Do Credit Default Swaps Matter After They Are Settled? Evidence from Debt Recovery Rates[*]

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January 12, 2016

[*] The views expressed in this paper are those of the authors, and do not necessarily reflect those of the Office of the Comptroller of the Currency, or the U.S. Department of Treasury. We thank Allen Berger, Christa Bouwman, Jean Helwege, Jing-Zhi Huang, Rainer Jankowitsch, and Wei Wang for their insightful comments. We also thank seminar and conference participants at University of South Carolina, the Office of the Comptroller of the Currency, the 2015 Midwest Finance Association meetings (Chicago), and the 2014 Interagency Risk Quantification Forum for helpful comments.

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Abstract

We provide the first empirical analysis on the effects of credit default swaps (CDS) on corporate distress resolution with a focus on debt recovery rate. CDS contracts are settled shortly after the occurrence of credit events such as restructuring or bankruptcy filings and, presumably, should cease to be relevant after the settlements. However, we find that the ultimate debt recovery rates, which are determined in the final resolution plan and long after the CDS settlements, are higher for the bankrupt firms with CDS contracts before bankruptcy filings. This CDS effect on recovery rates is more pronounced for bonds than for loans. The overall evidence is consistent with the view that CDS trigger earlier bankruptcy filings, leaving more valuable assets for bondholders in the bankrupt entities.

JEL classification: G33; G34; G32; G30; G10

Key words: Credit default swaps; CDS; Recovery rate; Loss given default (LGD); Credit risk

1. Introduction

Creditor protection is important in financial markets including developed economies such as the U.S. as evidenced by recurrent violations of absolute priority rules during bankruptcy resolutions.[1] Creditors traditionally rely on court proceedings or contract renegotiations to protect their credit exposures. The rise of credit default swaps (CDS) market since mid-1990s significantly changed this situation. Creditors now can buy CDS directly in the credit derivatives market to insure against adverse credit events and protect their investments. However, a new concern is that creditors may subsequently become excessively tough in forcing bankruptcy filings if their exposures are protected by CDS and they may gain from such actions. Such "empty creditor" problem is modeled by Bolton and Oehmke (2011) and empirically documented by Subrahmanyam, Tang and Wang (2014). An important consideration that naturally arises after bankruptcy filings is the distress resolution process. In this paper, we empirically examine the impact of CDS trading on the resolution of financial distress and creditor recovery rates.

Understanding the determinants of recovery rates is a major outstanding task in the research of credit risk. Defaults are rare events and it takes long time to resolve financial distress, making it difficult to have good understanding of the resolution process and outcome.[2] Nevertheless, recovery rates are key inputs in the pricing of both corporate bonds and CDS contracts. If recovery rates are affected by the trading of CDS, then the pricing models for CDS should take such feedback effects into account instead of using prevailing recovery rate assumptions based on pre-CDS data. Furthermore, insights from studying recovery rates can help advance our understanding on the real effects of CDS.

Intuitively, CDS should not matter to debt recovery which is determined long after CDS contracts are settled and the contracting relationship is terminated. However, the mere presence of CDS trading prior to bankruptcy filings can affect post-bankruptcy recovery rates in a number of ways. In a CDS contract, the protection buyer pays the seller a premium before credit events

[1] See Bharath, Panchapegesan and Werner (2010) and Senbet and Wang (2010) for discussion of violations of absolute priority rules during Chapter 11 bankruptcies.

[2] *Moody's Special Report*, July 7, 2011: "A review of firm-wide recovery rates for 107 companies emerging from default during the recent credit cycle shows them to be uncorrelated with fundamental credit metrics in advance of default, illustrating the difficulty of forecasting firm-wide recovery rates."

for a potential return, which is approximately the expected loss rate of the reference debt. If dealers are net CDS sellers who are liable for potential payments to buyers, they may have incentives to push up recovery rates, such as during CDS auctions, to lower their payouts. Although the ultimate recovery rates are determined in the negotiation process by the involved stakeholders rather than CDS auctions, the auction rate can be an anchor and sets a benchmark for ultimate recovery rate. Besides strategic considerations, supply-demand imbalance and signaling can also affect the valuation of the assets of the defaulted borrower when there was CDS trading prior to bankruptcy. In terms of real supply and demand, selling CDS can be regarded as a synthetic form of buying bonds. After default, CDS are settled and become unavailable, then there could be more investment interests in the physical bonds (Che and Sethi (2014), Oehmke and Zawadowski (2015a)). In short, CDS may increase the participation in bidding for the assets of the bankrupt firm, leading to higher recovery rates. CDS can provide information for both probability of default and loss given default (LGD) before actual bankruptcy filing, in the same logic as Batta, Qiu, and Yu (2015). CDS trading is more likely when the issuer's bond market is more fragmented (Oehmke and Zawadowski (2015b)). If CDS trading helps concentrate bond-holding, then it may lead to higher recovery rates.

Contrasting to above positive CDS effects on recovery rates, other factors may potentially lead to lower recovery rates associated with CDS trading. For example, accounting conservatism can decline after a firm's debt is referenced by CDS contracts (Martin and Roychowdhurry (2015)). If recovery rates are higher for borrowers with more conservative accounting, as shown by Donovan, Frankel, and Martin (2015)), we would expect lower recovery rates for firms traded in the CDS market. Moreover, CDS trading can reduce bond market liquidity (Das, Kalimipalli, and Nayak (2014)), and less liquid bonds may become less valuable even during the reorganization process. We discuss these counteracting factors in more details in the next section. Ultimately, the relationship between CDS trading and recovery rate is an empirical issue.

Data is a paramount challenge for empirical studies of both CDS and recovery rates. With access to good quality data, we construct a comprehensive dataset of CDS markets and recovery rates over an extended period. Our CDS trading is from Markit, which has been used by prior studies. The recovery rate data is from Moody's Default & Recovery Database. The rich data set covers restructuring as well both Chapter 11 reorganization and Chapter 7 liquidation.

Our primary finding is that, for U.S. default events over the period 2002-2012, recovery rates are significantly higher for defaulted firms which had CDS trading prior to the credit events. This finding is robust to controls for debt characteristics, firm characteristics, and economic conditions, as well as alternative model specifications such as the fractional response regression. This finding is also robust to analyses that control for endogeneity and selection bias, and to analyses using different recovery rate measures.

We provide additional evidence to understand the mechanisms driving the CDS effects. Even though CDS contracts can be linked to both restructuring and bankruptcy events, the effect of CDS on restructuring recovery rates is much weaker than its effect on Chapter 11 bankruptcies. Moreover, the CDS effect is stronger in recent time period, such as the post-2005 era, when CDS auctions became the method to determine the recovery rate for CDS payments. We note that CDS contracts often exclude restructuring as credit events in recent period, especially after the 2009 CDS Big Bang. Therefore, the CDS effect evolves over time and is largely associated with bankruptcy filings.

We find that firms have relatively lower leverage at the time of bankruptcy filings when they have CDS, suggesting that earlier bankruptcy filings were one reason for the higher recovery rates. Importantly, even though the increases in recovery rates are concentrated in corporate bonds, loan recovery rates are not adversely affected. The lack of wealth transfer from bank lenders to bondholders suggests the main effect of CDS trading is to prevent shareholder risk-shifting and squandering assets near bankruptcy. Finally, CDS trading prior to bankruptcy is associated with longer resolution time, possibly because the remaining bondholders bargain harder after other creditors have received CDS payments and have no economic stakes on the bargaining table.

Our empirical results add to the growing literature on the implications of CDS trading for corporate finance and asset pricing. Prior studies have investigated the effect of the availability of CDS contracts on borrowers' cost of debt (Ashcraft and Santos, 2009) and credit supply (Saretto and Tookes, 2013). Subrahmanyam, Tang, and Wang (2014) find that the probabilities of credit rating downgrade and bankruptcy both increase after the inception of CDS trading on the underlying firms. Ours is the first study, to the best of our knowledge, to specifically examine the links between CDS trading and loss severity using a large sample of ultimate recovery data of corporate defaults.

CDS trading has been subject to recurring controversies. A large portion of Dodd-Frank Act is on regulating and improving CDS market. Some have even argued for the closure of the market while others such as BlackRock have appealed to revive the CDS market.[3] Our finding that early bankruptcy filings triggered by CDS can result in higher recovery rates sheds light on the "bright side" of CDS. Ivashina, Iverson, and Smith (2015) find that higher ownership concentration within a debt class is associated with a higher recovery rate for that debt class. If CDS allows investors to accumulate more bonds and increase ownership concentration, then the higher recovery rate for CDS-referenced bonds would be consistent with the findings from Ivashina, Iverson, and Smith (2015).

The rest of this paper proceeds as follows. Section 2 provides a brief review of the institutional background and the related literature. Section 3 describes the data and the empirical design. Section 4 presents the main estimation results. Section 5 provides additional evidence to understand the main findings. Section 6 concludes.

2. Institutional Background and Related Literature

This study is related to the literature on the real effects of CDS trading and the literature on financial distress and corporate restructuring. A CDS is a credit derivative contract to transfer the default risk of one or more reference entities from the protection buyer to the protection seller.[4] Under a CDS contract, the protection buyer is entitled to protection on a specified face value (i.e., the notional amount of the contract) if a credit event occurs to the reference entity (e.g., default, bankruptcy, or other credit events specified in the contract). In return for this protection, the protection buyer pays a periodic fee (i.e., the premium or CDS spread) to the protection seller until the maturity date of the CDS contract.

