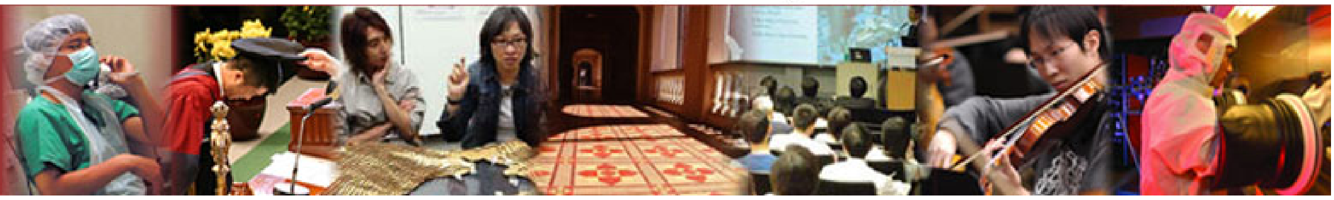

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DOES THE TAIL WAG THE DOG? THE EFFECT OF CREDIT DEFAULT SWAPS ON CREDIT RISK

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

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Abstract

Credit default swaps (CDS) are derivative contracts that are widely used as tools for credit risk management. However, in recent years, concerns have been raised about whether CDS trading itself affects the credit risk of the reference entities. We use a unique, comprehensive sample covering CDS trading of 901 North American corporate issuers, between June 1997 and April 2009, to address this

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question. We find that the probability of both a credit rating downgrade and bankruptcy increase, with large economic magnitudes, after the inception of CDS trading. This finding is robust to controlling for the endogeneity of CDS trading. Beyond the CDS introduction effect, we show that firms with relatively larger amounts of CDS contracts outstanding, and those with relatively more “no restructuring” contracts than other types of CDS contracts covering restructuring, are more adversely affected by CDS trading. Moreover, the number of creditors increases after CDS trading begins, exacerbating creditor coordination failure for the resolution of financial distress.

Keywords: Credit Default Swaps, Credit Risk, Bankruptcy, Empty Creditor

1. Introduction

Credit default swaps (CDS) are insurance-type contracts that offer buyers protection against default by a debtor. The CDS market grew by leaps and bounds from $180 billion in 1997 to $62 trillion in 2007, measured by notional amount outstanding.[1] CDS are arguably the most controversial financial innovation of the past two decades, extolled by some and disparaged by others.[2] CDS played a prominent role in the bankruptcy of Lehman Brothers, the collapse of AIG, and the sovereign debt crisis of Greece. Although the CDS market shrank considerably following the global financial crisis, it nevertheless stood at about $29 trillion by December 2011. In spite of misgivings about the role of CDS in potentially destabilizing markets, their role as indicators of credit quality has, in fact, expanded. CDS spreads are widely quoted by practitioners and regulators for the assessment of credit risks, for both individual corporate debtors and the overall sovereign risk of a country. Meanwhile, on-shore CDS trading was launched in China and India after the credit crisis. In contrast to the intense public debate, theoretical arguments and policy initiatives, empirical evidence on the real effects of CDS trading on corporations referenced by CDS contracts is sparse. In this paper, we attempt to fill this gap in the literature, using a comprehensive dataset to empirically examine the effects of CDS on the credit risk of the reference firms.

Derivatives are often assumed to be redundant securities in pricing and hedging models and hence have no effect, adverse or benign, on the price of the underlying asset or the integrity of markets. In structural models of credit risk along the lines of Merton (1974), default risk is driven principally by leverage and asset volatility. In the spirit of that framework, CDS are regarded as “side-bets” on the value of the firm and hence do not have an impact 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 even the possibility of a credit rating downgrade.

Many of the issues mentioned in the context of derivatives, in general, have also been raised in the specific case of CDS regarding their effect on the underlying asset.[3] Apart from common concerns that apply to all derivatives, CDS contracts are somewhat different. CDS contracts are traded over-the-counter, where price transparency and discovery are less clear-cut than in the exchanges on

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1 Semiannual OTC Derivative Statistics, Bank for International Settlements (BIS). CDS market statistics are also regularly published by the International Swaps and Derivatives Association (ISDA) and the British Banker's Association (BBA).

2 Former Federal Reserve Chairman Alan Greenspan argued that “these increasingly complex financial instruments have contributed, especially over the recent stressful period, to the development of a far more flexible, efficient, and hence resilient financial system than existed just a quarter-century ago.” (See “Economic Flexibility”, Alan Greespan, Speech given to Her Majesty's Treasury Enterprise Conference, London, January 26, 2004.) In striking contrast, Warren Buffett, the much-acclaimed investor, weighed against derivatives, in general, by describing them as “time bombs, for the parties that deal in them and the economic system” and went on to conclude that “in my view, derivatives are financial weapons of mass destruction, carrying dangers that, while now latent, are potentially lethal.” (See the Berkshire Hathaway Annual Report for 2002.) In a similar vein, George Soros, a legendary hedge fund manager, argued that “CDS are toxic instruments whose use ought to be strictly regulated.” (See “One Way to Stop Bear Raids”, *Wall Street Journal*, March 24, 2009.)

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

which most equity derivatives are listed. Moreover, financial institutions, including the bank creditors of the reference entities, are major participants of the CDS market. CDS typically have much longer maturities than most exchange-traded derivatives, allowing the traders more flexibility in adjusting their positions. If creditors selectively trade CDS linked to their borrowers, CDS positions can change the creditor-borrower relationship and play an important role in determining the borrower credit risk that determines CDS payoffs. On the one hand, CDS allow creditors to hedge their credit risk; therefore they may increase the supply of credit to the underlying firm. Such improved access to capital may increase borrowers' financial flexibility and resilience to financial distress.[4] On the other hand, lenders may not be as vigilant in monitoring the borrowers once their credit exposures are hedged. Consequently, firms, in turn, may take on more risky projects. Furthermore, CDS-protected creditors are likely tougher during debt renegotiations, once the borrowers are in financial distress, by refusing debt workouts and making borrowers more vulnerable to bankruptcy.

We empirically examine the effects of CDS trading on the credit risk of reference entities using a comprehensive dataset dating back to the broad inception of the CDS market for corporate names in 1997. It should be emphasized that it is difficult to obtain accurate data on CDS transactions from a single source, since CDS trading does not take place on centralized exchanges. Indeed, the central clearing of CDS is a relatively recent phenomenon. Our identification of CDS inception and transactions 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 that provides daily valuations based on quotes from major sell-side institutions. Our combined dataset covers 901 North American firms with a CDS trading history during the period from 1997 to 2009. The list of bankruptcies for North American firms is comprehensively constructed from major data sources such as New Generation Research, the UCLA-LoPucki Bankruptcy Database, the Altman-NYU Salomon Center Bankruptcy List, the Fixed Income Securities Database (FISD), and Moody's Annual Reports on Bankruptcy and Recovery. Over the same time period, our overall sample of firms covers 3,863 rating downgrades from Standard & Poor's and 1,628 bankruptcy filings.

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

4 Indeed, this argument has been cited as the motivation for the invention of CDS by JPMorgan, which lent to Exxon Mobil in 1994 in the aftermath of the Exxon Valdez oil spill lawsuit. In a pioneering transaction, JPMorgan hedged part of its credit exposure using a CDS transaction with the European Bank for Reconstruction and Development (EBRD). See Tett (2009).

The selection of firms for CDS trading and the endogeneity of the timing of CDS inception need to be addressed in order to make a causal inference about the effect of CDS trading. CDS firms and non-CDS firms are quite different in terms of their key characteristics. There could be unobserved omitted variables that drive both the selection of firms for CDS trading and changes in bankruptcy risk. Also, the timing of CDS inception can be endogenous as CDS trading is more likely to be initiated when market participants anticipate the *future* deterioration in the credit quality of the reference firm. We address these two concerns in several ways besides the basic fixed effects controls. Specifically, we construct a model to predict CDS trading for individual firms. This model allows us to measure the treatment effect of CDS inception using an instrumental variable (IV) approach, run a propensity score matching analysis for firms with and without CDS trading, and conduct a difference-in-difference estimation. We find two IVs for CDS trading. The first IV is the foreign exchange (FX) hedging position of lenders and bond underwriters. Lenders with a larger FX hedging position are more likely, in general, to trade the CDS of their borrowers. The second is the lenders' Tier One capital ratio. Banks with lower capital ratios have a greater need to hedge the credit risk of their borrowers via CDS. It seems valid to exclude both IVs from the credit risk predictions of firms since they only affect borrower credit risk via CDS market activities. We also show that both IVs are significant determinants of CDS trading and that they are not weak instruments. Furthermore, the Sargan over-identification tests fail to reject the hypothesis that both IVs are exogenous. The positive relationship between CDS trading and bankruptcy risk remains significant, even after controlling for the selection and endogeneity of CDS trading.

The effect of CDS trading on credit risk goes beyond the simple binary categorization of firms' CDS status. It is conceivable that CDS will be more influential when the market is more liquid and when more contracts are outstanding. Indeed, we find that the likelihood of bankruptcy increases with the number of live CDS contracts outstanding. Therefore, the effect of CDS works in both directions: bankruptcy risk increases as CDS positions gather force and decreases when the amount of CDS trading is reduced. These findings further strengthen the evidence that the increase in credit risk after CDS trading begins is not completely due to selection and endogeneity.

After establishing our primary finding that the reference firms' credit risk increases after CDS trading begins, we investigate potential mechanisms for channeling the effect of CDS trading on credit risk. CDS can affect firm fundamentals such as the leverage and the interest burden. The credit risk of a firm clearly increases as it becomes more leveraged. Indeed, we find that firm leverage increases significantly after CDS trading begins. The increase in leverage can be due to either enlarged credit supply or reduced debt financing restrictions imposed by lenders after CDS trading has begun.[5] Therefore, we control for leverage (both before and after CDS trading) in our regression analysis in order to isolate the leverage channel from other possibilities. The credit risk of a firm can also increase if it is more vulnerable in financial distress. One source of vulnerability arises from the

[5] Saretto and Tookes (2012) focus on the effect of CDS trading on leverage and confirm the hypothesis of increased leverage.

creditor's unwillingness to work out troubled debt. Another source is the potential failure of coordination among the distressed firm's creditors.

Anecdotal evidence suggests that CDS positions can play an important role in the process of distress resolution. To cite one such instance, CIT Group attempted to work out its debt from late 2008 to mid-2009. In the event, however, some creditors with CDS protection rejected the firm's exchange offer.[6] CIT Group eventually filed for Chapter 11 bankruptcy on November 1, 2009. Hu and Black (2008) term such CDS-protected debt-holders "empty creditors", meaning that they have all the same legal rights as creditors, but do not have positive risk exposure to borrower default; hence, their financial interests are not aligned with those of other creditors who do not enjoy such protection.[7]

The empty creditor problem is formally modeled by Bolton and Oehmke (2011).[8] Their model predicts that, under mild assumptions, lenders will choose to become empty creditors by buying CDS protection. Consequently, they will be tougher in debt renegotiation when the firm is under stress. Empty creditors are even willing to push the firm into bankruptcy if their total payoffs including CDS payments would be larger in that event. In their model, CDS sellers anticipate this empty creditor problem and price it into the CDS premium, but they cannot directly intervene in the debt renegotiation process (unless they buy bonds or loans so as to become creditors).

Our data do not include trader identities; therefore, we cannot directly observe the presence and extent of empty creditors; neither are we aware of other data sources that would allow direct detection of empty creditors. In an indirect test, we find that firm bankruptcy risk is positively related to the total CDS amount divided by total debt. We further construct a more effective test of tough creditor implications. Our combined dataset contains contract terms that allow us to test a unique prediction of the empty creditor model. Specifically, we know for each CDS contract whether restructuring is covered as a credit event or not. Buyers of "no restructuring" CDS contracts will be paid only if the reference firm files for bankruptcy or there is a failure to pay. However, buyers of other types of CDS contracts that include restructuring as a credit event will be compensated even when the debt of the reference firm is restructured. Clearly, creditors with "no restructuring" CDS protection will have a stronger incentive to force bankruptcy than buyers of other CDS contracts without this restrictive clause. Indeed, we find that the effects of CDS trading are stronger when a larger fraction of the CDS contracts contain the "no restructuring" credit event clause. This result also provides evidence of the causal effects of CDS trading, particularly since there is no significant effect from other types of CDS

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

7 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.

8 Table 1 of Bolton and Oehmke (2011) lists other cases of suspected empty creditors, demonstrating that the CIT example is not that unique. Other studies such as Duffie (2007), Stulz (2010), and Jarrow (2011) also offer relevant discussions on creditor incentives.

contracts and, even more so, since this measure does not directly rely on the selection of firms for CDS trading.

The availability of CDS contracts may render more banks willing to lend, due to the possibility of risk mitigation and enhanced bargaining power via CDS contracts. However, such an expanded lender base can also hinder debt workouts. The greater the number of lenders, the more likely that some lenders will choose to become empty creditors, and the more severe will be the problems of coordination in a stressed situation, when a workout may be necessary. Therefore, CDS trading may affect lending relationships, and in particular the number of lenders. Indeed, we find that more creditors lend to the firms after reference CDS become available. Consistent with prior findings, we also find that bankruptcy risk increases with the number of lenders due to creditor coordination failure, thus providing another channel for the adverse effect of CDS trading on bankruptcy risk.

In sum, rather than being an instrument providing insurance against borrower default, CDS trading can increase the likelihood of borrower default (“the tail wags the dog”). Our main contribution is documenting a real effect of the trading of CDS on the survival probabilities of firms. We are among the first to formally test and support the empty creditor model of Bolton and Oehmke (2011). Our study complements Ashcraft and Santos (2009) and Saretto and Tookes (2012), who find that the cost of debt of risky firms, and their leverage, increase after CDS trading has started.

Our findings have implications for investors in credit markets as well as firms. These entities need to consider the impact of CDS trading on the likelihood of bankruptcy in their pricing of corporate debt. Financial regulators and policy makers need to take the increase in credit risk following CDS trading into account in their regulatory actions. In particular, banking regulators need to incorporate this effect in their risk weighting formulae, while securities regulators may require further disclosures of CDS positions, so that investors are made aware of the extent of the potential impact of CDS trading on credit risk.

The remainder of this paper is organized as follows. Section 2 develops testable hypotheses in relation to the literature. The construction of our dataset is described in Section 3. Section 4 presents our empirical results for the effect of CDS trading along with a detailed examination of the endogeneity concerns and the mechanisms for the effect. Section 5 concludes.

