ratio	4.187	14.585
CDS Active Marginal Effect	0.80%	0.37%
Sample Probability of a Downgrade(Bankruptcy)	0.58%	0.14%

Table VII
Impact of Credit Default Swaps Trading on Bankruptcy: Analyst Coverage

This table investigates the impact of credit default swaps (CDS) trading on a firm's probability of bankruptcy in a sample including firms with High(Low) analyst coverage. Analyst coverage has been used to proxy the availability of private information. *Low Coverage* is an indicator for firms with low analyst coverage. *ln(E)* is the logarithm of the firm's equity value. *ln(F)* is the logarithm of the firm's debt. $1/\sigma_E$ is the inverse of the firm's annualized equity volatility. $r_{it-1} - r_{mt-1}$ is the firm's excess return over the past year, and *NI/TA* is the firm's ratio of net income to total assets. The coefficients of interest are those of *CDS Active* and *CDS Active*Low Coverage*. 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		
	Low Analyst Coverage	High Analyst Coverage	Full Sample
ln(E)	$-0.596***$	$-0.713***$	$-0.712***$
	(0.032)	(0.024)	(0.024)
ln(F)	$0.584***$	$0.711***$	$0.710***$
	(0.032)	(0.023)	(0.023)
$1/\sigma_E$	$-1.773***$	$-1.626***$	$-1.660***$
	(0.209)	(0.131)	(0.133)
$r_{it-1} - r_{mt-1}$	$-1.286***$	$-1.320***$	$-1.319***$
	(0.156)	(0.111)	(0.111)
NI/TA	-0.026	$-0.038***$	$-0.039***$
	(0.017)	(0.013)	(0.013)
CDS Firm	-1.537	$-2.009***$	$-2.021***$
	(1.006)	(0.711)	(0.711)
CDS Active	$1.986*$	$2.373***$	$2.329***$
	(1.044)	(0.729)	(0.737)
CDS Active Low Coverage*			0.134
			(0.359)
Low Coverage			$-0.129*$
			(0.070)
Time Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
R-Square	20.12%	28.71%	24.21%
N	256404	402562	658966
# of Bankruptcies	450	490	940
CDS Active Marginal Effect	0.34%	0.32%	0.32%
Sample Probability of Bankruptcy	0.18%	0.12%	0.14%

Table VIII
Credit Default Swaps Trading and Credit Rating

This table investigates the impact of credit rating and credit default swaps (CDS) trading on the probability of bankruptcy. The hazard model analysis of the probability of bankruptcy is conducted in a sample including firms with CDS and non-CDS firms matched by their propensity score. *ln(E)* is the logarithm of the firm's equity value. *ln(F)* is the logarithm of the firm's debt. $1/\sigma_E$ is the inverse of the firm's annualized equity volatility. $r_{it-1} - r_{mt-1}$ is the firm's excess return over the past year, and *NI/TA* is the firm's ratio of net income to total assets. *CDS Firm* equals one, if the firm is in the CDS sample and zero otherwise. *CDS Active* is a dummy variable that equals one, if the firm has CDS traded on its debt, one year before month t. *Unrated* equals one, if there is no credit rating on the firm. The coefficients of interest are those of *CDS Active*, *Unrated**CDS Active* and *Downgrade*. 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		
	Model 1	Model 2	Model 3
ln(E)	−0.492∗∗∗	−0.482∗∗∗	−0.486∗∗∗
	(0.091)	(0.09)	(0.091)
ln(F)	0.593∗∗∗	0.577∗∗∗	0.586∗∗∗
	(0.090)	(0.089)	(0.090)
$1/\sigma_E$	−1.883∗∗∗	−1.674∗∗∗	−1.675∗∗∗
	(0.269)	(0.266)	(0.267)
$r_{it-1} - r_{mt-1}$	−0.799∗∗∗	−0.741∗∗∗	−0.670∗∗∗
	(0.262)	(0.264)	(0.259)
NI/TA	1.869	2.251∗	2.174∗
	(1.139)	(1.179)	(1.185)
CDS Firm	−1.819∗∗	−1.837∗∗	−1.780∗∗
	(0.732)	(0.732)	(0.732)
CDS Active	1.865∗∗	1.729∗∗	1.634∗∗
	(0.760)	(0.774)	(0.775)
Unrated		0.580∗	0.656∗
		(0.347)	(0.344)
*Unrated*CDS Active*		1.144∗∗	1.056∗
		(0.561)	(0.558)
Downgrade			1.456∗∗∗
			(0.330)
Time Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
R-Square	27.64%	28.67%	29.74%
N	113731	113731	113731
# of Bankruptcies	82	82	82
CDS Active Odds Ratio	6.456	5.635	6.773
Downgrade Odds Ratio			4.406
CDS Active Marginal Effect	0.13%	0.12%	0.11%
Unrated*CDS Active Marginal Effect		0.08%	
Downgrade Marginal Effect			0.10%
Sample Probability of Bankruptcy	0.07%	0.07%	0.07%