Each CDS transaction specifies terms such as reference entity, credit events, maturity, notional amount, premium, settlement method, and other transaction-specific terms. The reference entity is the party on which the protection is written. For a single-name CDS, the reference entity is an individual corporation or government. The reference entity is not a party to the contract, and neither the buyer nor seller needs to obtain the reference entity's consent to enter into a CDS transaction. A CDS contract specifies a set of credit events that must occur

[3] See, for example, "Wall St Eyes Revival of Crisis Derivative", *Financial Times*, May 19, 2015.
[4] Augustin, Subrahmanyam, Tang, and Wang (2014) provide review on the mechanics and risks of CDS, and the evolution of the CDS market over time.

before the protection seller compensates the buyer. Typical credit events include failure to pay, bankruptcy, or certain types of restructuring.

There are two types of settlement methods: physical settlement and cash settlement. Under physical settlement, the protection buyer delivers to the protection seller the defaulted debt of the reference entity with a face value equal to the notional amount specified in the contract in return for payment of the bond's par value. Under cash settlement, an auction of the defaulted bonds takes place to determine the post-default market value. Under the auction procedure, participants submit bid and offer prices for the defaulted bonds and the resulting post-default price is used as the basis for the compensation for losses.[5] Once this value is determined, the protection seller pays the buyer the difference between the par value and the post-default market value of the default bonds. Settlements generally occur within thirty days of the credit event determination date.

Because of the explosive growth of the CDS market, the notional amount of CDS contracts can be multiple times larger than the amount of bonds actually available to settle trades when a credit event occurs. This is because many market participants buy CDS for speculative purposes, without actually owning any debt that they wanted to insure against default. This imbalance called into question the ability of the industry to achieve physical settlement in an orderly manner. To address this challenge, the International Swaps and Derivatives Association (ISDA) proposed a new protocol in 2005 that allows market participants to shift from physical settlement to cash settlement. However, institutions still have the option to choose to settle physically with their dealers.

According to the 2006 British Bankers' Association (BBA) Credit Derivatives Report, banks and securities firms are dominant players in the CDS market, accounting for 59% of protection buyers and 44% of protection sellers in 2006. Hedge funds have also become major players in the CDS market, accounting for 28% of protection buyers and 32% of protection sellers. Finally, insurance companies account for 17% of protections sellers in 2006. The CDS market in the US is highly concentrated, particularly among the sellers. According to Siriwardane (2014), the top five sellers account for 50% of all net selling, while the top five buyers account for 25% of all net buying. The top five net sellers were mostly dealers during 2010-2012, but split between

[5] According to Chernov, Gorbenko, and Makarov (2013), the auction procedure includes safeguards, such as penalizing crossed bids and offers, as well as requiring that bid and offer prices are within a fixed spread of each other to deter aggressive bidding to manipulate the auction results.

dealers and hedge funds since 2012.

The existing literature suggests that CDSs can be used for different purposes. First, a debt-holder can hedge its risk by entering into a CDS contract as the buyer of protection, which can increase the supply of credit to firms by making corporate debt more attractive to a broad group of investors unwilling to hold credit risk (Saretto and Tookes, 2013). Second, banks can use credit default swaps to reduce regulatory capital requirements (Shan et al., 2014). For instance, as of December 31, 2007, approximately $379 billion of the $527 billion in notional exposure of AIG Financial Products' super senior CDS portfolio represents derivatives written for the purpose of providing financial institutions "with regulatory capital relief rather than risk mitigation."[6] Third, CDSs opened up important new avenues to speculators. The CDS market allows speculators to buy and sell protection without owning debt of the reference entity. These "naked credit default swaps" are estimated to account for 80% of the CDS market.[7]

Similar to loan sales, CDS can lead to adverse selection and moral hazard problems. One commonly cited cost of CDS contracts is that they reduce incentives for lenders to analyze and monitor credit quality because they now have the ability to off-load credit risk, resulting in a decrease in overall credit quality. Additionally, the information asymmetry between protections buyers and sellers can lead to different forms of adverse selections. For instance, if protection buyers exploit their inside information about the credit quality of the reference entities, as indicated in Acharya and Johnson (2007), it will lead to the classical "lemons" market problem (Akerlof, 1970). On the other hand, if protection sellers have informational advantage over protection buyers, they will selectively choose to enter into CDS contracts that are in their favor.

A growing strand of literature examines the implications of CDS trading for the debtor-creditor relationship and their consequences on credit risk. For example, Ashcraft and Santos (2009) find that, contrary to the widespread perception that CDS contracts have lowered the cost of debt financing to firms by creating new hedging opportunities, the onset of CDS trading does not significantly lower the cost of debt financing for the average borrower. Saretto and Tookes (2013) find that firms with traded CDS contracts on their debt are able to maintain higher leverage ratios and longer debt maturities. Shan et al. (2014) find that that active engagement in the CDS market allows banks to assume more risk, which is contrary to the intended effect of

[6] Source: http://www.aig.com/Chartis/internet/US/en/2007-10k_tcm3171-440886.pdf (page 122)
[7] Source: http://www.bloomberg.com/apps/news?pid=newsarchive&sid=awJDsS9.OHjc

managing banks' credit risk exposure.

Of particular interest is the empty creditor problem (Bolton and Oehmke, 2011; Hu and Black, 2008), which predicts that empty creditors, who have little credit risk exposure with CDS protection, have different economic interests compared to unprotected creditors. When the borrower is under financial distress, empty creditors are less willing to negotiate to restructure the debt, and more willing to push the firm into bankruptcy. Several recent studies have tested the empty creditor hypothesis and yield mixed results. Subrahmanyam et al. (2014) find declines in the credit quality of reference entities following the introduction of CDS. Studying a sample of 80 distressed exchange offers between 2006 and 2011, Danis (2015) finds that the participation rates in distressed exchanges offered by CDS-referenced entities are significantly lower. Narayanan and Uzmanoglu (2015) examine a sample of 84 distressed exchange offers between 2004 and 2011 and find that distressed debtors circumvent empty creditors by restructuring their debt strategically. On the other hand, Bedendo et al. (2015) study a sample of 163 bankruptcy filings and out-of-court renegotiations between 2007 and 2011 and do not find that CDS contracts are associated with higher probabilities of bankruptcy, contrary to the predictions of the empty creditor hypothesis. Demiroglu and James (2015) also do not find evidence that restructuring/bankruptcy choices are associated with CDS trading. Additionally, ISDA published a research note in 2009 that questions the validity of the empty creditor hypothesis. Our research complements these studies by demonstrating a negative relationship between loss severity and CDS trading using a large sample of loss recovery data.

When firms become financially distressed, they usually attempt a debt workout with their major creditors. If workout agreements can be made, the firm can restructure its debt. If CDS contracts include restructuring events, then CDS auctions will be conducted to settle those affected contracts. If there are no CDS contracts for restructuring, then no auction will be conducted. The firm may ultimately file for bankruptcy protection either through Chapter 11 reorganization or Chapter 7 liquidation. In such case, a CDS credit event will be triggered and CDS auction will be conducted. The firm may eventually emerge once the bankruptcy judge approves the reorganization plan. Figure 1 illustrates the timeline from financial distress to bankruptcy resolution for CDs-referenced firms.

Valuation of financially distressed firms and distribution of remaining value across different stakeholders during bankruptcy process are important research questions.[8] It is well documented that absolute priority rules are often violated in U.S. bankruptcy cases. However, a recent, rising trend is that sophisticated activist investors are playing more important roles in bankruptcy resolutions, resulting in more creditor control and fewer APR violations during Chapter 11 reorganizations (see, e.g., Ayotte, Hotchkiss, and Thorburn (2013), Bharath, Panchapagesan, and Werner (2010), Jiang, Li, and Wang (2012), Demiroglu and James (2015), Ivashina, Iverson, and Smith (2015)).

While there are several studies that examine the implications of empty creditors on distressed exchanges, none of these studies focuses on the relationship between CDS trading and LGD. For instance, the focus of Narayanan and Uzmanoglu (2015) is on whether distressed debtors can strategically execute distressed exchanges to circumvent empty creditors, while Bedendo et al. (2015) are interested in the question about whether CDS trading would affect the choice of distressed firms between in- and out-of-court debt restructuring. Furthermore, these studies often rely on a small number of observations over a short period. Inevitably, the empirical results from these studies contradict each other. For instance, while Narayanan and Uzmanoglu (2015) document a positive association between recovery rates and CDS trading using a small sample of distressed exchanges (DE), Bedendo et al. (2015) find no significant relationship between recovery rates and CDS trading.

This study adds to the strand of studies on recovery of defaulted debt including Shleifer and Vishny (1992), Altman, et al. (2005), Bris, Welch, and Zhu (2006), and Acharya, Bharath, and Srinivasan (2007). Jankowitsch, Nagler, and Subrahmanyam (2014) analyze the immediate recovery rates of defaulted U.S. corporate bonds. They examine the determinants of recovery rates and highlight the role of bond trading around bankruptcy filing dates. Our sample is substantially larger, covering a much longer period (2002-2012), using multiple measures of ultimate recovery (i.e., the settlement, trading price, and liquidity methods), and with more debt types (e.g., term loans, revolvers, and bonds) than the samples used in the existing studies. Our focus on CDS distinguishes our study from the aforementioned studies. Furthermore, the findings in our study provide additional insights to the existing studies. Our paper builds on the recent work of Qi and Zhao (2011) which compares different modeling methods for LGD and

[8] See Gilson, Hotchkiss, and Ruback (2000), Hotchkiss, John, Thorburn, and Mooradian (2008), Senbet and Wang (2010), Eckbo and Thorburn (2013).

find that complicated modeling methods do not significantly improve the model prediction over the OLS regression approach. We also use their measure of debt seniority that has higher prediction power over traditional debt seniority measures.