2. Related Literature and Testable Hypotheses

CDS were originally invented to help banks to transfer credit risk, maintain relationships with borrowers, and expand their business. The availability of CDS has indeed afforded banks the flexibility and opportunity to manage their credit risk. Over time, other agents including hedge funds, mutual funds and other investors have become active in the CDS market. We place our research in the context of the literature on the CDS market, with particular reference to studies that address issues relating to the relationship between firms and their creditors.[9]

Several recent theoretical studies model the role of CDS in debt financing. Bolton and Oehmke (2011) argue that credit supply can increase because creditors will be tougher and have more bargaining power in debt renegotiation when they use CDS to protect their exposure, thereby reducing borrowers' incentives for strategic default. On the other hand, Che and Sethi (2012) conjecture that CDS can crowd out lending as creditors can sell CDS instead of making loans or buying bonds, effectively reducing credit supply and increasing the cost of debt. Campello and Matta (2012) point out that the effect of CDS depends on macroeconomic conditions. The empirical evidence relating to the effect of CDS on the cost and supply of debt is mixed. Ashcraft and Santos (2009) find that, after CDS introduction, the cost of debt increases for low-quality firms and decreases for high-quality firms. While Hirtle (2009) finds no significant increase in bank credit supply after the initiation of CDS trading, Saretto and Tookes (2012) find that the reference firm's leverage increases.

There are potentially both positive and negative influences of CDS trading on the credit risk of reference entities. On the one hand, if the leverage of a firm increases after CDS trading has begun, it follows that its bankruptcy risk also increases correspondingly. Moreover, as we illustrate in Appendix A, the lenders' willingness to restructure the firm's debt in the event of financial distress is affected by their respective CDS positions. Some CDS-protected lenders may prefer the bankruptcy of borrowers, if the payoffs from their CDS positions are high enough. Although there are other reasons why lenders may be unwilling to restructure the debt of a firm in financial distress (for example, they may believe that the borrower could eventually go bankrupt even after a debt restructuring), their CDS positions will be a factor in their decision. On the other hand, issuers could benefit from CDS trading on their names. Allen and Carletti (2006) show that, under certain conditions, CDS improve risk sharing and are good for both borrowers and lenders. Parlour and Winton (2012) construct a model showing that CDS can help improve lending efficiency for high-quality borrowers. Norden, Silva-Buston, and Wagner (2012) show that lenders with more CDS activities offer lower loan rates and help their borrowers during periods of financial crisis. It follows that, if CDS are beneficial to the lenders, then some of the benefits may be passed on to or shared with the borrowers, thus making firms safer. If the risks outweigh the benefits of financial flexibility, then we expect firms to be riskier after CDS trading.:

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

[9] There is a vast literature on other aspects of CDS trading. Longstaff, Mithal, and Neis (2005), Stanton and Wallace (2011), and Nashikkar, Subrahmanyam and Mahanti (2012) discuss the pricing of CDS. Apart from individual firms in the economy, CDS trading may also have an effect on the aggregate economy. For instance, Duffee and Zhou (2001) and Allen and Carletti (2006) show that CDS trading may hurt financial stability when firms are interconnected. Arping (2004) and Morrison (2005) argue that CDS can reduce the lender-borrower combined welfare.

One could alternatively examine the related hypothesis that CDS trading reduces the success rate of restructuring for distressed firms. This latter question has been addressed in three complementary studies, albeit with smaller samples, by Bedendo, Cathcart, and El-Jahel (2012), Danis (2012) and Narayanan and Uzmanoglu (2012), with conflicting conclusions. While Danis (2012) finds significant impact of CDS trading on restructuring, Bedendo, Cathcart, and El-Jahel (2012) and Narayanan and Uzmanoglu (2012) fail to find such effects. Our analysis applies to the full sample of firms, both healthy and distressed. Bankruptcy may be a better testing framework than restructuring as bankruptcy events are more easily observed than restructuring events. Moreover, defining distressed firms in the context of restructuring is a subjective assessment, which poses challenges for the researcher (and may explain the mixed evidence from above-mentioned studies). Therefore, we focus on bankruptcy filings in our analysis here.

The effect of CDS trading can vary considerably even among CDS firms. Indeed, Minton, Stulz, and Williamson (2009) find that banks' use of CDS depends on the market liquidity of the particular instrument. The larger is the holding of CDS relative to debt outstanding, the greater is the benefit to CDS buyers, and hence, their incentive to tilt the firm towards bankruptcy. Therefore, we quantify the CDS effect based on the amount of CDS trading in the following hypothesis.:

Hypothesis 2 (CDS Exposure) *The increase in the bankruptcy risk of a firm after the introduction of trading in CDS contracts referencing its default is larger for a firm with a greater number of CDS contracts outstanding.*

Another distinctive feature of our study is that we test for the quantitative implications of CDS trading. Peristiani and Savino (2011) document that higher bankruptcy risk is significant in the presence of CDS during 2008, but insignificant overall in their sample. Our study uses a comprehensive database and rigorous econometric procedures to provide more powerful tests than the binary CDS introduction events.

We next address the issue of the mechanisms by which CDS trading affects bankruptcy risk, with particular emphasis on the incentives of tough creditors.[10] Empty creditors do not completely determine the fate of the reference entities. In some cases, the reference firms survive without any credit events, or with straightforward debt rollover, if other creditors support the borrower and outweigh the influence of empty creditors. In such cases, empty creditors will lose the *additional* premium they paid to the CDS sellers without any concomitant benefits. However, if credit events do occur, empty creditors and other CDS buyers will likely make profits. (Thompson (2010) shows that the insurance buyer will also need to worry about whether the seller can honor its commitment.) Whether the overall effect of CDS trading is significant or not depends on the incentives of the marginal creditors, and will be borne out in the data. If we can make the assumption that the presence

[10] One natural related question is: are creditors tougher under CDS trading? The recent decline in the absolute priority deviation during bankruptcy resolution documented by Bharath, Panchapagesan, and Werner (2010) is consistent with tougher creditors and coincides with the development of the CDS market. However, this issue merits more detailed investigation.

of CDS implies a higher probability of empty creditors than there are for non-CDS firms, then our primary hypothesis will also answer this question. Moreover, we take advantage of information on the amount of CDS relative to debt outstanding and the presence of the restructuring clause in the CDS contracts.

Hypothesis 3 (Tough Creditors) *The increase in the bankruptcy risk of a firm after the introduction of trading in CDS contracts on it is larger if (a) there is a greater notional amount of CDS contracts relative to debt outstanding ("over-insurance"), and (b) "no restructuring" (NR) contracts account for a larger proportion of all CDS contracts referencing its default.*

The third hypothesis suggests a unique test of the empty creditor mechanism by using a special feature of the CDS contracts. If CDS contracts cover restructuring as a credit event, then creditors will be compensated, whether the distressed firm restructures or declares bankruptcy. However, if restructuring is not covered in the restructuring clause, the default event may be triggered, but the empty creditor will only get compensated if there is a failure to pay or the firm files for bankruptcy. Therefore, we hypothesize that the empty creditor mechanism is even more effective for NR CDS. We note that Bolton and Oehmke (2011) endogenize the pricing of CDS contracts so that the CDS seller takes this "empty creditor" incentive into account.

The hypothesis above emphasizes the *ex post* effect (after the loan and CDS positions are given) of CDS due to lenders that are tougher in debt renegotiation, although not every creditor would want to become an empty creditor. Gopalan, Nanda, and Yerramilli (2011) show that the lead bank suffers reputation damage from borrower bankruptcies. From an *ex ante* perspective, lenders could be strategic in their use of CDS and lending decisions. Bolton and Oehmke (2011) show that lenders are more willing to lend when CDS permit them the possibility of risk mitigation. It follows that more banks are willing to lend to a firm when CDS are available.[11] Such an expansion in the lender base and the level of lending has two consequences. First, the likelihood of empty creditors is higher when there are more lenders. Second, the probability of bankruptcy is higher when there are more lenders due to the potential for coordination failure. Gilson, John, and Lang (1990) show that creditor coordination failure increases the risk of bankruptcy. Brunner and Krahnen (2008) show that distress workouts are less successful when there are more creditors. Therefore, we generate our last hypothesis in two parts.

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

[11] Borrowers may also want to broaden their lender base if they anticipate that some lenders could take advantage of their respective CDS positions. Acharya and Johnson (2007) suggest that bank lenders engage in insider trading in the CDS market. Hale and Santos (2009) show that, if banks exploit their information advantage, firms respond by expanding their borrowing base to include lenders in the public bond market or by adding more bank lenders.

3. Dataset on CDS Trading and Bankruptcy

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 and the type of contract traded. Unlike voluntary dealer quotes that are non-binding and may be based on hypothetical contract specifications, transaction data contain multi-dimensional information on the actual CDS contracts, including price, volume and settlement terms. Our CDS transactions data are obtained from two separate sources: CreditTrade and GFI Group. CreditTrade was the main data source for CDS transactions during the initial phase of the CDS market, before GFI Group took over as the market leader.[12] Combining data from these two sources allows us to assemble a comprehensive history of North American corporate CDS trading activities.

Our CreditTrade data cover the period from June 1997 to March 2006, while our GFI data cover the period from January 2002 to April 2009. Both datasets contain complete information on intra-day quotes and trades such as the type of contract, the time of the transaction, order type, and the CDS price. Since CDS contracts are traded over-the-counter, unlike stocks or equity options, which are mostly traded on exchanges, the first trading date for each firm's CDS is hard to pinpoint with a time stamp. However, because we have overlapping samples from these two data sources between January 2002 and March 2006, we are able to cross-check the two records to 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. To ensure greater accuracy, we also cross-check trading-based CDS data with the Markit CDS database, a commonly used CDS dealer quote database, and confirm our identification of firms for which CDS are traded and the date of inception of trading.[13] It should be stressed that any remaining noise in identifying the precise introduction date 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 the complete set of transaction data in our empirical analysis of non-sovereign North American corporate CDS. First, our sample starts in 1997, which is generally acknowledged to be the year of inception of the broad CDS market.[14] Therefore, our identified first CDS trading dates will not be contaminated by censoring of the data series. Second, our CDS transaction data include the complete contractual terms, such as the specification of the credit event, maturity, and security terms, at the contract level. Aggregate position or quote data obtained from broker-dealers or, more recently, clearing houses or data aggregators, would generally

12 Previous studies have used the same data sources. For example, Acharya and Johnson (2007) and Blanco, Brennan, and Marsh (2005) utilize CreditTrade data. Nashikkar, Subrahmanyam, and Mahanti (2011) use CDS data from GFI. GFI ranked first in the Risk Magazine CDS broker ranking from 2006-2010. (CreditTrade was acquired in 2007 by Creditex, which merged with the CME in 2008.)

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

14 See Tett (2009) for a historical account.

not include such detailed information. The credit event specification allows us to investigate the effect of restructuring clauses. The maturity information at the contract level allows us to calculate the amount of the outstanding CDS positions at each point in time. Our sample of CDS introductions ends in April 2009 for an important institutional reason: the market practice in CDS changed significantly in April 2009 due to the “Big Bang” implemented by ISDA, including for example the removal of restructuring as a standard credit event. In addition, we need an observation window of three years *after* the introduction of CDS trading to capture its potential effects in our empirical analysis.

Based on our merged dataset, there are 901 North American firms that have CDS initiated on them at some point during the 1997-2009 sample period. The industry distribution of the CDS firms in our sample is quite diverse.[15] In our baseline 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, we also construct measures of the amount of CDS outstanding and the fraction of CDS contracts with various restructuring clauses, based on more detailed transaction information, to further understand how CDS trading affects credit risk.

We assemble a comprehensive bankruptcy dataset by combining data from various sources for North American corporations filing bankruptcies in U.S. courts. Our initial bankruptcy sample is derived from New Generation Research's Public and Major Company Database, available at www.BankruptcyData.com. This database includes information on public companies filing for bankruptcy and also significant bankruptcies of private firms. We further validate and augment this initial sample with additional bankruptcy-filing data sources, including the Altman-NYU Salomon Center Bankruptcy List, the Mergent Fixed Income Securities Database (FISD), the UCLA-LoPucki Bankruptcy Research Database (BRD), and Moody's Annual Reports on Bankruptcy and Recovery. We use Dealscan Loan Pricing Corporation (LPC) and FISD data to identify the lenders and underwriters to a firm. We obtain data on foreign exchange hedging from the Federal Reserve call reports and bank capital ratio data from the Compustat Bank file. Our firm data are drawn from the Compustat database. Our sample covers bankruptcies of both large and small firms (many studies in the literature only examine large firms).

We link the bankruptcy dataset with our CDS sample to identify the bankrupt firms that had CDS trading prior to their bankruptcy filings. Table 1 presents the yearly 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 the number of bankrupt firms with and without CDS trading. The last row of Table 1 shows a total figure of 1,628 bankruptcy filings during the 1997-2009 sample period. Many bankruptcies were filed in the period 1999-2003 and 2008-2009, accounting 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* firms and the number of firms with *Active CDS* trading firms across the

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

years, respectively. More CDS contracts were introduced in the period 2000-2003 than in earlier or later periods. Among the 901 distinct CDS trading firms, 60 (6.7%) subsequently filed for bankruptcy protection. Bankruptcies among CDS firms represent a small fraction of the total number of bankruptcies, since only relatively large firms, by asset size and debt outstanding, have CDS trading. However, the bankruptcy rate of 6.7% for CDS firms is close to the 4-year overall (or 11-year BBB-rated) cumulative default rate of U.S. firms (Standard & Poor's (2012)).

4. CDS Trading and Credit Risk: Empirical Results

This section presents our empirical findings on the effect of CDS trading on a firm's credit risk. We use several common measures of credit risk, including credit rating, probability of bankruptcy, and expected default frequency, in our analysis. First, we report our baseline results on the effects of the introduction of CDS trading. Second, we address the issue of selection and endogeneity in the introduction of CDS trading. Third, we examine the effect of CDS positions and contract terms, and investigate the mechanisms through which CDS trading affects credit risk.

4.1 Rating Distributions Before and After CDS Introduction

A straightforward ordinal measure of credit risk is the credit rating that is widely used in industry. We study the characteristics of CDS firms by first analyzing their credit ratings around the time of the introduction of CDS trading. If the issuer credit quality changes after the introduction of CDS trading, the credit ratings may reflect this CDS effect if rating agencies perform reasonable credit analysis. Rating agencies incorporate information on both bankruptcies and restructuring into rating decisions (Moody's (2009)). In addition, since a credit rating downgrade is often the first step towards bankruptcy and is an indicator of an increase in bankruptcy risk, it may convey useful information about the probability of bankruptcy.

We obtain the time series of Standard & Poor's (S&P) long-term issuer ratings from Compustat and FISD. We then conduct an “event study” of the effect of the introduction of CDS trading on credit ratings to gain a high-level understanding of the evidence. This is a basic “within-firm” analysis, in which we compare the distribution of credit ratings in the year right before CDS trading (year $t-1$), with the rating distribution two years after CDS trading has begun (year $t+2$), for all firms with such contracts traded at some point in our sample. These rating distributions, one year before and two years after the introduction of CDS trading, are plotted in Figure 1. Our first observation from Figure 1 is that A and BBB ratings are the most common issuer ratings at the time 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, with only a small proportion of firms being unrated at this juncture. Compared to the general corporate rating distribution documented in Griffin and Tang (2012), our sample includes more BBB-rated firms relative to other investment grade (AAA, AA, A-rated) firms, but also has fewer non-investment grade firms. Overall, firms in our sample are of relatively good credit quality, as measured by credit ratings, at the time of CDS inception.