Table IX
Active CDS Outstanding and Empty Creditor Problem

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 total active CDS outstanding during month t scaled by total debt (*Active CDS Outstanding/Debt*). *CDS Firm* equals one, if the firm is in the CDS sample and zero otherwise. The coefficient of interest is that of *Active CDS Outstanding/Debt*, which captures the impact of CDS induced empty creditor problem. *ln(E)* is the logarithm of the firm's equity value. *ln(F)* is the logarithm of firm's debt. $1/\sigma_E$ is the inverse of the firm's annualized equity volatility. $r_{it-1} - r_{mt-1}$ is the firm's excess return over the past year, and *NI/TA* is the firm's ratio of net income to total assets. 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
ln(E)	$-0.689***$
	(0.026)
ln(F)	$0.652***$
	(0.026)
$1/\sigma_E$	$-1.533***$
	(0.104)
$r_{it-1} - r_{mt-1}$	$-0.620***$
	(0.075)
NI/TA	$-0.076***$
	(0.023)
CDS Firm	$-0.582***$
	(0.211)
Active CDS Outstanding/Debt	$0.071**$
	(0.032)
Time Fixed Effects	Yes
Industry Fixed Effects	Yes
R-Square	15.82%
N	658966
# of Bankruptcies	940
Active CDS Outstanding/Debt Odds Ratio	1.074
Active CDS Outstanding/Debt Marginal Effect	0.01%
Sample Probability of Bankruptcy	0.14%

Table X
Restructuring Specification of CDS Contracts

This table investigates the impact of the restructuring clause 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 No Restructuring as the restructuring clause. In Model 1, for each CDS firm, we include a variable for *No Restructuring CDS*, which is the total amount of active CDS contracts with No Restructuring as the restructuring clause during month t, scaled by total number of CDS contracts trading on this firm. In Model 2, for each CDS firm, we calculate *Modified Restructuring CDS*, which is the total amount of active CDS contracts with Modified Restructuring as the restructuring clause during month t, scaled by total number of CDS contracts trading on this firm. *CDS Firm* equals one if the firm is in the CDS sample and zero otherwise. The coefficient of interest is that of *No Restructuring CDS* which captures the impact of CDS induced empty creditor problem. *ln(E)* is the logarithm of the firm's equity value. *ln(F)* is the logarithm of firm's debt. $1/\sigma_E$ is the inverse of the firm's annualized equity volatility. $r_{it-1} - r_{mt-1}$ is the firm's excess return over the past year, and *NI/TA* is the firm's ratio of net income to total assets. 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		
	Model 1	Model 2	Model 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	$1.315**$		$1.557***$
	(0.565)		(0.599)
Modified Restructuring CDS		0.572	0.858
		(0.492)	(0.528)
Time Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
R-Square	24.06%	24.04%	24.08%
N	658966	658966	658966
# of Bankruptcies	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 Bankruptcy	0.14%	0.14%	0.14%

Table XI
Bank Relationships and Empty Creditor Problem

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. $\triangle$ *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 (-1,2). $\triangle$ *Ln(Asset)* is the change in logarithm of the firm's Total Assets value. $\triangle$ *ROA* is the change in firm's return on asset. $\triangle$ *Leverage* is the change in leverage. $\triangle$ *Tangible Asset/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 if the firm has CDS traded on its debt. *ln(E)* is the logarithm of the firm's equity value. *ln(F)* is the logarithm of firm's debt. $1/\sigma_E$ is the inverse of the firm's annualized equity volatility. $r_{it-1} - r_{mt-1}$ is the firm's excess return over the past year, and *NI/TA* is the firm's ratio of net income to total assets. *CDS Firm* equals one if the firm is in the CDS sample and zero otherwise. *Number of Banks* is the number of bank relationships in month t. 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

	$\triangle$ Number of Banks
$\triangle$ *Ln(Asset)*	6.291***
	(1.849)
$\triangle$ *ROA*	−0.396
	(2.76)
$\triangle$ *Leverage*	8.581*
	(5.201)
$\triangle$ *Tangible Asset/Total Asset*	−1.586
	(10.84)
CDS Active	2.432**
	(1.069)
Time Fixed Effects	Yes
Industry Fixed Effects	Yes
R-Square	9.75%
N	496

Panel B

	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
R-Square	24.32%
N	658966
# of Bankruptcies	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%