3. Data and Empirical Design

3.1. Data

Our LGD data is from Moody's Default & Recovery Database (DRD), which covers over 1,000 corporate default events of North American commercial and industrial companies since 1987, each with more than US$50 million in total debt at the time of default. Moody's has opted to exclude financial institutions, as they are highly regulated, making their recovery data unsuitable for developing a general understanding of LGD. Moody's DRD covers four types of defaults:

- Bankruptcy: A company files for Chapter 11 or Chapter 7 in a U.S. Bankruptcy Court;
- Distressed exchange: A company exchanges all or parts of securities for new securities of lesser value;
- Default and cure: A company defaults on debt then cures the default outside of the 30 day grace period;
- Other restructuring: Any other non-Bankruptcy restructuring with a loss.

There are only a few observations of "default and cure" and "other restructuring" during our sample period. Therefore, we will focus on bankruptcies and distressed exchanges in this study.

Moody's DRD offers three different methods for ultimate recovery: the settlement method, the liquidity method, and the trading price method. The settlement method calculates the recovery using the values of settlement instruments at or close to the emergence from the default resolution process. The liquidity method calculates the recovery using values of settlement instruments at the time of a liquidity event, such as the maturity of an instrument, the call of an instrument, or a subsequent default event. The trading price method calculates the recovery using the trading price of the defaulted instrument taken at or post-emergence. For a given default, it also indicates the preferred method, which reflects the best valuation and the most representative of the actual recovery of that default based on the knowledge and experience of Moody's analysts. The most common preferred method is the settlement method. Our main results are based on the recovery rates using the preferred method, and the results based on alternative recovery methods are also reported for robustness check.

To obtain ultimate recovery, each nominal recovery is discounted back to the last time when interest was paid using the instrument's pre-petition coupon rate. The starting point for discounting for the trading price method is the date of the first available trading price at or following emergence from default. The starting point for the settlement method is the first point in time when each settlement instrument can be priced. The starting point for the liquidity method is the date of the liquidity event.

We obtain the CDS data from the Markit CDS dataset. Our sample period is from 2002 to 2012 because the Markit CDS dataset starts in 2001. We identify firms with CDS prior to bankruptcy filings or restructuring events through the daily dealer quoting activities. This dataset was previously used by, among others, Batta, Qiu, and Yu (2015).

We merge Moody's DRD data with Compustat and the Center for Research on Securities Prices' stock prices database (CRSP) to obtain information on firms' income and financial condition, their long-term credit ratings, and stock prices and returns. To construct instrumental variables, we use the data from the shared national credit (SNC) program and the Mergent Fixed Income Securities Database (FISD) to identify lenders and bond underwriters of each firm. We then obtain financial data for these lenders and underwriters through Compustat, the Consolidated Reports of Condition and Income for Commercial Banks (the Call Report), and the Federal Reserve Consolidated Financial Statements for Holding Companies ("FR Y-9C"). The SNC Program is an interagency effort established in 1977 to provide a periodic credit risk assessment of the largest and most complex credits held by federally supervised financial institutions. A SNC is any loan or credit of $20 million or more extended to a borrower and shared by three or more unaffiliated supervised institutions. The SNC data is an annual panel data set that contains basic information about facility, borrower and syndicate structure. For each facility, it reports information about the type, the credit limit, the current balance, the maturity, the risk ratings assigned by the agent bank, the obligor name, location, industry, and the shared of each participating syndicate members.

3.2. An Illustrative Case on Eastman Kodak

Eastman Kodak filed for Chapter 11 bankruptcy on January 16, 2012. On January 19, 2012 the ISDA Americas Credit Derivatives Determinations Committee resolved that a bankruptcy credit event occurred in respect of Eastman Kodak Company and that an auction would be held.[9] ISDA published detailed settlement terms[10] and a list of deliverable obligations (6 bonds), and asked eligible market participants to submit obligations for consideration for inclusion on the list of deliverable obligations for the CDS auction, or to challenge to obligations included in the supplementary list. The auction is for bonds, as there is no loan CDS for auction. On February 22, 2012, the auction was held to settle the credit derivatives trades for Eastman Kodak CDS, with auction settlement date on February 29, 2012. With 13 bidders participating, the auction reached a final price of 23.875 (out of 100). On September 3, 2013, Kodak emerged from bankruptcy. For those four senior unsecured bonds in our sample, the recovery rate is about 2% (1.83%, 1.91%, 1.96%, and 1.96%, respectively). The recovery rates for senior secured bonds and bank revolvers are 100%.

3.3. Empirical Design

To examine the relationship between loss severity and CDS trading, we estimate the following regression model:

$$\begin{aligned} LGD_{i,t} &= A_0 + A_1 \cdot (\text{CDS trading})_{i,t} + A_2 \cdot (\text{Debt characteristic})_{i,t-1} \\ &+ A_3 \cdot (\text{Firm characteristic})_{i,t-1} + A_4 \cdot (\text{Other control variables})_{i,t-1} + \text{Error Term}_{i,t}\ . \end{aligned} \tag{1}$$

The dependent variable, LGD, is defined as one minus the ultimate recovery rate.[11] The key explanatory variable is "CDS trading", a dummy variable that equals one if the following two conditions are met: (1) The firm was quoted in CDS contracts within the past 3 months before the default date; (2) The firm was quoted in CDS contracts between 12-24 months before the default date. The first condition ensures that the CDS of the firm are actively traded in the market right before the default event, and the second condition ensures that the trading of CDS on the firm is not caused by reverse causality. Lenders may buy CDS protection if they anticipate

[9] http://www2.isda.org/news/isda-credit-derivatives-determinations-committee-eastman-kodak-company-credit-event
[10] http://www.isda.org/companies/EastmanKodak/docs/Kodak%20AST.pdf
[11] The economic and statistical significance of our estimation is the same whether we use recovery rate or loss given default (LGD).

that a credit event will occur. On the other hand, if the CDS trading took place long before the credit event, it is less likely that the CDS trading was driven by the anticipation of a credit event.

Table 1 defines all variables used in our analysis. The explanatory variables for LGD modeling include debt characteristics, firm characteristics, and macroeconomic conditions. For debt characteristics, we define the following categories of debt types: senior unsecured bonds, senior secured bonds, subordinated bonds, term loans, and revolvers. We also include the seniority index (1-percent above-percentage *pari passu*/2).

We define the following collateral types: unsecured, cash/receivable/inventory, guarantees, properties, capital stocks, and other assets. The "other assets" category includes the following categories reported by Moody's DRD: "Most assets", "First lien on substantially all assets", "Second lien on substantially all assets", "Third lien on substantially all assets", "All non-current assets", "Other", "Intellectual property" and "Inter-company debt". We classify collateral types under the following considerations.. First, in our sample, there is no observation in the "Intellectual property" category, and there is only one observation in the "Inter-company debt" category. Therefore, we decide to include these two categories in the new "Other assets" category. Second, instead of defining the "Equipment" category, we define a "Properties" category that includes the following collateral types reported by Moody's DRD: "Equipment", "PP&E", "Oil and Gas Properties", and "Real Estate".

Firm-level explanatory variables include firm size, leverage, earning-to-asset ratio, profitability, coverage, tangibility, Tobin's Q, current ratio, cash ratio, bonds debt ratio, and utility dummy. We also calculate the distance-to-default measure using Merton's model. To control for macroeconomic and industry conditions, we include monthly aggregate default rate, industry default rate, and the three-month T-bill rate. Table 1 summarizes the definition of dependent and explanatory variables included in regressions and additional variables mentioned in this study.

It should be noted that our identification strategy for CDS trading differs from those of Ashcraft and Santos (2009), Saretto and Tookes (2013), and Subrahmanyam et al. (2014) in several aspects. All these studies have a panel data sample where a firm can appear in multiple periods. Therefore, their major concern is to control for correlation within the same firm over multiple periods. In addition, their focus is on the timing of CDS trading. For instance, Subrahmanyam et al. (2014) create two dummy variables: "CDS firm" and "CDS active". "CDS firm" equals one for firms with CDS traded at any point of time during the sample period, while "CDS active" is a dummy variable that equals one after the inception of the firm's CDS trading and zero before CDS trading. Therefore, their identification strategy hinges on the switching of "CDS active" from zero to one. By contrast, our loss recovery data is not a panel data sample because each firm can only appear in the sample at a single point of time.[12] Thus, our identification strategy has to be different. Moreover, we do not need to worry about the time-series correlation for the same firm over multiple periods. Therefore, the focus of this paper is to examine the difference in LGD between firms that are CDS referenced entities and firms that are not. In addition, because our sample is not panel data, we can estimate the average treatment effects of CDS trading using different treatment-effect estimators.

3.4. Descriptive Statistics

Panel A of Table 2 reports the summary statistics of the LGD of defaulted debts from bankruptcies and distressed exchanges by year. Our sample consists of 1696 observations of ultimate debt recoveries from bankruptcies and distressed exchanges, including 1370 observations from bankruptcies and 326 observations from distressed exchanges. As Panel A of Table 2 shows, the average LGD of bankruptcies over the entire sample is 42.9%, which is substantially larger than the average LGD of distressed exchanges (14.9%).