Figure 1 shows a discernible shift to lower credit quality after the introduction of CDS trading. While the proportion of BBB-rated firms is about the same before and after CDS trading begins, the proportion of AA-rated and A-rated firms decreases. At the same time, the proportion of non-investment grade and unrated firms increases. The Kolmogorov-Smirnov test statistic for the distributional difference before and after CDS trading begins is significant at the 1% level, indicating that the credit rating distribution shifts to the right (lower rating quality) after CDS trading begins. Specifically, 54% of the firms maintain the same ratings before and after the introduction of CDS trading, 37% of the firms experience rating downgrading but only 9% of firms experience a rating improvement.[16] These results provide preliminary evidence that the credit quality of the reference entities deteriorates following the inception of CDS trading.

4.2 Baseline Hazard Model Results on Downgrading and Bankruptcy

We next run multivariate tests to discern systematic statistical evidence, with appropriate control variables, regarding the effect of the inception of CDS trading on credit risk. We include firms with and without CDS traded in a panel data analysis, using monthly observations. We examine both credit rating downgrades and bankruptcy filings in our baseline analysis.

There is a large literature on bankruptcy prediction dating back to the *Z*-score model of Altman (1968). Bharath and Shumway (2008) and Campbell, Hilscher, and Szilagyi (2008) discuss the merits of simple bankruptcy prediction models over their more complicated counterparts and argue that the simple models perform quite well in predicting bankruptcy. In keeping with this perspective, our approach is a proportional hazard model for bankruptcy using panel data.[17] 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}:

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

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 the previous period. A higher level of $\alpha + \beta' X_{it-1}$ represents a higher probability of bankruptcy. We follow Bharath and Shumway (2008) to include five fundamental determinants of default risk in X_{it-1}: the logarithm of the firm's equity value (*ln(E)*), the firm's stock return in excess of market returns over the past year ($r_{it-1} - r_{mt-1}$), the

16 We also find that, compared to non-CDS firms from the same industry and of similar size, there are 2.6% more rating downgrades for CDS firms after CDS trading starts than for non-CDS firms at the same time.

17 We also perform robustness checks on this model specification later on.

logarithm of the book value of the firm's debt (*ln(F)*), the inverse of the firm's equity volatility $(1/\sigma_E)$, and the firm's profitability measured by the ratio of net income to total assets (*NI/TA*).[18] We obtain firm accounting and financial data from CRSP and Compustat.

In addition to these five fundamental variables we include two CDS variables, *CDS Firm* and *CDS Active*, in the hazard model specifications to estimate the impact of CDS trading on bankruptcy risk, similarly to Ashcraft and Santos (2009) and Saretto and Tookes (2012). *CDS Firm* is a dummy variable that equals one for firms with CDS traded at any point during our sample period. It is a firm fixed characteristic and does not change over time. *CDS Firm* is used to control for unobservable differences between firms with and without CDS. *CDS Active* is a dummy variable that equals one after the inception of the firm's CDS trading and zero before CDS trading. *CDS Active* equals zero for non-CDS firms. Hence, the coefficient of interest is that of *CDS Active*, which captures the marginal impact of CDS introduction on bankruptcy risk. Since the variables *CDS Firm* and *CDS Active* are positively correlated, we report results both with and without the control of *CDS Firm* in our main analysis. We also control for year and industry fixed effects in the panel data analysis. We apply the same specification to the analysis of the probability of a rating downgrade.

The proportional hazard model estimation results are presented in Table 2. We follow Shumway (2001) and correct the standard errors by the average number of observations per cross-sectional unit. The first column lists the independent variables in the model estimation. The dependent variable for Specifications 1 and 2 is the probability of a credit rating downgrade in the observation month. The dependent variable for Specifications 3 and 4 is the probability of a bankruptcy filing in the observation month. The coefficient estimate for *CDS Active* is positive and significant for all four specifications. The effect of *CDS Active* is not driven by fundamental differences between CDS firms and non-CDS firms. Specifications 2 and 4 show that the effect of *CDS Active* is significant, even without controlling for *CDS Firm*. The coefficient estimates for the variable *CDS Firm* are statistically significant at the 1% level in both Specification 1 and Specification 3, but with opposite signs. That is, compared to non-CDS firms, CDS firms are, in general, more likely to be downgraded but less likely to go bankrupt. Such a diametrically opposite effect of *CDS Firm* is in contrast to the consistently positive *CDS Active* effect, further attenuating the concern that the effect of *CDS Active* is driven by multi-collinearity with *CDS Firm*.

The positive coefficients of *CDS Active* in Specifications 1 and 2 indicate that firms are more likely to be downgraded after the inception of CDS trading. In both specifications, the effect of CDS trading is statistically significant at the 1% level. The economic magnitude is also large: compared to the average downgrading probability of 0.58% in Specification 1, the marginal effect of CDS trading on the probability of a downgrade is 0.39%. Specification 3 reports similar findings for bankruptcy filing. Bankruptcy risk increases after CDS trading has begun: against an average firm bankruptcy probability of 0.14%, the marginal effect of CDS trading on the bankruptcy probability is 0.33%. The

[18] 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.

odds ratio for *CDS Active* (the likelihood of downgrading/bankruptcy after CDS trading divided by the likelihood of downgrading/bankruptcy before CDS trading) for credit downgrades and bankruptcy predictions are 1.925 and 10.73 respectively, indicating that credit events are much more likely after CDS trading begins.

The effect of *CDS Active* is not driven by industry effects as we control for them throughout our analysis. The estimation results for the other control variables in Table 2 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 higher leverage and greater equity volatility are more likely to be downgraded or go bankrupt, all else being the same. As is to be expected, profitable firms are less likely to file for bankruptcy. Lastly, the pseudo-R^2s, about 15% for the downgrade regressions and 24% for the bankruptcy regressions, suggest that bankruptcy filings are better explained by these explanatory variables than downgrades.

In sum, Table 2 of our baseline analysis shows consistent results that the credit quality of reference firms declines after CDS trading begins. We also run a battery of robustness checks on our baseline results for bankruptcy filing. First, we consider firm fixed effects rather than industry fixed effects. We cannot include firm fixed effects in our bankruptcy analysis as the estimation does not converge due to its nonlinear specification. Therefore, we use distance-to-default as the dependent variable. Such a specification allows us to include firm fixed effects (in this case we do not need to include the *CDS Firm* control). Moreover, we show that our findings are robust to alternative model specifications, rating drift consideration and other firm exits.[19] Next we present the results of several alternative approaches, used to address the selection and endogeneity concerns in CDS trading.

4.3 Selection and Endogeneity in CDS Trading

The previous subsection shows a strong relation between CDS trading and the subsequent increase in credit risk. However, the main challenges to inferring a *causal* relationship showing that CDS trading leads to a deterioration in credit quality are the potential selection and endogeneity in CDS trading. Selection effects would be a concern if CDS firms were fundamentally different from non-CDS firms, and such fundamental differences were related to the subsequent deterioration in credit quality. Nevertheless, the selection of firms into the CDS sample may not be our biggest concern, since our focus is on the *timing* of CDS trading.[20] Essentially, we are interested in the "within-firm" effect, where the timing of the introduction of CDS trading may be endogenous. It is conceivable that CDS traders

[19] The robustness checks are reported in the additional table file as an Internet Appendix. First, as shown in Table A1 for distance-to-default, we control for fixed effects and find that the coefficient of *CDS Active* is still significant. Second, we consider the bankruptcy prediction model used by Campbell, Hilscher, and Szilagyi (2008) and report the results in Table A2, which shows similar results. Third, we take into account the initial credit quality and the natural drift in credit quality, and show in Tables A3-A6 that our finding of the CDS effect is robust to such considerations. Fourth, as shown in Table A7, the CDS effect is stronger for non-investment grade firms. Fifth, Table A8 shows that our results are similar when we exclude firms that exit the sample as a consequence of mergers and acquisitions.

[20] Recall from Figure 1 that CDS firms typically have investment grade ratings at the time of CDS introduction. Therefore, the initiation of CDS trading is not necessarily attributable to poor *initial* credit quality.

anticipate the deterioration in a firm's credit quality and initiate trading in its CDS contract. Therefore, *CDS Active*, the variable measuring the effect of the timing of CDS introduction, is the main endogenous variable of concern. We note that examining *CDS Active* for endogeneity also takes *CDS Firm* (the selection of firms into the CDS sample) into account as *CDS Active* is always zero for non-CDS firms. We use several standard econometric approaches to address the endogeneity and selection issues, as suggested by Li and Prabhala (2007) and Roberts and Whited (2012): IV estimation, the Heckman treatment effects model, propensity score matching, and difference-in-difference estimation.

We need to first have a good understanding of the determinants of CDS trading before we can effectively apply the various econometric approaches to address the endogeneity and selection issues. We aim to find the most appropriate model for the selection of CDS trading on firms, so that we can then adjust for this selectivity in our analysis of credit risk changes after the start of CDS trading. We follow Ashcraft and Santos (2009), Saretto and Tookes (2012), and other studies with similar endogeneity concerns for the specification of the CDS trading selection model. Moreover, we take into account additional considerations in choosing the explanatory variables for the CDS trading model, given that our focus is explicitly on credit risk.

We employ two instrumental variables: FX hedging activities by banks and underwriters, *Lender FX Usage*, and the Tier One capital ratio of the lenders, *Lender Tier 1 Capital*.[21] We first identify lenders and bond underwriters for our sample firms based on DealScan data (for lenders) and FISD data (for bond underwriters). We then look at Federal Reserve call report data for the FX derivatives positions for these lenders and bond underwriters. For each firm in each quarter, *Lender FX Usage* is constructed as the average amount of FX derivatives usage for hedging purposes relative to their total assets, across banks that have either served as a lender or a bond underwriter over the previous five years. To construct the instrument *Lender Tier 1 Capital*, we further link the identifications of the lenders and bond underwriters with the Compustat Bank file containing lenders' Tier One capital ratio data. For each firm in each quarter, the *Lender Tier 1 Capital* ratio is defined as the average of the Tier One capital ratios across banks that have either served as lenders or bond underwriters for this firm over the previous five years. Besides these two instruments as explanatory variables for CDS trading, we also include firm size: larger firms naturally attract more attention from CDS traders since the chance of hedging demand arising from any investor is greater for larger firms. In addition, we include a set of firm characteristics such as sales, tangible assets, working capital, cash holdings and capital expenditure. Furthermore, we include credit risk variables such as leverage, profitability, equity volatility, and the credit rating status of the firm, for predicting the inception of CDS trading.

We use data from 1997 until the first month of CDS trading for CDS firms, and all observations for non-CDS firms, to predict the introduction of CDS trading for a firm. The prediction is estimated using a probit model: the dependent variable is equal to one after the firm starts CDS trading, and zero prior

[21] Saretto and Tookes (2012) also use the the first of these, *Lender FX Usage*.

to that. The probit regression results are reported in Table 3. We confirm that larger firms are more likely to have CDS contracts trading on them. CDS trading is more likely for firms with higher leverage but with investment grade ratings. Unrated firms are less likely to have CDS trading. Firms with high profitability, tangibility, and large working capital are more likely to have CDS trading. Overall, it appears that firms have relatively high credit quality and visibility (a stronger balance sheet and larger size) at the time of CDS inception. Both our instrumental variables, *Lender FX Usage* and *Lender Tier 1 Capital*, are significant predictors of CDS trading, even after controlling for other variables.

Table 3 shows that CDS trading can be reasonably explained by the chosen variables, with pseudo-R^2s of around 38.9% across the three model specifications (Models 1 and 2 include one IV at a time and Model 3 includes both IVs). In the following analysis, we will use these three CDS trading prediction models to conduct our IV estimation, treatment effects, propensity score matching, and difference-in-difference analyses, to re-examine the relationship between CDS trading and bankruptcy risk. We focus on the probability of bankruptcy in the remaining analysis to conserve space, although the results for the probability of a credit rating downgrade point to the same conclusion, and are available upon request.

4.3.1 Instrumental Variable Estimation

We first present our IV estimation results to address the selection and endogeneity concerns. Undoubtedly, the quality of the instrumental variables is important for the consistency of such estimation results. In particular, the instruments need to satisfy the relevance and exclusion restrictions. Table 3 shows that CDS trading is significantly associated with *Lender FX Usage* and *Lender Tier 1 Capital*, demonstrating their relevance to CDS trading. The exclusion restriction is impossible to test formally, as argued by Roberts and Whited (2012). The instruments we use are economically sound, because they are associated with the overall hedging interest of the lenders or credit suppliers, and their Tier One capital adequacy ratio. Moreover, the instruments we use are not weak: the *F*-test statistics are 56, 11, and 68 individually, and jointly they are above 10 for both IVs, which are statistically significant.

We next perform additional analysis to account for the discreteness of the *CDS Active* variable since the fitted values of the first stage of the two-stage least squares (2SLS) would be continuous variables. We classify *CDS Active* as one if the probability of having CDS trading is above the median (in the top 50%), or in the top 25% respectively.[22] Table 4 shows the second-stage estimation result using both *Lender FX Usage* and *Lender Tier 1 Capital* as IVs. Our instrumented *CDS Active* variable is significant in all our specifications. Furthermore, we run the Sargan over-identification test and cannot reject the hypothesis that both IVs are exogenous. Note that the purpose of the IV estimation is to control the endogeneity in the specific *timing* of CDS introduction. We next directly address the *selection* of firms into the CDS sample.

[22] Cohen, Frazzini, and Malloy (2012) employ a similar method.

4.3.2 Heckman Treatment Effects Model

The selection of firms for CDS trading is analogous to the missing data problem in the spirit of Heckman (1979) as we do not observe the counterfactual outcome (CDS active firms without CDS trading). Therefore, correcting for self-selection can be viewed as including an omitted variable that is proxied by the *Inverse Mills Ratio* from the first stage of the Heckman procedure to produce a consistent estimate.[23] The selection models for CDS trading are the same probit models that underlie Table 3. Based on the estimated model parameters from the first stage, we calculate the *Inverse Mills Ratio*, which is a transformation of these predicted individual probabilities of CDS trading. Then, the second stage of the hazard model analysis includes the *Inverse Mills Ratio* as an additional explanatory variable. We include all firm observations in our second-stage analysis.

The second-stage results of the Heckman correction with instrument variables are presented in Table 5. We use all three CDS prediction models for the first-stage estimation to generate the *Inverse Mills Ratio*. We find that *CDS Active* has a positive and significant coefficient estimate in all specifications. In other words, firms are more likely to go bankrupt after the introduction of CDS trading. The economic magnitude of the coefficient is also large. For example, from Model 3 in the first stage, the marginal effect of CDS trading on bankruptcy filing is 0.37%, compared with the average bankruptcy probability of 0.14% in the overall sample. Testing the significance of the *Inverse Mills Ratio* is a test of whether the private information possessed by CDS traders explains the outcome, i.e., bankruptcy filing. The coefficient of *Inverse Mills Ratio* is insignificant. These results show that the positive relationship between CDS trading and bankruptcy risk is robust to the selection of firms for CDS trading.[24]

4.3.3 Propensity Score Matching

We now re-estimate our baseline model using a propensity score matched sample. Propensity score matching makes the “treatment effect” easy to interpret as the difference between the CDS firms and those without CDS traded is measured by the coefficient of *CDS Active*. For each CDS firm, we find one matching non-CDS firm with the nearest propensity score for CDS trading. We then run the hazard rate model on this matched sample. We use the three CDS prediction models from Table 3 and three different matching criteria: (1) the one non-CDS firm with the nearest distance, in terms of

[23] We note that the Heckman model assumes a bivariate normal distribution for the error terms of the first-stage and second-stage regressions. Thus far, there is no theory regarding alternative distributional assumptions. Theoretically, the exclusion restriction is not necessary in all applications of the Heckman selection model if the model is identified merely on account of its nonlinearity, although it is safe to impose the exclusion restriction as the selection can be approximately linear in the relevant region. Also, employing multiple instruments can be helpful if they improve the predictability of the first stage.

[24] We also tried two other instrumental variables: *TRACE Coverage* and *Post CFMA*. The pricing of CDS might be easier for firms in the TRACE (Trade Reporting and Compliance Engine) database of the Financial Industry Regulatory Authority (FINRA), due to the ease of obtaining market information in a timely manner in an OTC market. This will increase the probability of CDS trading for these firms. The Commodity Futures Modernization Act of 2000 (CFMA) ensures the deregulation of OTC derivatives. Therefore, firms are more likely to have CDS trading in the post-CFMA period. As expected, we find these instruments to be significant determinants of CDS trading. The CDS effect is also significant using these instruments, although they are not our first choices, as shown in Table A9.

propensity score, to the CDS firm; (2) the one firm with the nearest propensity score but within a difference of 1%, and (3) the two firms with propensity scores closest to the CDS-trading firm. We find that there are no significant differences in either the propensity scores or the *Z*-score between the CDS firms and the matching firms, for all prediction models.

Table 6 presents the regression results for our CDS-trading propensity-matched sample. In all specifications, the coefficient estimates for *CDS Active* are significantly positive. Therefore, the probability of bankruptcy increases after CDS trading has begun, even adjusting for the propensity for CDS trading. *CDS Firm* is not significant in any specification. (We only present the results for the bankruptcy prediction and for the specification with the control, *CDS firm*, to conserve space.) Therefore, after matching by the propensity for CDS trading, CDS firms are no longer statistically significantly different from non-CDS firms in terms of credit quality deterioration, attesting to the effectiveness of our matching procedure. We use CDS prediction Model 3 and the “nearest one” matching as a benchmark case (reported in the second column of Table 6). When we modify the matching criterion from the “nearest one” to the “nearest one with propensity score difference within 1%”, the results are similar to those in column 2 without the 1% restriction. As an alternative, we choose two matching firms with the nearest propensity scores from Model 3, and still find a significant coefficient estimate for *CDS Active*. Furthermore, we also use Models 1 and 2 with the nearest-one propensity score matching. These models produce different matching samples, due to the data available to calculate propensity scores for each prediction model. *CDS Active* is significant in all these other specifications.

4.3.4 Difference-in-Difference Analysis

Another approach that can be used to address the endogeneity concerns and identify the treatment effect (of the introduction of CDS trading) is difference-in-difference analysis. Similarly to in our propensity score matching analysis, we identify non-CDS firms matching the CDS firms using all three CDS prediction models presented in Table 3 and three different matching criteria: (1) the one non-CDS firm with the nearest distance, in terms of propensity score, to the CDS firm; (2) the one firm with the nearest propensity score but within a difference of 1%, and (3) the two firms with propensity scores closest to the CDS-trading firm in question. Furthermore, we consider three windows for the event analysis: year $t-1$ to year $t+1$, year $t-1$ to year $t+2$, and year $t-1$ to year $t+3$ (where year t is the year of introduction of CDS trading).

We cannot run the difference-in-difference analysis on the binary bankruptcy event directly. Therefore, we examine a continuous measure of probability of default: the expected default frequency (*EDF*), which is a normal transformation of the distance-to-default ($EDF = N(-DD)$). The calculation of *DD* follows Bharath and Shumway (2008), with an adjustment for the leverage ratio of financial firms. There are several advantages to choosing *EDF* as the relevant variable to track. First, *EDF* is a continuous measure of credit quality. Therefore, the estimation has more power and the CDS introduction effect can be more easily identified. Second, using *EDF* enriches our empirical framework of credit risk measured by downgrading and bankruptcy filing. While also being a measure of credit risk, the *EDF* measure is sufficiently different from rating downgrades and bankruptcy filing, as it is inferred from stock prices and balance sheet variables. Last, *EDF* is an *ex ante* measure of credit risk, while we can only observe downgrading and bankruptcy *ex post*. Using an alternative credit risk measure also helps demonstrate the robustness of our conclusion.

Panel A of Table 7 shows that the *EDF* difference-in-difference estimates are both statistically and economically significant for the ($t-1, t+2$) and ($t-1, t+3$) event windows regardless of the CDS prediction model or matching criteria. For example, compared to the "nearest-one" propensity score matched firm from CDS Prediction Model 3, the *EDF* is 4.0% higher three years after CDS introduction. Recall that the average CDS firms has a BBB rating at the time of CDS introduction. Such an increase in *EDF* is substantial, given that the average BBB (BB) U.S. firm's 3-year default probability was about 1.2% (5.4%), from 1981 to 2011, according to Standard & Poor's (2012). The difference-in-difference estimates are insignificant for event window ($t-1, t+1$), except when we use two matching firms. Therefore, the decline in credit quality after beginning CDS trading is rather gradual: there is little noticeable effect in the first year, but the effect is significant thereafter.

In Panel B of Table 7, we find that the leverage ratios of the reference firms also increase significantly after CDS introduction. In the difference-in-difference estimation using CDS Prediction Model 3 for the matching and event window ($t-1, t+2$), leverage increases by between 1.0% and 1.2% after CDS introduction. Our finding regarding the magnitude of the change in leverage following the instigation of CDS trading is consistent with the conclusions of Saretto and Tookes (2012). Further, the leverage reaction seems more rapid: the leverage increases occur mostly in the first year after CDS trading begins.

4.3.5 Falsification Test

We have considered the appropriate approaches to addressing selection and endogeneity concerns suggested by the literature.[25] Since CDS are traded over-the-counter, there could be measurement error resulting from the (unobservable) exact date of CDS introduction. Such a measurement error may lead to an attenuation bias, although this may not always be the case. We further conduct a falsification test as suggested by Roberts and Whited (2012). When we shift forward the CDS introduction by one year, the effect of *CDS Active* becomes insignificant, as shown in Table A10. This finding demonstrates the importance of the correct identification of the timing of CDS introduction, as well as the effect of CDS trading. Therefore, our falsification test of shifting the year of CDS introduction by one year suggests that the measurement error would indeed attenuate or even eliminate our results.

[25] We also considered the BBB/BB boundary for the separation between investment and speculative grades in the spirit of a regression discontinuity. Although we do not present a detailed economic model for how this boundary, and its clientele effects among investors, affects CDS trading, the results in Table A7 show that the effect of CDS trading is more pronounced for speculative grade firms.

4.4 Effect of Outstanding CDS Positions

Our analysis so far has focused on the CDS introduction effect captured by a binary variable, *CDS Active*, which is a permanent regime variable. That is, once CDS trading is initiated for a firm, it cannot go back to being a non-CDS firm. Such a regime variable ignores much of the information in the *variation* in CDS trading over time. Indeed, CDS trading activity varies considerably across firms. Such variations may generate additional implications for the effects of CDS trading on credit risk. If the CDS trading activity of a firm is very thin or illiquid, the corresponding CDS effect may be less pronounced. Also, a larger outstanding position in CDS may generate greater monetary consequences for CDS traders. Intuitively, for instance, if CDS trading causes credit risk changes, the influence of CDS on credit risk should disappear when all outstanding CDS contracts mature and are extinguished. In this subsection, we provide a stronger test for such a symmetric and continuous effect of CDS trading.

A unique advantage of our CDS transactions database is that it includes details about the notional amount of the CDS contracts outstanding and the contractual specifications of each contract. Such detailed information is useful for forming other measures of CDS trading. As pointed out by Li and Prabhala (2007), the magnitude of the selection variable (i.e., quantity of CDS trading or amount outstanding) introduces an independent source of variation and helps the identification of the treatment effect, while ameliorating the selection concern.

We use CDS transaction records to measure outstanding CDS contracts (similar to cumulative trading volume) in our sample. We use the *Number of Live CDS Contracts*, measured by the number of CDS contracts initiated but yet to mature as of the observation month, as a measure of open interest.[26] This variable measures the breadth and consistency of CDS trading activity. CDS exposure computed as the *Number of Live CDS Contracts* may go up or down as and when new CDS contracts are created or old contracts mature. Therefore, this continuous measure is not as strongly affected by the selection issue analyzed at length in Section 4.3.

We conjecture that CDS effects will be stronger for firms with greater amounts of CDS outstanding. We estimate the hazard model of bankruptcy filing using the CDS exposure measure instead of the indicator variable *CDS Active*. Table 8 reports our estimation results. We set outstanding CDS positions at zero for all non-CDS firms and include both CDS and non-CDS firms in Specification 1 of Table 8. The estimation result shows that bankruptcy risk increases with the number of live CDS contracts, evidenced by the significant positive coefficient estimate for the *Number of Live CDS Contracts*. The marginal effect of this variable on the probability of bankruptcy is 0.03%. That is, when the number of CDS contracts outstanding increases by 33, its probability of default increases by 1%.

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

The pseudo-R^2 for Specification 1 of Table 8 is lower than in the previous analysis using the variable *CDS Active*. It is possible that the aggregate continuous variable, *Number of Live CDS Contracts*, is a noisy measure of the incentives of individual creditors, who may be "over-insured". Moreover, the incentive effects implied by the size of the CDS position may be concave: they may flatten out when the outstanding amount of CDS reaches a certain level.

In Specification 2 of Table 8, we only include CDS firms for the bankruptcy prediction using *Number of Live CDS Contracts*. The result shows that, the greater is the *Number of Live CDS Contracts*, the higher is the probability of bankruptcy. Therefore, even within the CDS sample, the number of CDS contracts outstanding plays a role in determining bankruptcy risk. In summary, a larger amount of CDS contracts outstanding is associated with a higher probability of firm bankruptcy.

4.5 The Mechanisms for the Effect of CDS on Credit Risk

Previous analysis shows a robust relation between CDS trading and the credit risk of the reference firms. In this subsection, we examine several mechanisms channeling the effect of CDS trading towards an increase in credit risk. There are two broad channels through which a firm's bankruptcy risk could increase. The first way is through a higher chance of getting into financial distress. The second is through a lower chance of getting out of financial distress, leaving bankruptcy as the more likely outcome. CDS contracts can affect a firm's credit risk in both of these ways.

Firms can slip into financial distress more easily when there is CDS trading if they take on more debt, increase their asset risk, become less profitable, or have more pro-cyclical cash flows (i.e., have higher downside risk correlated with market conditions). Indeed, both our result in Panel B of Table 7 and the findings in Saretto and Tookes (2012) show that firm leverage increases following the inception of CDS trading. The increase in leverage naturally leads to an increase in credit risk. Therefore, we control for firm leverage in our regressions, both before and after the introduction of CDS, and focus on other mechanisms.

CDS can reduce profitability if there is negative feedback from the CDS market to the product market. In such a case, a negative shock, even though it could be pure noise, would reduce the sales and profits of the firm. This feedback effect could be used by market manipulators to accentuate the effect of the shock. Firm performance can become more correlated with the CDS market if the CDS market transmits negative information to market participants. This type of information mechanism is especially harmful during downturns. However, CDS can also reduce the information available about firms if lenders reduce monitoring and produce less information about the borrowers when their exposure to borrower default is hedged with CDS. Before we discuss these fundamental mechanisms, we study two other mechanisms that reduce the chance of successful debt workouts for firms in financial distress. The first is that lenders can be tougher once they are protected by CDS. The second is that creditor coordination is more difficult when there is CDS trading since their interests may not be aligned.

4.5.1 Tough Creditors Opposing Restructuring

The first mechanism besides leverage that we investigate is due to tougher creditors, as in the Bolton and Oehmke (2011) model for empty creditors. That is, creditors insured with CDS protection will be tougher in the renegotiation of existing debt obligations, and consequently restructuring will be less successful, as shown in the illustrative example presented in Appendix A.[27] The driver of the empty creditor mechanism is the extent of over-insurance by lenders using CDS contracts. This over-insurance with CDS directly drives the lenders' incentive to force borrowers into bankruptcy by rejecting restructuring proposals, precipitating a default event and therefore receiving payments from CDS sellers. The greater the degree of over-insurance by the empty creditor, the larger will be the benefit from rejecting a restructure and potentially triggering bankruptcy.

Our data do not reveal the identity of individual CDS traders. Hence, we cannot *directly* observe the presence of individual empty creditors or their portfolio positions. Consequently, we have to make do with aggregate proxies for the inception of CDS trading as a (noisy) proxy for the potential influence of empty creditors. If we make the assumption that the presence of CDS implies a higher probability of empty creditors than among non-CDS firms, then our baseline finding is consistent with the empty creditor prediction. We calculate the ratio of the notional dollar amount of CDS contracts outstanding to the total dollar amount of debt outstanding at the same time, *CDS Notional Outstanding/Total Debt*.[28] We scale the CDS position by total debt to relate the dollar amount of CDS outstanding to creditors' exposure. *CDS Notional Outstanding/Total Debt* is a somewhat more informative, but still noisy, measure of the extent of the empty creditor concern. We emphasize that we do not need all creditors to become empty creditors for the empty creditor mechanism to manifest itself; it may take just a few or even one large empty creditor to holdout a restructuring proposal. We conjecture that bankruptcy risk is higher when *CDS Notional Outstanding/Total Debt* is larger. The estimation results, reported in Table 9, are consistent with the conjecture: a larger dollar amount of CDS contracts outstanding relative to firm's debt outstanding is associated with a higher probability of firm bankruptcy.

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

[27] 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.

[28] The maximum value for *CDS Notional Outstanding/Total Debt* is 4.14, which is suggestive of over-insurance for such firms and the potential presence of “empty creditors”. (The mean is 0.10 and the median is 0.02.)