Panel B of Table 2 reports the summary statistics of LGD by default type, CDS trading status, and resolution time, which shows that all defaulted debts from distressed exchanges are resolved within one year. In addition, for the distressed exchange subsample, the average LGD for firms that are actively traded in the CDS market is slightly higher than the average LGD for firms not actively traded in the CDS market. By contrast, a majority of bankrupted debts are resolved over more than one year. Furthermore, the average LGD of bankrupted debts for firms that are actively traded in the CDS market are lower than that of firms not actively traded in the CDS market.

4. CDS Trading Prior to Bankruptcy and Recovery Rates

This section reports the estimation results on the impacts of CDS trading on the loss given

[12] It is very rare for a firm to default multiple times and appear in the Moody's loss recovery data multiple times. We do not observe multiple defaults of the same firm in our sample.

default (LGD) of defaulted debts from bankruptcies and distressed exchanges. While we find a significant and negative correlation between CDS trading and the LGD of defaulted debts from bankruptcies in Section 4.1, this correlation is not significant for defaulted debts from distressed exchanges. Subsequent sections then focus on examining the relationship between CDS trading and the LGD of defaulted debts from bankruptcies. Specifically, Section 4.2 examines the impacts of CDS trading on the LGD of defaulted debts of bankrupted firms using OLS and fractional response regressions. Section 4.3 employs a two-step endogenous treatment regression model (Heckman, 1978) to control for the potential endogeneity and selection bias of CDS trading. Section 4.4 performs further robustness tests by employing different treatment-effects estimators to control for selection bias.

4.1. Recovery Rates and CDS Trading: Bankruptcies versus Distressed Exchanges

Table 3 reports estimation results for OLS regressions that compare the impacts of CDS trading on the LGD of defaulted debts from bankruptcies and distressed exchanges. The sample period is 2002–2012. The dependent variable is LGD, which equals 1 minus the recovery rate of a defaulted debt. The key explanatory variable is "CDS trading", a dummy variable that equals one if the firm was quoted in CDS contracts both within the past 3 months before the default date and in the period of 12-24 months before the default date. Column (1) reports the regression results on a subsample of defaulted debts from bankruptcies. Column (2) reports the regressions results on a subsample of defaulted debts from distressed exchanges. Both regressions include control variables at the debt and firm levels. In addition, both regressions include three monthly macroeconomic variables (i.e., aggregate default rate, industry default rate, and the 3-month T-bill rate) and the quarterly time fixed effects. All variables are defined in Table 1.

As Table 3 shows, the coefficient of "CDS trading" is negative and statistically significant for the bankruptcy subsample but is insignificant for the distressed exchange sample. This finding suggests that CDS trading has significant impacts on the LGD of bankrupted debts, but not on the LGD of distressed exchange. This difference can be interpreted as the indirect evidence that supports the empty creditor hypothesis, which predicts that empty creditors prefer bankruptcies to distressed exchanges. Given above findings, we focus on examining the impacts of CDS trading on the LGD of bankrupted debts in subsequent sections.

4.2. CDS Trading and the LGD of Bankrupted Debts: Fractional Response Regressions

As we discussed above, fractional response regression can be an alternative estimation approach. To demonstrate the robustness of our finding, we use fractional response regressions to re-estimate the effect of CDS trading on the recovery rates of bankrupt debts.

Table 4 reports estimation results for fractional response regressions that examine the impacts of CDS trading on the LGD of defaulted debts from bankruptcies. The estimation is based on a sample of defaulted debts of bankrupted firms over the period of 2002–2012. For comparison with the estimation results of OLS regressions, we report the values of average marginal effects rather than the actual coefficients

The table includes five columns. Specification (1) is the baseline model that includes only debt-level variables as control variables. Specification (2) adds firm-level variables. Specification (3) adds three monthly macroeconomic variables: "Aggregate default rate", "Industry default rate", and "T-bill rate".[13] Specification (4) adds time fixed effects to control for business cycles, other observed and unobserved macroeconomic factors. Finally, to examine the explanatory power of the CDS trading indicator, we also include specification (5) that excludes the CDS trading indicator from specification (3).

Across all of the four specifications with independent variable "CDS trading", the coefficient estimates are negative and statistically significant. Overall, these results suggest that the difference in LGD between firms with and without CDS trading is between -7% to -20%. This reduction is substantial given the fact that the average LGD for the entire sample is 42.9%. In addition, comparing the estimation results of specification (5) with specification (4), we note that the adjusted R-squared decreases from 59.7% to 52.1%. Therefore, CDS trading indicator indeed improves explanatory power in predicting LGD.

4.3. Potential Endogeneity of CDS Trading: Instrumental-variables (IV) Estimations

If the selection of firms for CDS trading is not random, the effect of CDS trading on LGD estimated from OLS regression may be biased due to possible endogeneity of CDS trading (Cameron and Trivedi, 2005). In this section, we address the potential endogeneity and selection

[13] When picking the macroeconomic variables, we have also considered two additional variables: "Industry distance-to-default" and "Market return". These two variables are not included because they are highly correlated with the three variables we have chosen. As a robustness check, we also run regressions using these variables. The results are very similar and are available upon request.

bias in CDS trading using an endogenous treatment regression model.[14]

Our approach of instrumental variable selection is similar to Saretto and Tookes (2013) and Subrahmanyam et al. (2014). We consider several candidates: "Bank ROA", "Bank NIM", "Bank RBCR", "Bank bought CDS ratio", "Bank FX derivatives ratio", "Bank interest rate derivatives ratio", and "Bank size". The definitions of these variables can be found in Table 1. For instance, "Bank ROA" is the average return on assets of all lenders for a given firm, while "Bank NIM" is the average net interest margin of all lenders for a given firm. "Bank RBCR" is the average risk-based capital ratio of all lenders of a given firm. Following Saretto and Tookes (2013) and Subrahmanyam et al. (2014), we also calculate the average foreign exchange derivatives to asset ratio ("Bank FX derivatives ratio"), the average interest rate derivatives ratio ("Bank interest rate derivatives ratio"), and the average notional amount of CDS protection to asset ratio of all lenders for a given firm ("Bank bought CDS ratio").

To construct these variables, we first identify the lenders and bond underwriters of each firm in the past five years using the SNC data and the FISD data. We next obtain the financial data of these lenders and bond underwriters by linking to the Call Report data, FR-Y9C data, and Compustat Bank data. Finally, we calculate each of these variables by taking the average across all lenders of a given firm.

Panel A of Table 5 reports the correlations of these variables with LGD and "CDS trading". Because "Bank NIM" and "Bank bought CDS ratio" have low correlations with the LGD (e.g., the exclusion condition) but substantially high correlations with "CDS trading" (e.g., the relevance condition), they are chosen as the instrument variables.

Panel B reports the second-stage IV estimation results, and Panel C reports estimation results of the first-stage probit regressions where the dependent variable is "CDS trading". There are three specifications. Specification (1) uses both "Bank NIM" and "Bank bought CDS ratio" as the instrumental variables. Specification (2) uses "Bank NIM" as the instrumental variable. Specification (3) uses "Bank bought CDS ratio" as the instrumental variable.

In all specifications of Panel B, the coefficient of "CDS trading" is negative and statistically significant. Therefore, we conclude that the negative relationship between LGD and CDS trading is robust after we control for potential endogeneity and selection bias of CDS trading.

[14] It is also known as an endogenous binary-variable model or as an endogenous dummy-variable model.

4.4. Treatment-effect Estimators

In this section, we perform further robustness tests using five different treatment-effect estimators. Specifically, we estimate the effects of CDS trading on LGD using regression adjustment (RA), inverse-probability weighting (IPW), inverse-probability-weighted regression adjustment (IPWRA), and two matching estimators: nearest-neighbor matching (NNM) and propensity-score matching (PSM). A brief review of treatment-effect estimators is provided in the Appendix.

The estimation results of different treatment-effect estimators are reported in Table 6. In this table, ATET is the average treatment effects on the treated (CDS trading=1), and POMEAN0 is the potential-outcome mean of LGD for untreated (CDS trading=0). The first estimator is the regression adjustment (RA) estimators (Cameron and Trivedi, 2005). The RA estimator is a control function estimator, which uses a regression model to predict potential outcomes conditioned on covariates. It estimates the outcome model without any assumptions about the treatment model. The conditional independence assumption implies we can estimate $E(y_0 \mid \mathrm{X})$ and $E(y_1 \mid \mathrm{X})$ directly from the observations for which D=0 and D=1, respectively. The RA method fits separate regressions for each treatment level and uses averages of the predicted outcomes over all the data to estimate means of the potential outcomes. The estimated ATE is the difference between POMEAN1 and POMEAN0. The estimated ATET is the difference between POMEAN1 and POMEAN0 over the treated observations. Table 6 shows that the ATET for RA estimator is -16.5% and is statistically significant, and the potential mean of untreated is 48.7%.

The second estimator is the inverse-probability-weighted (IPW) estimator (Wooldridge, 2007). The IPW estimator uses weighted averages of the observed outcome variable to estimate means of the potential outcomes. The weights account for the missing data inherent in the potential-outcome framework. For a subject that receives the treatment, the weight is the inverse of the estimated probability that it receives the treatment. For a subject that does not receive the treatment, the weight is the inverse of the estimated probability that it does not receive the treatment. In contrast to the RA estimator, the IPW estimator models the probability of treatment without any assumptions about the outcome model. Table 6 shows that the ATET for IPW estimator is -13.6% and is statistically significant. The potential mean for the untreated is 45.7%.