We investigate the effect of differences in contractual terms on the credit risk consequences of CDS trading. Appendix B describes the restructuring clauses in CDS contracts and their historical evolution. Essentially, there are four types of CDS contract, based on the definition of credit events: full restructuring (FR), modified restructuring (MR), modified-modified restructuring (MMR), and no restructuring (NR). For FR contracts, any type of restructuring qualifies as a trigger event, and any debt obligation with a maturity of up to 30 years can be delivered in that event. Under MR also, any restructuring is included as a credit event; however, the deliverable obligations are limited to those with maturities within 30 months of the CDS contract's maturity. For MMR contracts, the deliverable obligations are relaxed to include those with maturities within 60 months of the CDS contract's maturity for restructured debt, and 30 months for other obligations. Under NR, restructuring is excluded as a credit event. Firms with more NR contracts are more subject to the empty creditor threat than those with other types of CDS. FR contracts would not be as strongly influenced by the empty creditor incentives, as illustrated by the analysis in Appendix A.[29]

Figure 2 plots the number of contracts of each type in each year as observed in our CDS transaction records. The majority of firms in our sample have the MR type of clause in their CDS contracts. Types FR and MMR have a negligible presence in our sample, which is quite representative of the market as a whole, although there could be some variation at the firm level. The figure shows that there were hardly any NR CDS contracts prior to 2002. Packer and Zhu (2005) show that, in their sample period, MR contracts were just slightly more expensive than NR contracts. In such circumstances, CDS buyers would probably buy MR contracts rather than NR contracts. The proportion of CDS contracts with NR specifications has increased dramatically in recent years, especially in 2007. The median (mean) fraction of NR contracts out of all CDS contracts for a reference entity is 0.61 (0.55). We also find that there is wide variation across firms in terms of the proportion of NR contracts. One may be concerned with the endogeneity in choice of contract type, i.e., CDS buyers expecting bankruptcy to be more likely than restructuring will buy CDS contracts covering bankruptcy only. However, such endogeneity would have the same implication as when holders of NR CDS contracts have a clear preference for bankruptcy.

We account for the differences in contractual specifications in the estimations reported in Table 10, which include variables measuring the type of CDS contract. *No Restructuring CDS Proportion* is the fraction of CDS contracts with NR clauses out of all CDS contracts on the same reference entity. (This measure would be zero for firms without CDS.) Similarly, *Modified Restructuring CDS Proportion* is the fraction of CDS with MR clauses out of all contracts on the same reference entity. Since there are very few contracts with the FR or MMR specification in our sample, we focus only on the MR and NR types. We run separate regressions with the two CDS-type variables (reported in Specification 1 and Specification 2), and also a combined one with both of them (Specification 3). The results in Table 10

[29] Another related issue is the type of settlement. In the past, most CDS contracts were settled by physical delivery (CDS buyers delivered bonds to sellers to receive the face value). More recently, cash settlement has been the norm (CDS sellers pay the difference between the face value and its recovery value directly to CDS buyers). Contracts settled by physical delivery may have an additional influence from the empty creditor problem, since they may cause a squeeze in the bond market. In addition, physical delivery confers an additional “cheapest to deliver” option on the CDS protection buyer. Unfortunately, however, we do not have data on the delivery method.

show that only for NR contracts do we find a significant positive relationship of CDS trading with bankruptcy risk, while the coefficient of the MR type is not statistically significant. The marginal effect of the *No Restructuring CDS Proportion* variable in the combined regression on the probability of bankruptcy is 0.22% in Specification 3: the default probability of a firm with all NR CDS is 0.22% higher than that of a firm with no NR CDS. This magnitude is large in comparison to the overall sample default probability of 0.14%. We include year dummies in our regressions to control for potential time series patterns in the composition of CDS contract types.[30]

We find that the regressions reported in Table 10 have higher pseudo-R^2s than those in Table 9, suggesting that the specification with restructuring information relating to the contracts fits the data better. Therefore, the effect of *CDS Active* seems to be driven by the CDS contracts with NR clauses. This finding on restructuring will likely be relevant to many more reference names in the future as more and more corporate CDS contracts use NR as the credit event specification (e.g., all CDS index constituents of the North America investment grade index CDX.NA.IG), especially after the CDS Big Bang in 2009.

The results on *CDS Notional Outstanding/Total Debt* and *No Restructuring CDS Proportion* are consistent with the empty creditor model. Therefore, one mechanism for the CDS effect on credit risk is due to creditors becoming tougher in debt renegotiation, and consequently causing firms to file for bankruptcy. We note two caveats. First, empty creditors are only part of the market. CDS can be traded by *any* buyer and seller pair, and not just by the current creditors. CDS trading by parties unrelated to the reference firms would weaken the empty creditor mechanism and make it less likely for us to find significant CDS trading effects. Second, not all empty creditors can successfully force the borrower into bankruptcy.

4.5.2 Creditor Coordination Failure

Besides tough creditors causing bankruptcy on individual bases, creditor coordination is another important consideration for debt workout. If firms borrow money from a larger number of lenders after the inception of CDS trading, creditor coordination will be more difficult and bankruptcy more likely. Lead banks will probably not want to appear to drive their borrowers into bankruptcy, as the long-run reputational damage may outweigh the short-run gains from empty creditor trading profits. However, other lenders such as hedge funds or private equity players, who are not similarly constrained, may take advantage of CDS trading more intensively. Therefore, CDS trading may affect the size and composition of lenders to a firm.

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 lending relationships available from

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

DealScan LPC data.[31] 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 lending to the firm. Δ *Number of Banks* is the change in the number of bank relationships from one year before the inception of CDS trading to two years after the inception of CDS trading. First, from a univariate difference-in-difference analysis, we find that the number of bank relationships of a firm increases significantly by 1.4, one year after the inception of CDS trading, and by 3, two years after CDS trading, relative to firms matched using the CDS trading prediction models discussed in Section 4.3. Second, we regress Δ *Number of Banks* from the year before to two years after CDS trading started on a set of firm characteristics, and the *CDS Active* variable for CDS firms only. These "event study" results are reported in Panel A of Table 11. We find that CDS trading significantly increases the number of lenders that a firm has. On average, firms have 2.4 more lenders two years after CDS introduction, controlling for other factors that may affect the number of lenders, such as firm size and leverage.

The relationship between the number of lenders and bankruptcy risk has previously been documented by, among others, Gilson, John, and Lang (1990) and Brunner and Krahnen (2008). We present similar evidence from our sample, also including the effect of CDS trading, in Panel B of Table 11. 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 the direct impact of CDS trading. Therefore, the results in Table 11 support Hypothesis 4 that CDS trading increases the number of creditors, which, in turn, increases bankruptcy risk.

4.5.3 Other Mechanisms and Further Discussion

Besides leverage, tough creditors and coordination failure, another potential channel for the CDS trading effect is via the feedback from CDS pricing. On the one hand, if CDS spreads are too high relative to the corresponding bond yield spreads, this may feed back to the firm's bond market through arbitrage between the two markets, making it more costly and difficult for the firm to refinance its obligations. In turn, this may cause the operating environment to worsen, leading to a deterioration of the firm's credit quality.[32] High CDS spreads also increase the cost of buying CDS protection, and hence reduce the incentive of creditors to become empty creditors and deter potential market manipulation. If, on the other hand, CDS spreads are underpriced or too low, informed traders have a

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

[32] See, "A Market Backfires and Investors Pay," by Henry Sender, *Wall Street Journal*, December 5, 2002.

greater incentive to buy CDS contracts and expect to make profits from the subsequent increase in CDS spreads.[33]

Our last consideration of mechanisms is the information content of CDS trading. CDS provide traders with a relatively simple instrument for going short a firm's credit. The CDS market can provide information about a firm's credit quality, especially its downside risk. Therefore, it is possible that some firms become riskier after CDS trading as information is impounded into prices more quickly, perhaps causing higher equity, bond, and asset volatility. This information channel could be consistent with our finding of higher credit risk after CDS trading.[34]

In summary, we do not find evidence for the feedback and information channels of CDS trading effects. On the other hand, we find strong evidence for the leverage, tougher creditor and coordination failure channels. Therefore, while we are less certain about whether CDS lead firms into financial distress, our evidence is relatively clear that CDS increase the chances of bankruptcy compared with restructuring, for financially distressed firms.

5. Concluding Remarks

We find strong evidence that the bankruptcy risk of reference firms increases after the inception of CDS trading, using a comprehensive dataset of North American corporate CDS transaction records over the period 1997-2009. This effect of CDS trading on credit risk is economically large: the odds of bankruptcy more than double after CDS trading begins for average firms. This finding is robust to the selection and endogeneity in CDS trading, using the lender's FX hedging and Tier One capital ratio as instrumental variables. We also find that the the effect of CDS trading is related to the amount of CDS outstanding. Therefore, the bankruptcy risk of firms increases when CDS positions accumulate, and decreases when CDS contracts expire. The effect of CDS on bankruptcy risk is more pronounced when CDS payments do not cover restructuring. Moreover, the number of lenders increases after CDS trading begins, exacerbating the problems of creditor coordination.

This study uncovers a real consequence of CDS trading and contributes to the ongoing debate on this important derivative market. We emphasize that, although according to our findings firms become more vulnerable to bankruptcy once CDS start trading on them, this does *not* imply that CDS trading necessarily reduces social welfare. Indeed, CDS can increase debt capacity, and many previously unqualified projects may get funded due to the possibility of credit risk mitigation afforded by the CDS. Therefore, the cost associated with an increase in bankruptcy risk could be offset by the benefits of an

[33] In Table A11, we find that the effect of CDS trading on bankruptcy risk is significant for both firms with CDS that is likely overpriced and those for which it is underpriced (as predicted by the basis between the CDS and bond yield spreads). Moreover, there is no statistically significant difference between these two groups.

[34] We split our sample by analyst coverage in Table A12, and find a significant CDS effect for firms with both high and low analyst coverage. The effect is not statistically different between those sub-samples, suggesting that the CDS effect is not related to the information environment in which a firm operates.

enlarged credit supply. Future work could examine the tradeoff between the increased debt capacity and the bankruptcy vulnerability caused by CDS, shedding light on the overall impact of CDS trading on allocative efficiency.

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Table 1. Credit Default Swaps Trading and Bankruptcies by Year

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

(1) Year	(2) Total # of Firms	(3) # of Bankruptcies	(4) # of New CDS Firms	(5) # of Active CDS Firms	(6) # of CDS Bankruptcies	(7) # 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 2. Impact of Credit Default Swaps Trading on Credit Quality

This table presents the estimates of the probabilities of credit downgrades and bankruptcy, using a logistic model in a sample including firms with credit default swaps (CDS) and all non-CDS firms. *ln(E)* is the logarithm of the firm's market value of equity. *ln(F)* is the logarithm of the book value of the firm's debt, where book debt is the sum of short-term debt and 50% of long-term debt. $1/\sigma_E$ is the inverse of the firm's annualized equity volatility. $r_{it-1} - r_{mt-1}$ is the firm's excess return over the past year, and *NI/TA* is the firm's ratio of net income to total assets. To estimate the impact of CDS trading on the probability of credit downgrades or bankruptcy, we include CDS variables in the model specification. *CDS Firm* equals one if the firm is in the CDS sample and zero otherwise. *CDS Active* is a dummy variable that equals one after the inception of CDS trading and zero before CDS trading. The coefficient of interest is that of *CDS Active*, which captures the impact of CDS trading on the probability of credit downgrades or bankruptcy after the inception of CDS trading. The sample period is 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	
	(1)	(2)	(3)	(4)
ln(E)	-0.735***	-0.736***	-0.713***	-0.710***
	(0.014)	(0.014)	(0.024)	(0.024)
ln(F)	0.507***	0.503***	0.711***	0.713***
	(0.015)	(0.015)	(0.023)	(0.023)
$1/\sigma_E$	-0.062**	-0.017	-1.626***	-1.675***
	(0.027)	(0.026)	(0.131)	(0.131)
$r_{it-1} - r_{mt-1}$	-0.281***	-0.252***	-1.320***	-1.331***
	(0.035)	(0.035)	(0.111)	(0.111)
NI/TA	-0.003	-0.000	-0.038***	-0.038***
	(0.025)	(0.024)	(0.013)	(0.013)
CDS Firm	0.755***		-2.009***	
	(0.057)		(0.711)	
CDS Active	0.691***	1.371***	2.373***	0.400**
	(0.067)	(0.045)	(0.729)	(0.177)
Time Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Pseudo R^2	15.08%	14.75%	24.18%	24.06%
N	658966	658966	658966	658966
# of Downgrades (Bankruptcy)	3863	3863	940	940
CDS Active Odds Ratio	1.925	3.939	10.730	1.492
CDS Active Marginal Effect	0.39%	0.78%	0.33%	0.06%
Sample Probability of a Downgrade (Bankruptcy)	0.58%	0.59%	0.14%	0.14%

Table 3. Probability of Credit Default Swaps Trading

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

	Probability of CDS Trading		
	CDS Prediction Model 1	CDS Prediction Model 2	CDS Prediction Model 3
Ln(Assets)	0.794***	0.798***	0.795***
	(0.005)	(0.005)	(0.005)
Leverage	0.401***	0.409***	0.400***
	(0.026)	(0.026)	(0.026)
ROA	-0.019	-0.018	-0.019
	(0.016)	(0.017)	(0.017)
$r_{it-1} - r_{mt-1}$	-0.100***	-0.099***	-0.100***
	(0.010)	(0.010)	(0.010)
Equity Volatility	0.067***	0.069***	0.068***
	(0.015)	(0.015)	(0.015)
PPENT/Total Asset	0.349***	0.358***	0.350***
	(0.029)	(0.029)	(0.029)
Sales/Total Asset	-0.021***	-0.021***	-0.021***
	(0.003)	(0.003)	(0.003)
EBIT/Total Asset	0.249***	0.261***	0.250***
	(0.059)	(0.060)	(0.060)
WCAP/Total Asset	0.149***	0.154***	0.149***

	(0.024)	(0.024)	(0.024)
RE/Total Asset	0.020***	0.020***	0.020***
	(0.005)	(0.005)	(0.005)
Cash/Total Asset	0.251***	0.254***	0.254***
	(0.035)	(0.035)	(0.034)
CAPX/Total Asset	-1.833***	-1.861***	-1.826***
	(0.115)	(0.115)	(0.115)
Investment Grade	0.916***	0.912***	0.915***
	(0.013)	(0.013)	(0.013)
Rated	0.957***	0.963***	0.957***
	(0.015)	(0.015)	(0.015)
Lender FX Usage	2.487***		5.523***
	(0.732)		(0.732)
Lender Tier 1 Capital		-2.369***	-2.458***
		(0.713)	(0.713)
F-statistic (instruments)	56.15	11.05	68.10
p-value (F-statistic)	0.000	0.001	0.000
Time Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
Pseudo R^2	38.95%	38.78%	38.97%
N	690111	690111	690111
#CDS Event	551	551	551

Table 4. Credit Default Swaps Trading and Probability of Bankruptcy: Instrumental Variable Estimation

This table presents the second-stage estimation results of the instrumental variable estimation. The second-stage analysis is for the probability of bankruptcy using a logistic model in a sample including firms with credit default swaps (CDS) and all non-CDS firms. *ln(E)* is the logarithm of the firm's market value of equity. *ln(F)* is the logarithm of the book value of the firm's debt, where book debt is the sum of short-term debt and 50% of long-term debt. $1/\sigma_E$ is the inverse of the firm's annualized equity volatility. $r_{it-1} - r_{mt-1}$ is the firm's excess return over the past year, and *NI/TA* is the firm's ratio of net income to total assets. To estimate the impact of CDS trading on the probability of bankruptcy, we include CDS variables in the model specification. *CDS Firm* equals one if the firm is in the CDS sample and zero otherwise. We classify *CDS Active* as one if the probability of having CDS trading is above the median (in the top 50%), or in the top 25% respectively, the resulting variables being defined as *Instrumented CDS Active*. The sample period is 1997-2009, based on monthly observations. (*** Significant at 1% level, ** significant at 5% level, and * significant at 10% level. The numbers in parentheses are standard errors.)