The third estimator is the inverse-probability-weighted regression-adjustment (IPWRA) estimator (Wooldridge, 2007). Unlike the RA and IPW estimators, the IPWRA estimator is a "doubly robust" estimator that combines the outcome modeling strategy of RA and the treatment modeling strategy of IPW. The "doubly robust" estimator has the desirable property that a consistent estimate of the treatment effect can be achieved if either the treatment model or the outcome model is misspecified, as long as one of these models is correctly specified. Table 5 shows that the ATET for IPWRA estimator is -14.7% and is statistically significant. The potential mean of the untreated is 46.8%.

The fourth estimator is the nearest-neighbor matching (NNM) estimator (Abadie and Imbens, 2006; Cameron and Trivedi, 2005). It is accomplished by calculating the Mahalanobis distance between pairs of observations with regard to a set of covariates and then matching each subject to comparable observations that are closest to it. Table 6 shows that the ATET for NNM estimator is -11% and is statistically significant.

The last estimator is the propensity-score matching (PSM) estimator (Cameron and Trivedi, 2005; Rosenbaum and Rubin, 1983). PSM matches on the estimated predicted probabilities of treatment, known as the propensity scores. Table 6 shows that the ATET for the PSM estimator is -17.4% and is statistically significant.

Overall, Table 6 shows that the ATET for CDS trading is between -11% and -17.4% and is statistically significantly across all estimators. Therefore, these results reinforce the findings in previous sections that CDS trading is associated with significantly lower LGD (higher recovery rates).

5. Robustness Tests and Understanding the Mechanisms

There are three potential explanations for the negative relationship between CDS trading and the LGD of defaulted debts. The first is the empty creditor hypothesis, which predicts that the CDS market strengthens the bargaining power of creditors in the debt renegotiations process, and empty creditors can force firms with higher net wealth values into bankruptcy. As a result, the recovery rates are higher for CDS referenced firms. Second, hedge funds can play an important role during the workout process. As a result of CDS trading, hedge funds specialized in distressed debt and the resolution process may become the final holders of the distressed debt. Consequently, their participation in the workout process can lead to higher recovery rates. Third, the lower LGD for CDS referenced firms can also arise from the information advantage of CDS protection sellers. If CDS sellers have informational advantage, they can selectively enter into CDS transactions for firms whose future realized LGD values are lower than the LGD values priced in the CDS contracts. As a result, the LGD of firms traded in the CDS market are likely to be lower than the LGD of firms not traded in the CDS market.

We first conduct robustness analyses using different measures of LGD. We then perform subsample analyses over different time period, bankruptcy points, and debt types. Finally, we examine the relationship between CDS trading and the resolution time of defaults debts from bankruptcies.

5.1. Alternative Recovery Measures

Table 7 reports the estimation results of LGD using four alternative measures of LGD. The first three measures are ultimate recovery measures. Specifically, the settlement method calculates the recovery using the values of settlement instruments at or close to the emergence from the default resolution process. The liquidity method calculates the recovery using values of settlement instruments at the time of a liquidity event, such as the maturity of an instrument, the call of an instrument, or a subsequent default event. The trading price method calculates the recovery using the trading price of the defaulted instrument taken at or post-emergence. The last measure is an immediate recovery measure calculated from the 30-day trading prices after defaults, which is relevant for a company that needs to off-load an investment prior to its ultimate workout.

Table 7 shows that the negative relationship between CDS trading and LGD is robust across all three ultimate recovery measures of LGD, with the results generally consistent with those using the preferred method except for the liquidity method, which produces a much larger difference in LGDs over a small sample of 333 observations. Furthermore, the estimation results based on the immediate recovery measure of LGD (i.e., 30-day trading prices after defaults) are qualitatively similar to those based on ultimate recovery measures.

5.2. CDS Market Development

It is conceivable that the effect of CDS becomes more prominent as the market gets more influential. Since the inception in mid-1990s, the CDS market has experienced significant developments, such as the 2003 ISDA Master Agreement. Initially, CDS contracts were settled physically, which turned out to be tricky and ambiguous, as shown in the case of Delphi bankruptcy. To address this issue, ISDA introduced the cash settlement and the CDS auction process in 2005. With CDS auctions, recovery rates become easier to decide. Moreover, following the 2009 CDS Big Bang, credit events are now determined by a committee under ISDA. Hence, the reduced uncertainty on the determination of credit events makes CDS more effective tools for protection buyers.

CDS contracts are settled through auctions since 2005. However, the auction design and results could be biased. If the auctioned recovery rate is higher, it may provide an anchor for the ultimate recovery rate, leading to a higher recovery rate. Indeed, Chernov, Gorbenko, and Makarov (2013) find that auctions undervalue bonds by an average of 6% (lower recovery rate, hence CDS buyers get more payments from CDS sellers). We note that this market development applies to all CDS cases. Hence, it is a potential mechanism at the aggregate level instead of being firm-specific or creditor-specific.

To test if the CDS effect on recovery rate indeed varies over time, we split the sample into two subsamples: 2002–2006 and 2007–2012. Table 8 reports the estimation results, which show that the coefficient of “CDS trading” is -0.124 and is statistically significant for the subsample of 2007–2012. On the other hand, although this coefficient is negative for the period of 2002–2006, it is not statistically significant. Therefore, these results suggest that the effects of CDS trading on LGD are larger over the recent period than earlier periods.

5.3. Bankruptcy Point

When to default or file for bankruptcy is often strategically chosen by equity-holders to maximize shareholder value. Creditors can suffer from excessive continuation during which shareholders may engage in risk-shifting. When final attempts for salvage equity value are failed, debtholders will end up with little to recover. Therefore, if bankruptcies were filed earlier when there is still relatively more residual value, creditors would recover more from the bankrupt firm. We examine whether the CDS effect on recovery rates varies by default point.

Table 9 reports the estimation results of LGD on several subsamples that are created based on the leverage and current ratio of obligors. We use the sample medians of leverage and current ratio to divide firms into subsamples of high leverage, low leverage, high current ratio, and low current ratio. This tables shows that the CDS trading effects are larger for firms with low leverage and low current ratios at the time of filing for bankruptcy. Therefore, these results imply that CDS effects are stronger for liquidity defaults. Moreover, liquidity defaults are more sudden and suggest less risk-shifting. For firms with relatively lower leverage, the creditors have more recover. Our findings are consistent with the conjecture that CDS effects on recovery rate is associated with earlier bankruptcies.

5.4. Different Classes of Debt: Bonds versus Loans

Although bonds and loans default jointly due to cross-default clauses, loans are often secured and have higher recovery rates. Moreover, banks are more informed and they may engage in insider trading prior to bankruptcy filings, as suggested by Acharya and Johnson (2007). If banks can gain more from CDS positions, their bargaining positions during bankruptcy negotiations can be weakened relative to bondholders. Therefore, the CDS effects on bonds and loans can be different. We identify debt types to empirically examine this conjecture.

Table 10 presents the estimation results of LGD using subsamples of different debt types, which shows that the effects of CDS on LGD are stronger for bonds than loans and revolvers. Consistent with our conjecture. It is worth emphasizing that, in contrast to higher recovery rates for bondholders, the recovery rates of loans are not adversely affected by CDS trading. Hence, the higher recovery rates for bondholders are not the result of lower recovery rates for bank lenders. Such findings imply that the additional recovery is either from equity value of saved bankruptcy costs, consistent with the early bankruptcy conjecture.

5.5. CDS Trading and the Resolution Time of Bankrupt Debts

In addition to ultimate recovery rates, the time to receive the recovery payments, or the resolution of bankruptcy, is another important consideration for creditors. The time value of money would suggest shorter time in bankruptcy will be preferred by creditors (equity-holders will often receive nothing whether the bankruptcy is resolved sooner or later). However, if bondholders insist on higher recovery rate, it may take longer to resolve bankruptcies. In our data of 337 bankrupted debt issues for CDS referenced firms, 305 (90.5%) are resolved over more than one year. By contrast, out of the 1033 bankrupted debts for non-CDS referenced firms, 779 (75.4%) are resolved over more than one year. It seems that CDS trading is associated with more lengthier bankruptcies. However, CDS bankruptcies are also bigger. Therefore, we examine the relationship between CDS trading and the resolution time of bankrupted debts in a multivariate analysis framework.

We specify a logistics regression model that links debt resolution time to CDS trading, debt characteristics, firm characteristics, and macroeconomic conditions. The dependent variable, “Resolution time longer than 1 year”, is an indicator variable that equals one if the resolution time is longer than 1 year and zero otherwise. Table 11 reports the estimations results. It consists of 5 specifications. Specification (1) is the baseline model that includes only debt-level variables as control variables. Specification (2) adds firm-level variables. Specification (3) adds three monthly macroeconomic variables: “Aggregate default rate”, “Industry default rate”, and “T-bill rate”.[15] Specification (4) adds time fixed effects to control for business cycles, other observed and unobserved macroeconomic factors. Finally, to examine the explanatory power of the CDS trading indicator, we also include specification (5) that excludes the CDS trading indicator from specification (3).