	Probability of Bankruptcy CDS Prediction Model 3			
	Top 50%		Top 25%	
ln(E)	-0.625***	-0.623***	-0.623***	-0.622***
	(0.023)	(0.023)	(0.023)	(0.023)
ln(F)	0.642***	0.642***	0.644***	0.644***
	(0.022)	(0.022)	(0.022)	(0.022)
$1/\sigma_E$	-1.487***	-1.505***	-1.454***	-1.477***
	(0.129)	(0.128)	(0.127)	(0.126)
$r_{it-1} - r_{mt-1}$	-1.334***	-1.336***	-1.336***	-1.340***
	(0.109)	(0.109)	(0.109)	(0.109)
NI/TA	-0.033**	-0.033**	-0.033***	-0.033***
	(0.013)	(0.013)	(0.013)	(0.013)
CDS Firm	-0.171		-0.261	
	(0.167)		(0.172)	
Instrumented CDS Active	0.302***	0.294***	0.339***	0.298***
	(0.083)	(0.083)	(0.101)	(0.098)
Time Fixed Effects	Yes	Yes	Yes	
Industry Fixed Effects	Yes	Yes	Yes	Yes
Pseudo R^2	22.30%	22.29%	22.28%	22.27%
N	657438	657438	657438	657438
# of Bankruptcy	940	940	940	940
CDS Active Odds Ratio	1.353	1.342	1.404	1.347
CDS Active Marginal Effect	0.04%	0.04%	0.05%	0.04%
Sample Probability of a Bankruptcy	0.14%	0.14%	0.14%	0.14%

Table 5. Credit Default Swaps Trading and Probability of Bankruptcy: Heckman Treatment Effects Model with Instrument Variables

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

	Probability of Bankruptcy		
	CDS Prediction Model 1	CDS Prediction Model 2	CDS Prediction Model 3
ln(E)	-0.639***	-0.639***	-0.639***
	(0.022)	(0.022)	(0.022)
ln(F)	0.645***	0.645***	0.645***
	(0.022)	(0.022)	(0.022)
$1/\sigma_E$	-1.400***	-1.399***	-1.400***
	(0.125)	(0.125)	(0.125)
$r_{it-1} - r_{mt-1}$	-1.330***	-1.330***	-1.330***
	(0.109)	(0.109)	(0.109)
NI/TA	-0.032**	-0.032**	-0.032**
	(0.013)	(0.013)	(0.013)
CDS Firm	-2.270***	-2.269***	-2.270***
	(0.710)	(0.710)	(0.710)
CDS Active	2.631***	2.624***	2.630***
	(0.746)	(0.746)	(0.746)
Inverse Mills Ratio	0.035	0.040	0.036
	(0.124)	(0.123)	(0.124)
Time Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
Pseudo R^2	22.42%	22.42%	22.42%
N	657438	657438	657438
# of Bankruptcy	940	940	940
CDS Active Odds Ratio	13.888	13.791	13.874
CDS Active Marginal Effect	0.37%	0.37%	0.37%
Sample Probability of a Bankruptcy	0.14%	0.14%	0.14%

Table 6. Credit Default Swaps Trading and Credit Quality: Propensity Score Matching

This table presents the estimates of the probability of bankruptcy using a logistic model in a sample including firms with credit default swaps (CDS) and non-CDS propensity score matched firms. Propensity score matched firms are selected based on propensity scores estimated from the model of probability of CDS trading presented in Table 3. *ln(E)* is the logarithm of the firm's market value of equity. *ln(F)* is the logarithm of the book value of the firm's debt, where book debt is the sum of short-term debt and 50% of long-term debt. $1/\sigma_E$ is the inverse of the firm's annualized equity volatility. $r_{it-1} - r_{mt-1}$ is the firm's excess return over the past year, and *NI/TA* is the firm's ratio of net income to total assets. To estimate the impact of CDS trading on the probability of bankruptcy, we include CDS variables in the model specification. *CDS Firm* equals one if the firm is in the CDS sample and zero otherwise. *CDS Active* is a dummy variable that equals one after the inception of CDS trading and zero before CDS trading. The coefficient of interest is that of *CDS Active*, which captures the impact of CDS trading on the probability of bankruptcy after the inception of CDS trading. The second column presents the analysis in the baseline matched sample, i.e. the "nearest one" propensity score matching firms selected based on CDS prediction model 3 in Table 3. The third column presents the same analysis, but for the "nearest one" with propensity score difference within 1%. The fourth column uses the two matching firms with the nearest propensity scores. The last two columns present the analysis in the matched sample selected based on CDS prediction models 1 and 2 in Table 3. The sample period is 1997-2009, based on monthly observations. (*** Significant at 1% level, ** significant at 5% level, and * significant at 10% level. The numbers in parentheses are standard errors.)

	Probability of Bankruptcy				
	CDS Prediction Model 3			CDS Prediction Model 1	CDS Prediction Model 2
	Nearest One Matching	Nearest One PS Diff < 1%	Nearest Two Matching	Nearest One Matching	Nearest One Matching
ln(E)	-1.009 ***	-1.005 ***	-0.869 ***	-1.152 ***	-0.989 ***
	(0.133)	(0.138)	(0.111)	(0.149)	(0.133)
ln(F)	0.965 ***	0.918 ***	0.881 ***	1.183 ***	0.993 ***
	(0.123)	(0.127)	(0.102)	(0.139)	(0.121)
$1/\sigma_E$	-0.069	-0.029	-0.309	-0.013	-0.163
	(0.295)	(0.295)	(0.292)	(0.309)	(0.301)
$r_{it-1} - r_{mt-1}$	-2.299 ***	-2.104 ***	-2.738 ***	-2.427 ***	-2.140 ***
	(0.641)	(0.647)	(0.595)	(0.699)	(0.628)
NI/TA	0.012	-2.478 ***	0.041	0.001	-0.006
	(0.190)	(0.790)	(0.122)	(0.177)	(0.165)
CDS Firm	-0.856	-0.979	-0.797	-0.425	-0.912
	(0.783)	(0.813)	(0.753)	(0.795)	(0.783)
CDS Active	1.968**	2.215 ***	1.935**	1.583**	1.947**
	(0.796)	(0.835)	(0.770)	(0.781)	(0.795)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	32.78%	32.79%	33.35%	37.25%	32.14%
N	120975	111331	173665	113886	120494
# of Bankruptcy	49	48	62	45	48
CDS Odds Ratio	7.156	9.161	6.924	4.870	7.008
CDS Marginal Effect	0.08%	0.09%	0.07%	0.05%	0.07%
Sample Probability of a Bankruptcy	0.04%	0.04%	0.04%	0.04%	0.04%

Table 7. Changes in EDF and Leverage around the Introduction of Credit Default Swaps: Difference-in-Difference Analysis

This table presents a univariate analysis of changes in EDF and leverage from one year before to one year, two years or three years after the introduction of credit default swaps (CDS) trading. The changes in EDF and leverage of CDS-trading firms are compared with those of the matching firms. Matching firms are selected based on propensity scores estimated from the models for the probability of CDS trading presented in Table 3. The change in *EDF* is the change in the firm's expected default frequency. *EDF* is calculated based on the Merton (1974) model. The change in leverage is defined as the change in the ratio of book debt to the sum of book debt and market equity, where book debt is the sum of short-term debt and 50% of long-term debt, and market equity is the measure of the number of common shares outstanding multiplied by the stock price. (*** Significant at 1% level, ** significant at 5% level, and * significant at 10% level.)

Panel A: Change in EDF									
		Year t-1 to t+1			Year t-1 to t+2			Year t-1 to t+3	
	Nearest One	Nearest One PS Diff $<$ 1%	Nearest Two	Nearest One	Nearest One PS Diff $<$ 1%	Nearest Two	Nearest One	Nearest One PS Diff $<$ 1%	Nearest Two
CDS Prediction Model 1	0.005	0.007	0.007*	0.017**	0.006*	0.020**	0.046***	0.035**	0.043***
CDS Prediction Model 2	0.007	0.001	0.015*	0.020*	0.010**	0.021***	0.033***	0.020***	0.035***
CDS Prediction Model 3	0.008	0.001	0.016*	0.024**	0.014*	0.027***	0.040***	0.028**	0.040***

Panel B: Change in Leverage									
		Year t-1 to t+1			Year t-1 to t+2			Year t-1 to t+3	
	Nearest One	Nearest One PS Diff $<$ 1%	Nearest Two	Nearest One	Nearest One PS Diff $<$ 1%	Nearest Two	Nearest One	Nearest One PS Diff $<$ 1%	Nearest Two
CDS Prediction Model 1	0.012**	0.011**	0.010**	0.011**	0.014**	0.012**	0.014***	0.018**	0.014**
CDS Prediction Model 2	0.008**	0.006**	0.009**	0.007*	0.009**	0.012**	0.013***	0.016**	0.013**
CDS Prediction Model 3	0.006*	0.008**	0.010**	0.010**	0.012**	0.012**	0.007**	0.008**	0.012**

Table 8. CDS Exposure and the Probability of Bankruptcy

This table investigates the impact of credit default swaps (CDS) exposure on a firm's probability of bankruptcy. Model 1 conducts the analysis in a sample including firms with CDS and all non-CDS firms. Model 2 only includes firms with CDS. *ln(E)* is the logarithm of the firm's market value of equity. *ln(F)* is the logarithm of the book value of the firm's debt, where book debt is the sum of short-term debt and 50% of long-term debt. $1/\sigma_E$ is the inverse of the firm's annualized equity volatility. $r_{it-1} - r_{mt-1}$ is the firm's excess return over the past year, and *NI/TA* is the firm's ratio of net income to total assets. *CDS Firm* equals one if the firm has CDS trading at any point in time and zero otherwise. CDS exposure is measured as the logarithm of the number of live CDS contracts (*Number of Live CDS Contracts*). The sample period is 1997-2009, based on monthly observations. (*** Significant at 1% level, ** significant at 5% level, and * significant at 10% level. The numbers in parentheses are standard errors.)

	Probability of Bankruptcy	
	(1)	(2)
ln(E)	-0.689***	-0.970***
	(0.026)	(0.167)
ln(F)	0.651***	0.995***
	(0.026)	(0.166)
$1/\sigma_E$	-1.535***	-1.163***
	(0.103)	(0.381)
$r_{it-1} - r_{mt-1}$	-0.622***	-0.518
	(0.075)	(0.383)
NI/TA	-0.076***	-0.643
	(0.023)	(1.541)
CDS Firm	-0.644***	
	(0.210)	
Number of Live CDS Contracts	0.240***	0.539 ***
	(0.077)	(0.203)
Time Fixed Effects	Yes	Yes
Industry Fixed Effects	Yes	Yes
Pseudo R^2	15.84%	25.53%
N	658966	70038
# of Bankruptcies	940	40
Number of Live CDS Contracts Odds Ratio	1.271	1.714
Number of Live CDS Contracts Marginal Effect	0.03%	0.03%
Sample Probability of a Bankruptcy	0.14%	0.06%

Table 9. Empty Creditors and the Probability of Bankruptcy

This table investigates the impact of credit default swaps (CDS) on a firm's probability of bankruptcy. *ln(E)* is the logarithm of the firm's market value of equity. *ln(F)* is the logarithm of the book value of the firm's debt, where book debt is the sum of short-term debt and 50% of long-term debt. $1/\sigma_E$ is the inverse of the firm's annualized equity volatility. $r_{it-1} - r_{mt-1}$ is the firm's excess return over the past year, and *NI/TA* is the firm's ratio of net income to total assets. *CDS Firm* equals one if the firm has CDS trading at any point in time and zero otherwise. The empty creditor problem is measured as the total notional CDS outstanding, scaled by the book value of the total debt (*CDS Notional Outstanding/Total Debt*). The sample period is 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)
CDS Notional Outstanding/Total Debt	0.071**
	(0.032)
Time Fixed Effects	Yes
Industry Fixed Effects	Yes
Pseudo R^2	15.82%
N	658966
# of Bankruptcies	940
CDS Notional Outstanding/Total Debt Odds Ratio	1.074
CDS Notional Outstanding/Total Debt Marginal Effect	0.01%
Sample Probability of a Bankruptcy	0.14%

Table 10. Restructuring Clauses of CDS Contracts and Probability of Bankruptcy

This table investigates the impact of the restructuring clauses of credit default swaps (CDS) on the probability of bankruptcy of firms in a sample including firms with and without CDS traded. The empty creditor problem is expected to be more significant for firms with more contracts with "no restructuring" as the restructuring clause. In Model 1, for each CDS firm, we include a variable for the *No Restructuring CDS Proportion*, which is the total amount of active CDS contracts with "no restructuring" as the restructuring clause, scaled by the total number of CDS contracts trading on it. In Model 2, for each CDS firm, we also calculate the *Modified Restructuring CDS Proportion*, which is the total amount of active CDS contracts with "modified restructuring" as the restructuring clause, scaled by the total number of CDS contracts trading on it. *CDS Firm* equals one if the firm has CDS trading at any point in time and zero otherwise. The coefficient of interest is that of *No Restructuring CDS Proportion*, which captures the impact of the CDS-induced empty creditor problem. *ln(E)* is the logarithm of the firm's market value of equity. *ln(F)* is the logarithm of the book value of the firm's debt, where book debt is the sum of short-term debt and 50% of long-term debt. $1/\sigma_E$ is the inverse of the firm's annualized equity volatility. $r_{it-1} - r_{mt-1}$ is the firm's excess return over the past year, and *NI/TA* is the firm's ratio of net income to total assets. The sample period is 1997-2009, based on monthly observations. (*** Significant at 1% level, ** significant at 5% level, and * significant at 10% level. The numbers in parentheses are standard errors.)

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

Table 11. CDS Trading, Bank Relationships and Probability of Bankruptcy

This table shows the results of an analysis of the impact of credit default swaps (CDS) on firm-creditor relationships. The creditor relationships are measured by bank relationships obtained from Dealscan LPC. For each firm, on a given date, we look back five years for any syndicated loan facilities extended to this firm. Summing over all such active facilities, we compute, on each date, the number of unique bank relationships. Δ *Number of Banks* is the change in the number of bank relationships from one year before to two years after the inception of CDS trading. Δ *ln(Asset)* is the change in the logarithm of the firm's total assets value. Δ *ROA* is the change in the firm's return on assets. Δ *Leverage* is the change in leverage. Δ *PPENT/Total Asset* is the change in the ratio of property, plant and equipment to total assets. *CDS Active* is a dummy variable that equals one after and zero before the inception of CDS trading. *ln(E)* is the logarithm of the firm's equity value. *ln(F)* is the logarithm of the book value of the firm's debt, where book debt is the sum of short-term debt and 50% of long-term debt. $1/\sigma_E$ is the inverse of the firm's annualized equity volatility. $r_{it-1} - r_{mt-1}$ is the firm's excess return over the past year, and *NI/TA* is the firm's ratio of net income to total assets. *CDS Firm* equals one if the firm has CDS trading at any point in time and zero otherwise. *Number of Banks* is the number of existing bank relationships. The coefficients of interest are those of *CDS Active* and *Number of Banks*. (*** Significant at 1% level, ** significant at 5% level, and * significant at 10% level. The numbers in parentheses are standard errors.)