As Table 11 shows, the coefficient of “CDS trading” is positive and statistically significant in specifications (1) through (4), suggesting that CDS trading is associated with longer resolution time for bankrupted debts. Combining the longer resolution time and the lower LGD associated with CDS trading, we conclude that CDS trading can improve the relative bargaining position of the creditors, especially bondholders, in the negotiation process, leading to a lower LGD (higher recovery rates). We note that it is important to consider the ultimate recovery value in this discussion as recovering higher nominal value but taking more time may not be a net benefit for bondholders. Our use of various measures of LGD and especially the ultimate recovery data provides a concrete answer to bondholder recovery post CDS trading.

6. Conclusions

In this paper, we examine the relationship between credit default swaps (CDS) trading and the recovery rate of defaulted corporate debts. Although CDS contracts are settled shortly after credit events, we find a negative and significant correlation between CDS trading and the loss given default (LGD) of defaulted debts for bankrupt firms. The negative correlation is robust to

[15] When picking the macroeconomic variables, we have also considered two additional variables: “Industry distance-to-default” and “Market return”. These two variables are not included because they are highly correlated with the three variables we have chosen. As a robustness check, we also run regressions using these variables. The results are very similar and are available upon request.

additional analyses that control for debt characteristics, firm characteristics, and macroeconomic conditions. It is also robust to analyses controlling for endogeneity and selection bias, and to analyses using different LGD measures. Additionally, we find that the impact of CDS trading on the LGD is stronger for corporate bonds than loans and revolving credits. Furthermore, this effect is stronger for bankrupt firms with lower leverage at the time of bankruptcy filing.

The overall evidence is consistent with the view that CDS trigger earlier bankruptcy filings, which allow bondholders to recover more. We also show that the CDS effect on recovery rates is more pronounced in the more recent period when CDS market becomes more developed and auctions are used to determine the settlement prices. However, CDS trading prior to bankruptcy filings is associated with longer resolution time. Our findings shed new light on the real effects of CDS. Future regulatory and research debates on CDS should not only concern the live contracts, but also the aftermath of CDS trading.

Appendix: The Treatment-Effect Estimators

We follow Cameron and Trivedi (2005) to define the potential outcome model under the treatment-effect framework.[16] The basis of treatment evaluation is defined by the triple: (D_i, y_{1i}, y_{0i}), $i = 1, \cdots, N$. The variable D_i indicates whether a subject receives the treatment. The two potential outcomes for each subject are y_{1i} and y_{0i}: y_{1i} is the outcome if the subject receives the treatment ($D_i = 1$), and y_{0i} is the outcome if the subject does not receive the treatment ($D_i = 0$). Depending on whether a subject receives the treatment, one of these two potential outcomes will be missing. Therefore, treatment-effect estimators are estimators that address this missing data problem.

The average treatment effect (ATE) is defined as

$$ATE = E\left(y_1 - y_0\right). \tag{2}$$

The average treatment effect on the treated (ATET) is defined as

$$ATET = E\left(y_1 - y_0 \mid D = 1\right). \tag{3}$$

Because the assumptions required to estimate the ATET are less restrictive than the assumptions required to estimate the ATE, we will focus on ATET in this study. The potential-outcome means (POMEAN) are defined as

$$\begin{aligned} POMEAN0 &= E(y_0) \\ POMEAN1 &= E(y_1). \end{aligned} \tag{4}$$

The ATET can be rewritten as

$$ATET = E(y_1 \mid D = 1) - E(y_0 \mid D = 1), \tag{5}$$

where the second term is not observable because it is the average outcome of treated subjects had they not received the treatment. What we can observe is the difference between the average outcomes of treated and untreated subjects:

$$\Delta = E(y_1 \mid D = 1) - E(y_0 \mid D = 0). \tag{6}$$

Therefore, the difference between ATET and Δ is the selection bias (SB), which is the difference between the average outcome of treated subjects had they not received the treatment

[16] The potential-outcome model is also known as the Rubin causal model or the counterfactual model.

and the observed average outcome of the untreated subjects:

$$SB = \Delta - ATET = E(y_0 \mid D = 1) - E(y_0 \mid D = 0). \tag{7}$$

Let X be a vector of covariates that affect the outcome or the treatment assignment, we can define the outcome model and treatment model as follows:

$$y_0 = X'\beta_0 + \varepsilon_0, \tag{8}$$

$$y_1 = X'\beta_1 + \varepsilon_1, \tag{9}$$

$$D = \begin{cases} 1 & \text{if } X'\alpha + \xi > 0 \\ 0 & \text{if } X'\alpha + \xi <= 0. \end{cases} \tag{10}$$

Different treatment-effect estimators can be employed to reduce the selection bias under conditional independence and overlap (e.g., common support) assumptions. The conditional independence assumption states that the potential outcomes are conditionally independent of the treatment if no unobservable variable affects both treatment assignment and the potential outcomes after conditioning on covariates:

$$(y_{1,} y_0) \perp D \mid X. \tag{11}$$

The overlap assumption holds when there is a positive probability of being both treated and untreated for each value of X:

$$0 < P(D = 1 \mid X) < 1. \tag{12}$$

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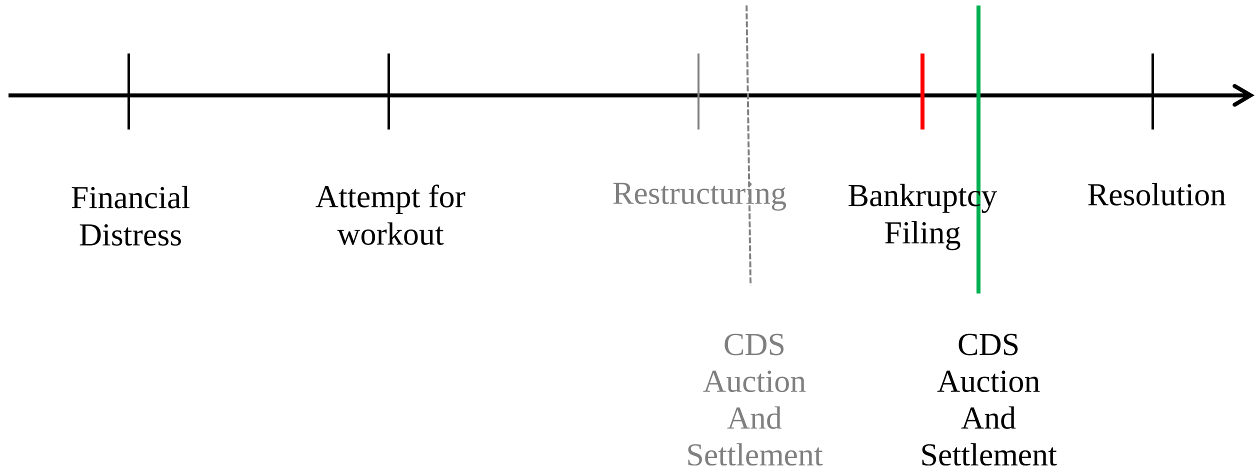

Figure 1. Timeline. This figure illustrates the timeline of a CDS-referenced firm's distress and resolution process. CDS contracts may or may not include restructuring clauses. If the firm restructures its debt and the CDS contracts include restructuring, then a CDS auction will be conducted. Otherwise there will not be CDS auction. Bankruptcy filings always trigger CDS credit events and will be followed with CDS auction.

Table 1 Variable Definitions

This table summarizes the definition of dependent and explanatory variables included in regressions and additional variables mentioned in this study.

Variable	Description
LGD	Loss given default is one minus the recovery rate
CDS trading	This dummy variable equals one if the following two conditions are both true: (1) The firm was quoted in CDS contracts within the past 3 months before the default date (2) The firm was quoted in CDS contracts between 12-24 months before the default date
Seniority index	The seniority index is proposed by Qi and Zhao (2013) and equals (1-percent above-percent pari passu/2)
Debt type	(1) Senior unsecured bonds (2) Senior secured bonds (3) Subordinated bonds (4) Term loans (5) Revolvers
Collateral type	(1) Unsecured (2) Cash/account receivable/inventory (3) Guarantees (4) Properties (equipment, PP&E, oil and gas Properties, real estate) (5) Capital stocks (6) Other assets (most assets, all assets, all non-current assets, other, second lien, third lien, intellectual property, inter-company debt)
Firm size	The natural logarithm of total assets (expressed in millions of U.S. dollars)
Distance-to-default	1-year distance-to-default calculated using Merton's model
Leverage	Debt to asset ratio
Earning-to-asset ratio	Earning to asset ratio
Profitability	EBIDTA/sales ratio
Coverage	EBIDTA/Interest expenses ratio
Tangibility	Property, plant and equipment to asset ratio (ppentq/asset)
Tobin's Q	Market value of asset to book value of asset ratio
Current ratio	Current asset to current liability ratio
Cash ratio	Cash and short-term investments/asset ratio
Bonds debt ratio	Bonds to total debt ratio
Utility dummy	This dummy variable equals one if the firm is in the utility sector
Aggregate default rate	Aggregate default rate
Industry default rate	Industry default rate
T-bill rate	3-month Treasury bill rate
Industry distance-to-default	Industry distance-to-default
Market return	Trailing 12 month value-weighted market return
Bank ROA	The average return on asset for all lenders of a given firm
Bank NIM	The average net interest margin for all lenders of a given firm
Bank RBCR	The average risk-based capital ratio for all lenders of a given firm

Variable	Description
Bank bought CDS ratio	The average CDS protection ratio of all lenders for a given firm. A bank's CDS protection ratio is the notional amount of CDS protection it purchased divided by its total assets.
Bank FX derivatives ratio	The average foreign exchange derivatives ratio of all lenders for a given firm. A bank's foreign exchange derivatives ratio is the notional amount of foreign exchange derivatives divided by its total assets.
Bank interest rate derivatives ratio	The average interest rate derivatives ratio of all lenders for a given firm. A bank's interest rate derivatives ratio is the notional amount of interest rate derivatives divided by its total assets.
Bank size	The average size for all lenders of a given firm. Bank size is the natural logarithm of a bank's total assets (expressed in thousands of U.S. dollars)
Resolution time longer than 1 year	This dummy variable equals one if the resolution time is longer than one year and zero otherwise.
Maturity longer than 5 years	This dummy variable equals one if the maturity of the debt is greater than 5 years and zero otherwise.