Panel A: CDS and Bank Relationships		Panel B: Bank Relationships and Bankruptcy Risk	
	Δ Number of Banks		Probability of Bankruptcy
Δ *ln(Asset)*	6.291***	*ln(E)*	-0.669***
	(1.849)		(0.026)
Δ *ROA*	-0.396	*ln(F)*	0.683***
	(2.76)		(0.024)
Δ *Leverage*	8.581*	$1/\sigma_E$	-1.763***
	(5.201)		(0.136)
Δ *PPENT/Total Asset*	-1.586	$r_{it-1} - r_{mt-1}$	-1.339***
	(10.84)		(0.111)
CDS Active	2.432**	*NI/TA*	-0.040***
	(1.069)		(0.013)
Time Fixed Effects	Yes	*CDS Firm*	-2.210***
Industry Fixed Effects	Yes		(0.712)
R^2	9.75%	*CDS Active*	2.378***
N	496		(0.728)
		Number of Banks	0.153***
			(0.035)
		Time Fixed Effects	Yes
		Industry Fixed Effects	Yes
		Pseudo R^2	24.32%
		N	658966
		# of Bankruptcy	940
		CDS Active Odds Ratio	10.783
		Number of Banks Odds Ratio	1.165
		CDS Active Marginal Effect	0.33%
		Number of Banks Marginal Effect	0.02%
		Sample Probability of Bankruptcy	0.14%

Additional Tables

Table A1. Firm Fixed Effect Regressions for Distance-to-Default and Credit Default Swaps

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

	Distance-to-Default
ln(E)	0.667***
	(0.002)
ln(F)	-0.644***
	(0.002)
$1/\sigma_E$	1.603***
	(0.003)
$r_{it-1} - r_{mt-1}$	0.099***
	(0.001)
NI/TA	0.031***
	(0.002)
CDS Active	-0.249***
	(0.008)
Time Fixed Effects	Yes
Firm Fixed Effects	Yes
R-Square	82.76%
N	648242

Table A2. Impact of Credit Default Swaps Trading on Bankruptcy: Alternative Model

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

	Probability of Bankruptcy	
	(1)	(2)
NIMTAAVG	-18.007***	-17.918***
	(1.697)	(1.695)
TLMTA	3.154***	3.268***
	(0.160)	(0.162)
EXRETAVG	-1.272*	-1.273*
	(0.743)	(0.741)
Sigma	0.829***	0.800***
	(0.131)	(0.130)
Rsize	0.114***	0.203***
	(0.031)	(0.034)
CASHMTA	-2.368***	-2.436***
	(0.402)	(0.404)
MB	0.001***	0.001**
	(0.000)	(0.000)
PRICE	-0.429***	-0.485***
	(0.071)	(0.071)
CDS Firm		-2.284***
		(0.456)
CDS Active		1.749***
		(0.482)
Time Fixed Effects	Yes	Yes
Industry Fixed Effects	Yes	Yes
Pseudo R^2	12.35%	12.77%
N	682053	682053
# of Bankruptcy	888	888
CDS Active Odds Ratio		5.749
CDS Active Marginal Effect		0.23%
Sample Probability of Bankruptcy	0.13%	0.13%

Table A3. Probability of Bankruptcy Controlling for Direct Effect of Downgrade

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. Propensity score matched firms are selected based on propensity scores estimated from the model of probability of CDS trading presented in Table 3. *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. *Downgrade* is a dummy variable that equals one if the firm was downgraded one year before month t. The sample period is 1997-2009, based on monthly observations. (*** Significant at 1% level, ** significant at 5% level, and * significant at 10% level. The numbers in parentheses are standard errors.)

	Probability of Bankruptcy			
	CDS Prediction Model 1		CDS Prediction Model 2	
	(1)	(2)	(3)	(4)
ln(E)	-1.130***	-1.141***	-1.005***	-1.022***
	(0.150)	(0.149)	(0.137)	(0.136)
ln(F)	1.143***	1.157***	0.996***	1.017***
	(0.137)	(0.137)	(0.123)	(0.123)
$1/\sigma_E$	0.068	0.084	0.033	0.049
	(0.244)	(0.234)	(0.230)	(0.220)
$r_{it-1} - r_{mt-1}$	-2.118***	-2.140***	-1.895***	-1.880***
	(0.674)	(0.671)	(0.615)	(0.607)
NI/TA	0.054	0.046	0.060	0.052
	(0.185)	(0.182)	(0.164)	(0.163)
CDS Firm	-0.576		-0.981	
	(0.799)		(0.787)	
CDS Active	1.656**	1.176***	2.107***	1.264***
	(0.798)	(0.398)	(0.810)	(0.388)
Unrated	1.309***	1.285***	1.876***	1.855***
	(0.403)	(0.401)	(0.368)	(0.367)
Downgrade	1.060**	1.060**	1.155***	1.168***
	(0.442)	(0.443)	(0.404)	(0.406)
Time Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Pseudo R^2	38.91%	38.83%	35.34%	35.12%
N	113886	113886	120494	120494
# of Bankruptcies	45	45	48	48
CDS Active Odds Ratio	5.238	3.241	8.224	3.540
Downgrade Odds Ratio	2.886	2.886	3.174	3.216
CDS Active Marginal Effect	0.11%	0.04%	0.08%	0.05%
Downgrade Marginal Effect	0.036%	0.04%	0.04%	0.04%
Sample Probability of Bankruptcy	0.06%	0.04%	0.04%	0.04%

Table A4. Rating Drift and the Impact of Credit Default Swaps

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

	Probability of Bankruptcy	
	(1)	(2)
ln(E)	-1.552 ***	-1.562 ***
	(0.153)	(0.153)
ln(F)	1.449 ***	1.463 ***
	(0.153)	(0.153)
$1/\sigma_E$	-0.548*	-0.528*
	(0.300)	(0.300)
$r_{it-1} - r_{mt-1}$	-0.695	-0.733
	(0.448)	(0.448)
NI/TA	-4.102 ***	-4.118 ***
	(0.643)	(0.639)
CDS Firm	-0.530	
	(0.779)	
CDS Active	2.431 ***	2.134 ***
	(0.667)	(0.465)
Time Fixed Effects	Yes	Yes
Industry Fixed Effects	Yes	Yes
Pseudo R^2	39.95%	39.91%
N	141006	141006
# of Bankruptcy	65	65
CDS Odds Ratio	11.370	8.449
CDS Marginal Effect	0.10%	0.09%
Sample Probability of a Bankruptcy	0.05%	0.05%

Table A5. Impact of Credit Default Swaps Trading on Credit Quality: Control for Distance-to-Default

This table presents the estimates of the probability of bankruptcy using a logistic model. The analysis is conducted in a sample including firms with credit default swaps (CDS) and all non-CDS firms. Besides the conventional determinants of bankruptcy risk, we also control for firm's distance-to-default (*DD*). *DD* is calculated from the Merton (1974) model. *ln(E)* is the logarithm of the firm's market value of equity. *ln(F)* is the logarithm of the book value of the firm's debt, where book debt is the sum of short-term debt and 50% of long-term debt. $1/\sigma_E$ is the inverse of the firm's annualized equity volatility. $r_{it-1} - r_{mt-1}$ is the firm's excess return over the past year, and *NI/TA* is the firm's ratio of net income to total assets. To estimate the impact of CDS trading on the probability of bankruptcy, we include CDS variables in the model specification. *CDS Firm* equals one if the firm is in the CDS sample and zero otherwise. *CDS Active* is a dummy variable that equals one after and zero before the inception of CDS trading. The coefficient of interest is that of *CDS Active*, which captures the impact of CDS trading on the probability of credit downgrades or bankruptcy after the inception of CDS trading. The sample period is 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)	-0.567***	-0.612***
	(0.020)	(0.036)
ln(F)	0.321***	0.638***
	(0.020)	(0.035)
$1/\sigma_E$	0.315***	-1.213***
	(0.035)	(0.178)
$r_{it-1} - r_{mt-1}$	-0.044	-1.125***
	(0.034)	(0.131)
NI/TA	0.006	-0.035***
	(0.017)	(0.013)
CDS Firm	0.862***	-1.823**
	(0.057)	(0.712)
CDS Active	0.721***	1.900**
	(0.068)	(0.751)
DD	-0.244***	-0.181***
	(0.017)	(0.054)
Time Fixed Effects	Yes	Yes
Industry Fixed Effects	Yes	Yes
Pseudo R^2	14.12%	18.66%
N	646923	646923
# of Downgrades(Bankruptcy)	3384	632
CDS Active Odds Ratio	2.056	6.686
CDS Active Marginal Effect	0.37%	0.18%
Sample Probability of a Downgrade(Bankruptcy)	0.52%	0.10%

Table A6. Impact of Credit Default Swaps Trading on Credit Quality: Distance-to-Default Matching

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

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

Table A7. Credit Rating and CDS Effects

This table investigates the impact of credit default swaps (CDS) trading on the probability of bankruptcy in subsamples of investment grade and non-investment grade firms. *ln(E)* is the logarithm of the firm's equity value. *ln(F)* is the logarithm of the book value of the firm's debt. $1/\sigma_E$ is the inverse of the firm's annualized equity volatility. $r_{it-1} - r_{mt-1}$ is the firm's excess return over the past year, and *NI/TA* is the firm's ratio of net income to total assets. To estimate the impact of CDS trading on the probability of credit downgrades/bankruptcy, we include CDS variables in the model specification. *CDS Firm* equals one if the firm is in the CDS sample and zero otherwise. *CDS Active* is a dummy variable that equals one if the firm has CDS traded on its debt one year before month t. The sample period is 1997-2009, based on monthly observations. (*** Significant at 1% level, ** significant at 5% level, and * significant at 10% level. The numbers in the parentheses are standard errors.)

	Probability of Bankruptcy		
	Full Sample	Investment Grade	Non-investment Grade
ln(E)	-0.713***	-0.705***	-0.704***
	(0.024)	(0.024)	(0.024)
ln(F)	0.711***	0.702***	0.702***
	(0.023)	(0.023)	(0.023)
$1/\sigma_E$	-1.626***	-1.825***	-1.625***
	(0.131)	(0.138)	(0.134)
$r_{it-1} - r_{mt-1}$	-1.320***	-1.262***	-1.323***
	(0.111)	(0.110)	(0.112)
NI/TA	-0.038***	-0.036***	-0.037***
	(0.013)	(0.013)	(0.013)
CDS Firm	-2.009***	-1.525	-2.182**
	(0.711)	(1.004)	(1.002)
CDS Active	2.373***	1.893*	2.721***
	(0.729)	(1.041)	(1.024)
Time Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
Pseudo R^2	24.18%	24.09%	23.64%
N	658966	634895	608773
# of Bankruptcies	940	912	924
CDS Active Odds Ratio	10.73	6.64	15.20
CDS Active Marginal Effect	0.33%	0.26%	0.40%
Sample Probability of Bankruptcy	0.14%	0.14%	0.15%

Table A8. Mergers & Acquisitions and the CDS Effect

This table presents the estimates of the probability of bankruptcy using a logistic model in a sample excluding firms with a Mergers & Acquisitions (M&A) event. M&A data are obtained from SDC Interface. *ln(E)* is the logarithm of the firm's market value of equity. *ln(F)* is the logarithm of the book value of the firm's debt, where book debt is the sum of short-term debt and 50% of long-term debt. $1/\sigma_E$ is the inverse of the firm's annualized equity volatility. $r_{it-1} - r_{mt-1}$ is the firm's excess return over the past year, and *NI/TA* is the firm's ratio of net income to total assets. To estimate the impact of CDS trading on the probability of credit downgrades or bankruptcy, we include CDS variables in the model specification. *CDS Firm* equals one if the firm is in the CDS sample and zero otherwise. *CDS Active* is a dummy variable that equals one after and zero before the inception of CDS trading. The coefficient of interest is that of *CDS Active*, which captures the impact of CDS trading on the probability of bankruptcy after the inception of CDS trading. The sample period is 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)	-0.685 ***
	(0.025)
ln(F)	0.697 ***
	(0.024)
$1/\sigma_E$	-1.907 ***
	(0.148)
$r_{it-1} - r_{mt-1}$	-1.380 ***
	(0.121)
NI/TA	-0.033**
	(0.014)
CDS Firm	-1.755**
	(0.712)
CDS Active	1.985 ***
	(0.735)
Time Fixed Effects	Yes
Industry Fixed Effects	Yes
Pseudo R^2	25.20%
N	563771
# of Bankruptcy	839
CDS Active Odds Ratio	7.279
CDS Active Marginal Effect	0.30%
Sample Probability of a Bankruptcy	0.15%

Table A9. Probability of Credit Default Swaps Trading: Additional Instruments

This table presents the estimates of the probability of credit default swaps (CDS) trading using a probit model. Propensity scores are estimated based on the model parameters. *ln(Asset)* is the logarithm of the firm's total assets value. *Leverage* is defined as the ratio of book debt to the sum of book debt and market equity, where book debt is the sum of short-term debt and 50% of long-term debt and market equity is the measure of the number of common shares outstanding multiplied by the stock price. *ROA* is the firm's return on assets. $r_{it-1} - r_{mt-1}$ is the firm's excess return over the past year. *Equity Volatility* is the firm's annualized equity volatility. *PPENT/Total Asset* is the ratio of property, plant and equipment to total assets. *Sales/Total Asset* is the ratio of sales to total assets. *EBIT/Total Asset* is the ratio of earnings before interest and tax to total assets. *WCAP/Total Asset* is the ratio of working capital to total assets. *RE/Total Asset* is the ratio of retained earnings to total assets. *Cash/Total Asset* is the ratio of cash to total assets. *CAPX/Total Asset* is the ratio of capital expenditure to total assets. *Investment Grade* is a dummy variable that equals one if the firm has an investment grade (BBB- or above) rating. *Rated* is a dummy variable that equals one if the firm is rated. *Trace Coverage* is a dummy that equals one for firms in the Trade Reporting and Compliance Engine (TRACE) database. *Post CFMA* is the a dummy that equals one for the period after the Commodity Futures Modernization Act of 2000 (CFMA). The *Inverse Mills Ratio* is calculated from the first-stage probit regression modeling the probability of CDS trading. The sample period is 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: Probability of CDS Trading

	Probability of CDS Trading	
	CDS Prediction Model 4	CDS Prediction Model 5
Trace Coverage	0.512***	
	(0.024)	
Post CFMA		0.386***
		(0.068)
Ln(Asset)	0.799***	0.797***
	(0.005)	(0.005)
Leverage	0.403***	0.417 ***
	(0.025)	(0.026)
ROA	-0.020	-0.012
	(0.016)	(0.016)
$r_{it-1} - r_{mt-1}$	-0.095***	-0.099 ***
	(0.010)	(0.010)
Equity Volatility	0.055***	0.068***
	(0.015)	(0.015)

PPENT/Total Asset	0.373***	0.357***
	(0.029)	(0.029)
Sales/Total Asset	-0.022***	-0.021 ***
	(0.003)	(0.003)
EBIT/Total Asset	0.311 ***	0.256***
	(0.060)	(0.060)
WCAP/Total Asset	0.144***	0.159***
	(0.023)	(0.024)
RE/Total Asset	0.018 ***	0.023 ***
	(0.005)	(0.006)
Cash/Total Asset	0.249***	0.251***
	(0.037)	(0.037)
CAPX/Total Asset	-1.914 ***	-1.862***
	(0.114)	(0.115)
Investment Grade	0.944 ***	0.916***
	(0.015)	(0.013)
Rated	0.957 ***	0.962 ***
	(0.015)	(0.015)
Time Fixed Effects	Yes	Yes
Industry Fixed Effects	Yes	Yes
Pseudo R^2	38.79%	38.76%
N	690111	690111
#CDS Event	551	551

Panel B. Treatment Effects Model with Instrumental Variables

	Probability of Bankruptcy	
	CDS Prediction	CDS Prediction
	Model 4	Model 5
ln(E)	-0.639***	-0.639***
	(0.022)	(0.022)
ln(F)	0.646 ***	0.645***
	(0.022)	(0.022)
$1/\sigma_E$	-1.400 ***	-1.400***
	(0.125)	(0.125)
$r_{it-1} - r_{mt-1}$	-1.330 ***	-1.330 ***
	(0.109)	(0.109)
NI/TA	-0.032**	-0.032**
	(0.013)	(0.013)
CDS Firm	-2.271 ***	-2.267 ***
	(0.710)	(0.710)
CDS Active	2.638 ***	2.628***
	(0.747)	(0.745)
Inverse Mills Ratio	0.030	0.035
	(0.128)	(0.124)
Time Fixed Effects	Yes	Yes
Industry Fixed Effects	Yes	Yes
Pseudo R^2	22.42%	22.42%
N	657438	657438
# of Bankruptcy	940	940
CDS Active Odds Ratio	13.985	13.846
CDS Active Marginal Effect	0.37%	0.37%
Sample Probability of a Bankruptcy	0.14%	0.14%

Table A10. Impact of Credit Default Swaps Trading on Credit Quality: CDS Event

This table presents the estimates of the probability of bankruptcy using a logistic model. In contrast to the baseline results in Table 2, we shift the CDS introduction date by one year as a falsification test. *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 sample period is 1997-2009, based on monthly observations. (*** Significant at 1% level, ** significant at 5% level, and * significant at 10% level. The numbers in the parentheses are standard errors.)

	Probability of Bankruptcy
ln(E)	-0.714***
	(0.024)
ln(F)	0.712***
	(0.023)
$1/\sigma_E$	-1.627***
	(0.131)
$r_{it-1} - r_{mt-1}$	-1.321***
	(0.111)
NI/TA	-0.038***
	(0.013)
CDS Firm	-12.674
	(168.47)
CDS Active	12.959
	(168.47)
Time Fixed Effects	Yes
Industry Fixed Effects	Yes
Pseudo R^2	24.20%
N	658966
# of Bankruptcy	940
CDS Active Odds Ratio	
CDS Active Marginal Effect	1.79%
Sample Probability of Bankruptcy	0.14%

Table A11. Impact of Credit Default Swaps Trading on Bankruptcy: The Feedback Mechanism

This table investigates the impact of credit default swaps (CDS) trading on a firm's probability of bankruptcy, controlling for firm's CDS spread status. *Over Priced* (*Under Priced*) is a dummy that equals one for firms that are likely to be overpriced (underpriced), as measured by the basis between the CDS and bond yield spreads. *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 sample period is 1997-2009, based on monthly observations. (*** Significant at 1% level, ** significant at 5% level, and * significant at 10% level. The numbers in the parentheses are standard errors.)

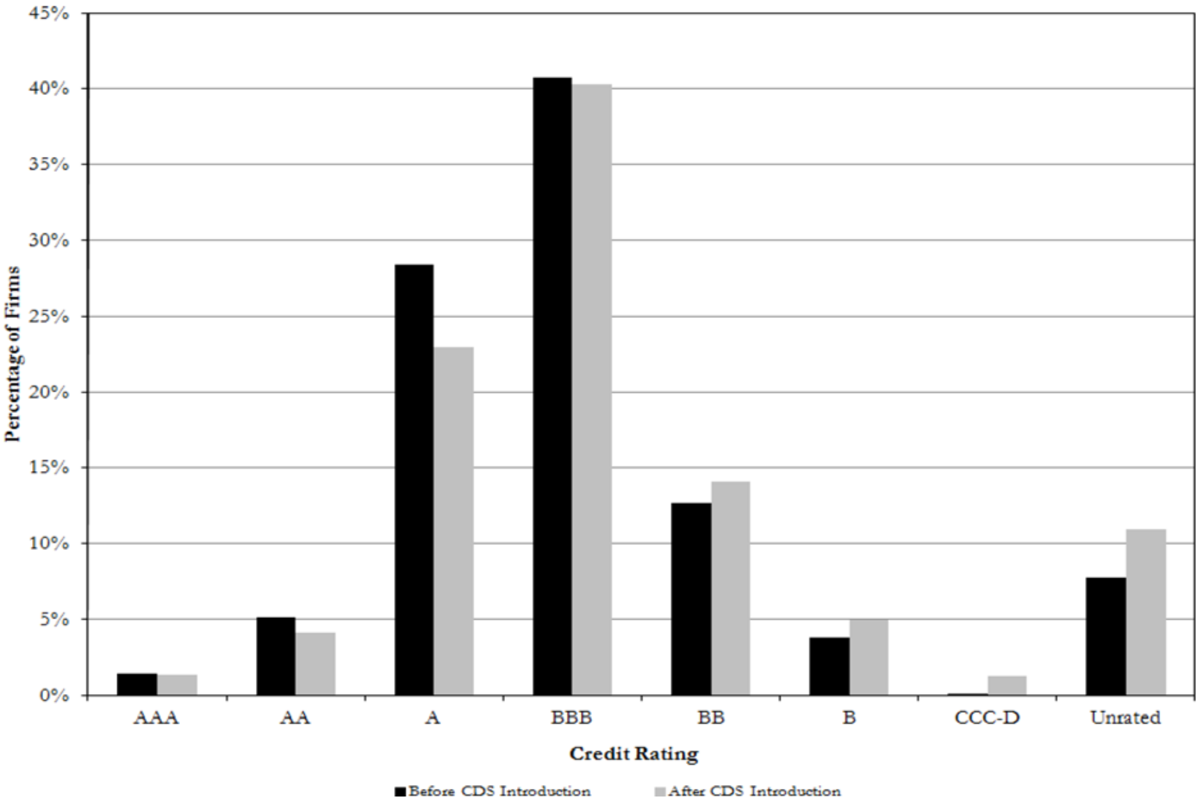
	Probability of Bankruptcy			
	Model 1	Model 2	Model 3	Model 4
ln(E)	-0.696***	-0.696***	-0.696***	-0.697***
	(0.030)	(0.030)	(0.030)	(0.030)
ln(F)	0.715***	0.714***	0.714***	0.715***
	(0.029)	(0.029)	(0.029)	(0.029)
$1/\sigma_E$	-1.630***	-1.628***	-1.626***	-1.632***
	(0.188)	(0.188)	(0.188)	(0.188)
$r_{it-1} - r_{mt-1}$	-1.750***	-1.747***	-1.750***	-1.749***
	(0.174)	(0.174)	(0.174)	(0.174)
NI/TA	-0.042**	-0.042**	-0.042**	-0.042**
	(0.018)	(0.018)	(0.018)	(0.018)
CDS Firm	-1.578	-1.532	-1.498	-1.497
	(1.005)	(1.005)	(1.005)	(1.005)
CDS Active	1.982*	2.066**	1.932*	1.932*
	(1.021)	(1.017)	(1.021)	(1.021)
*CDS Active*Over Priced*	7.804		9.851	
	(211.54)		(573.80)	
Over Priced	-7.205		-9.284	
	(211.54)		(573.80)	
*CDS Active*Under Priced*		-1.946	-1.833	
		(613.85)	(616.39)	
Under Priced		-9.876	-9.909	
		(486.90)	(486.85)	
*CDS Active*Mis-pricing*				8.796
				(195.73)
Mis-pricing				-8.410
				(195.72)
Time Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Pseudo R^2	27.54%	27.54%	27.56%	27.53%
N	398638	398638	398638	398638
# of Bankruptcies	530	530	530	530
CDS Active Odds Ratio	7.257	7.893	6.903	6.903
CDS Active Marginal Effect	0.25%	0.26%	0.25%	0.25%
Sample Probability of Bankruptcy	0.13%	0.13%	0.13%	0.13%

Table A12. 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 as a proxy for the availability of private information. High (low) analyst coverage is indicated by the number of analysts of a firm being above (below) the median in the sample. *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 sample period is 1997-2009, based on monthly observations. (*** Significant at 1% level, ** significant at 5% level, and * significant at 10% level. The numbers in the parentheses are standard errors.)

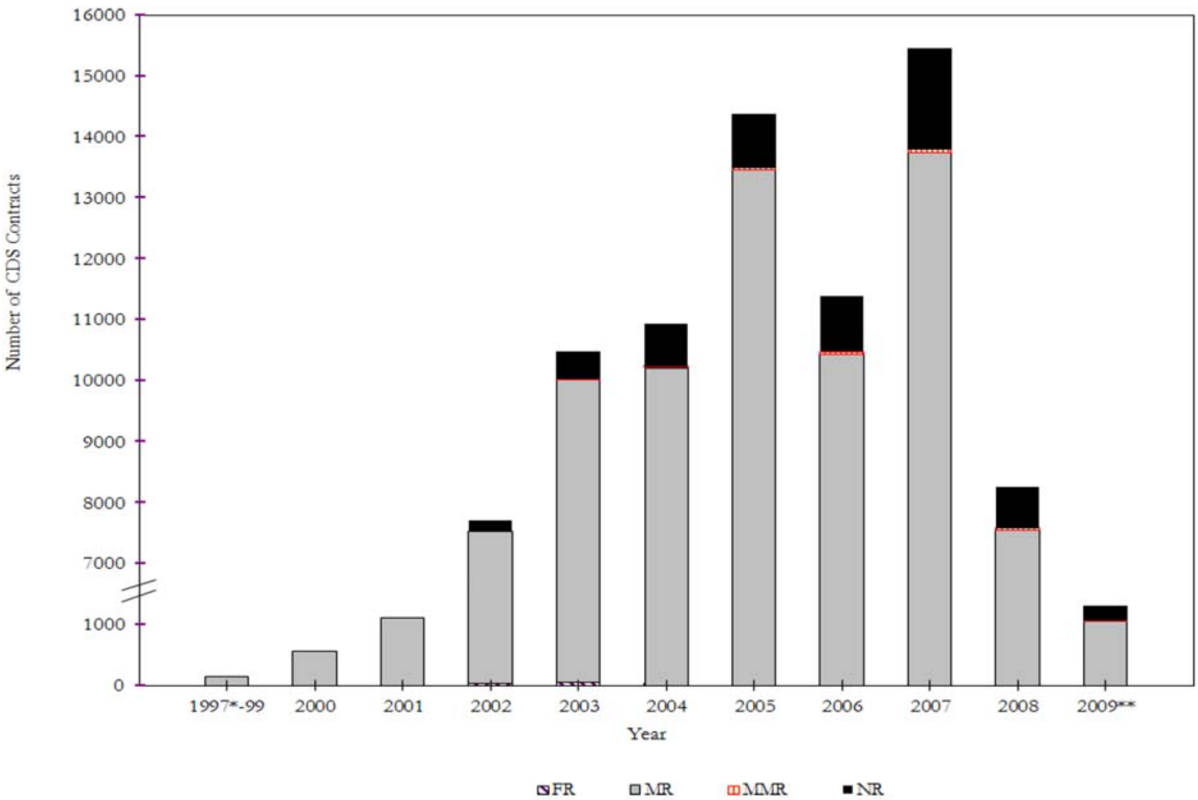
	Probability of Bankruptcy		
	Low Analyst Coverage	High Analyst Coverage	Full Sample
ln(E)	-0.596***	-0.713***	-0.712***
	(0.032)	(0.024)	(0.024)
ln(F)	0.584***	0.711***	0.710***
	(0.032)	(0.023)	(0.023)
$1/\sigma_E$	-1.773***	-1.626***	-1.660***
	(0.209)	(0.131)	(0.133)
$r_{it-1} - r_{mt-1}$	-1.286***	-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
Pseudo R^2	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%

Figure 1. Rating Distribution around the Introduction of Credit Default Swaps



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

Figure 2. Credit Default Swaps Restructuring Clauses by Year



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

Appendix A. Illustration of CDS Effects on Bankruptcy Risk

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

First, consider the case where there is no CDS traded on a firm. Assume that creditors lend X to the firm. If the firm is in financial distress and consequently declares bankruptcy, creditors will recover $r \times X$, where r is the recovery rate in bankruptcy. Consider, on the other hand, that the creditors allow the firm to restructure the debt, since the recovery value of the assets in bankruptcy is less than its value as a going concern. Suppose the firm offers the creditors part of the difference between the "going concern" value and the recovery value of the assets in bankruptcy, and agrees to pay them say $R \times X$, with $R > r$. Clearly, the creditors would consider such a restructuring favorably, and try to avoid bankruptcy.[35] In general, restructuring would dominate bankruptcy.

Suppose next that the creditors can also buy CDS protection against the firm's credit events. Clearly, bankruptcy would always be defined as a credit event. However, restructuring may or may not be defined as a credit event, as per the clauses of the CDS contract. If restructuring is included as a credit event, we call the contract a "full restructuring" (FR) CDS. If it is not, we call it a "no restructuring" (NR) CDS.[36] In the case of FR CDS, assume that the CDS premium (price) is F, in present value terms, at the time of default and that the creditors buy CDS against Y of notional value of the CDS. If the firm defaults, the creditors' total payoff with CDS protection is $[r \times X + (1-r-F) \times Y]$ in the event of bankruptcy, and $[R \times X + (1-R-F) \times Y]$ if the debt is restructured. Therefore, the creditors are better off with bankruptcy than with restructuring if

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

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

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

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

company as any new financing would require the existing creditors' approval. CDS sellers are not part of this negotiation process.

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

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

or when

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

which can be true even when $Y < X$, since $R < 1$. Thus, for NR CDS, bankruptcy is preferred when even a relatively small amount of CDS are purchased; hence, bankruptcy is the preferred outcome for a larger range of holdings of NR CDS by the creditors. It is also evident that buying CDS protection with NR CDS contracts is more profitable in bankruptcy than restructuring without CDS protection, so long as

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

which is equivalent to saying that [37]

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

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

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[37] 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.

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

Appendix B. 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 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 will benefit by delivering the least expensive instrument in the event of default. The broad definition of deliverable obligations was intended to create a standard hedge contract with a wide range of protection possibilities for the credit risk of the reference entity.

However, the restructuring of Conseco Finance on 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 a 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 has not included restructuring as a credit event for North American CDS contracts.

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