Table 2
Summary Statistics, 2002–2012

Panel A reports the summary statistics of LGD by year and default type. Panel B reports the summary statistics of LGD by default type, CDS trading status, and resolution time. Panel C reports the summary statistics of LGD by different categories (CDS status, instrument type, collateral type). Panel D reports the summary statistics of continuous variables. Variables are defined in Table 1. Firm size is the natural logarithm of total assets (expressed in millions of U.S. dollars). Bank size is the natural logarithm of a bank's total assets (expressed in thousands of U.S. dollars). All other values are expressed in real value. "N" denotes number of observations; "Std" denotes standard deviation; "P5" and "P95" denote the 5th and 95th percentiles.

Panel A: Summary statistics of LGD by year and default type

	Bankruptcy			Distressed exchange		
Year	N	Mean	Median	N	Mean	Median
2002	500	0.607	0.759	78	0.138	0.000
2003	241	0.270	0.058	17	0.180	0.033
2004	87	0.342	0.334	20	0.035	0.000
2005	151	0.210	0.087	28	0.150	0.120
2006	41	0.313	0.082			
2007	15	0.204	0.000	4	0.000	0.000
2008	69	0.516	0.728	60	0.190	0.000
2009	192	0.461	0.420	100	0.144	0.000
2010	11	0.415	0.000	3	0.129	0.075
2011	47	0.164	0.000	6	0.157	0.000
2012	16	0.329	0.000	10	0.277	0.196
All	1370	0.429	0.389	326	0.149	0.000

Panel B: Summary statistics of LGD by default type, CDS status, and resolution time

		Resolution time					
		Less than one year			One year or longer		
		N	Mean	Median	N	Mean	Median
Default type	CDS trading						
Bankruptcy	No (0)	254	0.447	0.455	779	0.469	0.453
	Yes (1)	32	0.362	0.303	305	0.317	0.125
Distressed exchange	No (0)	145	0.144	0.000			
	Yes (1)	181	0.153	0.000			

Table 2 -- *continued*

Panel C: Summary statistics of LGD by different categories, bankruptcy subsample

	N	Mean	Median	Std
CDS trading				
No (0)	1033	0.464	0.454	0.375
Yes (1)	337	0.322	0.126	0.364
Debt type				
Senior unsecured bonds	471	0.568	0.610	0.333
Senior secured bonds	279	0.417	0.427	0.340
Subordinated bonds	142	0.776	0.935	0.329
Term loans	241	0.232	0.000	0.319
Revolvers	237	0.159	0.000	0.278
Collateral type				
Unsecured	623	0.617	0.753	0.347
Cash/receivable/inventory	45	0.051	0.000	0.164
Guarantees	6	0.016	0.000	0.038
Properties	207	0.449	0.443	0.326
Capital stocks	48	0.365	0.339	0.341
Other assets	441	0.206	0.000	0.301
Utility				
No (0)	1260	0.445	0.414	0.379
Yes(1)	110	0.244	0.090	0.301
Resolution time longer than 1 year				
No (0)	286	0.438	0.420	0.379
Yes (1)	1084	0.427	0.388	0.377
Maturity longer than 5 years				
No (0)	399	0.245	0.000	0.349
Yes (1)	971	0.504	0.527	0.362

Table 2 -- *continued*

Panel D: Summary statistics of continuous variables, bankruptcies and distressed exchanges

	N	Mean	Median	Std	P5	P95
LGD	1696	0.375	0.307	0.372	0.000	0.990
Seniority index	1696	0.500	0.500	0.245	0.084	0.922
Firm size	1696	8.038	7.891	1.721	5.436	10.251
Distance-to-default	1696	0.201	-0.416	3.330	-2.854	3.768
Leverage	1696	0.598	0.608	0.233	0.218	0.929
Earning-to-asset ratio	1696	-0.049	-0.012	0.091	-0.321	0.022
Profitability	1696	0.049	0.059	0.259	-0.526	0.379
Coverage	1696	1.513	1.036	1.822	0.000	4.890
Tangibility	1696	0.434	0.448	0.226	0.056	0.768
Tobin's Q	1696	1.166	1.034	0.547	0.742	1.877
Current ratio	1696	1.005	0.946	0.647	0.150	2.221
Cash ratio	1696	0.066	0.038	0.071	0.002	0.188
Bonds debt ratio	1696	0.630	0.660	0.278	0.000	1.000
Aggregate default rate	1696	0.008	0.007	0.004	0.003	0.016
Industry default rate	1696	0.017	0.009	0.020	0.000	0.065
T-bill rate	1696	0.014	0.013	0.012	0.000	0.040
Industry distance-to-default	1696	4.269	4.062	2.185	1.223	8.229
Market return	1696	-0.069	-0.120	0.202	-0.386	0.276
Bank ROA	1452	0.009	0.010	0.005	-0.002	0.015
Bank NIM	1452	0.029	0.030	0.005	0.021	0.036
Bank RBCR	1452	0.131	0.122	0.025	0.114	0.171
Bank bought CDS ratio	1452	0.250	0.087	0.351	0.016	1.054
Bank foreign derivatives ratio	1452	1.153	0.917	0.760	0.388	2.732
Bank interest rate derivatives ratio	1452	10.089	7.972	7.034	3.015	25.543
Bank size	1452	19.354	19.344	1.055	17.861	20.981
Resolution month	1696	13.243	9.000	13.180	0.000	38.000

Table 3
CDS Trading and Loss Given Default: Bankruptcies versus Distressed Exchanges

This table presents the OLS regressions of LGD on CDS trading status, debt and firm characteristics, and macroeconomic variables on subsamples of defaulted debts from bankruptcies and distressed exchanges. The sample period is 2002–2012. All variables are defined in Table 1. The dependent variable, LGD, equals one minus recovery rate. The key explanatory variable is "CDS trading", a dummy variable that equals one if a firm was quoted in CDS contracts both within the past three months before default and in the period of 12-24 months before default. Column (1) reports the regression results on a subsample of defaulted debts from bankruptcies. Column (2) reports the regressions results on a subsample of defaulted debts from distressed exchanges. "N" denotes number of observations. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	(1) Bankruptcy	(2) Distressed exchange
CDS trading	-0.070***	-0.019
	[0.027]	[0.055]
Seniority index	-0.575***	-0.135
	[0.049]	[0.139]
Senior secured bonds	0.075	0.060
	[0.047]	[0.130]
Subordinated bonds	0.066**	-0.026
	[0.029]	[0.059]
Term loans	-0.047	-0.038
	[0.044]	[0.134]
Revolvers	-0.049	-0.045
	[0.042]	[0.136]
Cash/receivable/inventory	-0.231***	-0.247*
	[0.054]	[0.128]
Guarantees	-0.388***	
	[0.086]	
Properties	-0.108**	-0.032
	[0.049]	[0.125]
Capital stocks	-0.044	0.062
	[0.057]	[0.113]
Other assets	-0.183***	-0.163
	[0.045]	[0.113]
Maturity longer than 5 years	0.030	0.064*
	[0.019]	[0.037]
Distance-to-default	-0.025***	0.017
	[0.005]	[0.012]
Leverage	-0.122**	-0.164
	[0.051]	[0.103]
Earning-to-asset ratio	0.465***	0.099
	[0.095]	[0.293]
Profitability	-0.180***	0.220*
	[0.037]	[0.119]
Tangibility	-0.036	0.183*

	[0.046]	[0.103]
Current ratio	0.015	0.015
	[0.014]	[0.034]
Cash ratio	-0.317*	-0.242
	[0.180]	[0.566]
Bonds debt ratio	-0.064	0.030
	[0.041]	[0.140]
Utility dummy	0.005	
	[0.040]	
Coverage	0.017**	-0.033***
	[0.008]	[0.011]
Tobin's Q	0.115***	-0.034
	[0.021]	[0.086]
Firm size	-0.014*	-0.059**
	[0.008]	[0.024]
Aggregate default rate	23.820**	-33.976
	[11.774]	[23.285]
Industry default rate	1.468***	-4.178***
	[0.463]	[1.531]
T-bill rate	-3.236	67.411***
	[8.921]	[20.584]
Quarterly time fixed effects	Yes	Yes
N	1370	326
Adjusted R^2	0.597	0.410

Table 4
CDS Trading and the LGD of Bankruptcies: Fractional Response Regressions

The fractional response regressions of LGD are based on a sample of defaulted debts of bankrupted firms over the period of 2002–2012. The dependent variable, LGD, equals one minus recovery rate. Variables are defined in Table 1. The key explanatory variable is "CDS trading", a dummy variable that equals one if the firm was quoted in CDS contracts both within the past three months before default and in the period of 12-24 months before default. The table reports only the coefficients of interest and omits an extensive set of control variables. Each panel includes five columns. Column (1) includes "CDS trading" and debt-level variables. Column (2) adds firm-level variables. Column (3) adds macroeconomic variables. Column (4) adds quarterly time fixed effects. Finally, column (5) excludes the "CDS trading" variable. We report the values of average marginal effects rather than the actual coefficients. "N" denotes number of observations. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)
CDS trading	-0.202***	-0.158***	-0.133***	-0.071***	
	[0.019]	[0.021]	[0.021]	[0.026]	
Aggregate default rate			18.404***	33.301***	18.939***
			[2.268]	[11.614]	[2.353]
Industry default rate			1.835***	1.419***	2.061***
			[0.402]	[0.464]	[0.404]
T-bill rate			2.146**	1.322	1.748**
			[0.837]	[9.927]	[0.804]
Debt-level control variables	Yes	Yes	Yes	Yes	Yes
Firm-level control variables	No	Yes	Yes	Yes	Yes
Quarterly time fixed effects	No	No	No	Yes	Yes
N	1370	1370	1370	1370	1370
Adjusted R^2	0.418	0.506	0.564	0.653	0.545

Table 5
CDS Trading and Bankruptcy LGD: Instrumental-variables (IV) Estimations

The IV estimations in this table control for the potential endogeneity of CDS trading. The estimation is based on a sample of defaulted debts of bankrupted firms over the period of 2002–2012. All variables are defined in Table 1. The dependent variable is LGD, which equals one minus recovery rate. The key explanatory variable is "CDS trading", a dummy variable that equals one if the firm was quoted in CDS contracts both within the past three months before default and in the period of 12-24 months before default. We assume that this variable is endogenous and use a two-stage IV estimator to control for the endogeneity bias. Panel A reports the correlations of several candidate instrumental variables with LGD and "CDS trading". We choose "Bank NIM" and "Bank bought CDS ratio" as the instrumental variables because they have low correlations with the LGD (e.g., exclusion condition) but substantially high correlations with "CDS trading" (e.g., relevance condition). Panel B reports the second-stage IV estimation results. Panel C reports estimation results of the first-stage probit regressions where the dependent variable is "CDS trading". The table reports only the coefficients of interest and omits an extensive set of control variables. Column (1) uses both "Bank NIM" and "Bank bought CDS ratio" as the instrumental variables. Column (2) uses "Bank NIM" as the instrumental variable. Column (3) uses "Bank bought CDS ratio" as the instrumental variable. "N" denotes number of observations; *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Panel A: Variable correlations

	LGD	CDS trading
LGD	1.000	
CDS trading	-0.161	1.000
Bank ROA	-0.070	-0.124
Bank NIM	0.009	-0.217
Bank RBCR	-0.165	0.207
Bank bought CDS ratio	-0.065	0.295
Bank FX ratio	0.061	0.017
Bank interest derivative ratio	0.030	0.041
Bank size	0.015	0.017

Table 5 — *continued*

Panel B: The second stage of the instrumental-variables method

	(1)	(2)	(3)
CDS trading	-0.199***	-0.232***	-0.263***
	[0.037]	[0.040]	[0.040]
Inverse Mills ratio	0.074***	0.093***	0.126***
	[0.027]	[0.028]	[0.027]
Debt-level control variables	Yes	Yes	Yes
Firm-level control variables	Yes	Yes	Yes
Macroeconomic variables	Yes	Yes	Yes
Quarterly time fixed effects	Yes	Yes	Yes
N	1157	1157	1157

Panel C: The first-stage probit regression of the instrumental-variables method

	(1)	(2)	(3)
Bank NIM	329.492***	77.122**	
	[60.892]	[37.497]	
Bank bought CDS ratio	4.063***		1.834***
	[0.696]		[0.528]
Firm-level control variables	Yes	Yes	Yes
Macroeconomic variables	Yes	Yes	Yes
Quarterly time fixed effects	Yes	Yes	Yes

Table 6
CDS Trading and Bankruptcy LGD: Treatment-effect Estimators

This table reports the impacts of CDS trading on the LGD of defaulted debts from bankruptcies, using different treatment-effect estimators. The estimation is based on a sample of defaulted debts from bankrupted firms over the period of 2002–2012. The dependent variable is LGD, which equals one minus recovery rate. Variables are defined in Table 1. ATET is the average treatment effects on the treated (CDS trading=1). POMEAN0 is the potential-outcome mean of LGD for untreated (CDS trading=0). All explanatory variables defined in Table 1 are included in the treatment and outcome models. The nearest-neighbor matching matches all explanatory variables defined in Table 1.

			Regression adjustment (RA)			
	Coefficient	Std. Err.	z	P>|z|	95% confidence interval	
ATET	-0.165	0.024	-6.76	0.000	-0.213	-0.117
POMEAN0	0.487	0.023	21.22	0.000	0.442	0.532
			Inverse-probability weighting (IPW)			
	Coefficient	Std. Err.	z	P>|z|	95% confidence interval	
ATET	-0.136	0.040	-3.40	0.000	-0.214	-0.058
POMEAN0	0.457	0.041	11.28	0.000	0.378	0.537
			Inverse-probability-weighted regression adjustment (IPWRA)			
	Coefficient	Std. Err.	z	P>|z|	95% confidence interval	
ATET	-0.147	0.026	-5.63	0.000	-0.198	-0.096
POMEAN0	0.468	0.026	18.15	0.000	0.418	0.519
			Nearest-neighbor matching (NNM)			
	Coefficient	Std. Err.	z	P>|z|	[95% confidence interval	
ATET	-0.110	0.032	-3.39	0.001	-0.173	-0.046
			Propensity-score matching (PSM)			
	Coefficient	Std. Err.	z	P>|z|	95% confidence interval	
ATET	-0.174	0.056	-3.10	0.002	-0.284	-0.064

Table 7
CDS Trading and Bankruptcy LGD: Alternative Measures of LGD

The OLS regressions in this table use different LGD measures that are based on the settlement, trading price, and liquidity methods, as well as the 30-day trading price after default. The estimation is based on a sample of defaulted debts of bankrupted firms over the period of 2002–2012. All variables are defined in Table 1. The dependent variable is LGD, which equals one minus the recovery rate. The key explanatory variable is “CDS trading”, a dummy variable that equals one if the firm was quoted in CDS contracts both within the past three months before default and in the period of 12-24 months before default. The table reports only the coefficients of interest and omits an extensive set of control variables. “N” denotes number of observations; *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Settlement method	Trading price method	Liquidity method	30-day trading price after default
CDS trading	-0.059*	-0.086***	-0.362**	-0.078**
	[0.031]	[0.032]	[0.176]	[0.030]
Debt-level control variables	Yes	Yes	Yes	Yes
Firm-level control variables	Yes	Yes	Yes	Yes
Macroeconomic variables	Yes	Yes	Yes	Yes
Quarterly time fixed effects	Yes	Yes	Yes	Yes
N	1309	961	333	855
Adjusted R^2	0.552	0.628	0.396	0.422

Table 8
CDS Trading and Bankruptcy LGD over Different Time Periods

This table presents OLS regressions of LGD for defaulted debts of bankrupted firms over two sub-periods: 2002–2006 and 2007–2012. All variables are defined in Table 1. The dependent variable, LGD, equals one minus recovery rate. The core variable of interest is "CDS trading", a dummy variable that equals one if a firm was quoted in CDS contracts both within the past three months before default and in the period of 12-24 months before default. The table reports only the coefficients of interest and omits an extensive set of control variables. "N" denotes number of observations; *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	2002–2006	2007–2012
CDS trading	-0.042	-0.122***
	[0.030]	[0.036]
Debt-level control variables	Yes	Yes
Firm-level control variables	Yes	Yes
Macroeconomic variables	Yes	Yes
Quarterly time fixed effects	Yes	Yes
N	1020	350
Adjusted R^2	0.592	0.592

Table 9
CDS Trading and Bankruptcy LGD: Subsamples by Leverage and Current Ratio

This table presents OLS regressions of LGD over subsamples of defaulted debts from bankruptcies grouped by leverage and current ratio. The sample period is 2002–2012. All variables are defined in Table 1. The dependent variable, LGD, equals one minus recovery rate. The key explanatory variable is "CDS trading", a dummy variable that equals one if the firm was quoted in CDS contracts both within the past three months before default and in the period of 12-24 months before default. We use the sample medians of leverage ratio and current ratio to divide firms into subsamples of high leverage, low leverage, high current ratio, and low current ratio. The table reports only the coefficients of interest and omits an extensive set of control variables. "N" denotes number of observations; *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Low leverage firms	High leverage firms	Low current ratio firms	High current ratio firms
CDS trading	-0.158***	-0.013	-0.127***	0.084
	[0.050]	[0.036]	[0.041]	[0.060]
Debt-level control variables	Yes	Yes	Yes	Yes
Firm-level control variables	Yes	Yes	Yes	Yes
Macroeconomic variables	Yes	Yes	Yes	Yes
Quarterly time fixed effects	Yes	Yes	Yes	Yes
N	698	672	768	602
Adjusted R^2	0.607	0.700	0.676	0.673

Table 10
CDS Trading and Bankruptcy LGD: Loans versus Bonds

This table presents OLS regressions of LGD on subsamples of different debt types. The estimation is based on a sample of defaulted debts of bankrupted firms over the period of 2002–2012. All variables are defined in Table 1. The dependent variable, LGD, equals one minus recovery rate. The key explanatory variable is "CDS trading", a dummy variable that equals one if the firm was quoted in CDS contracts both within the past three months before default and in the period of 12-24 months before default. The table reports only the coefficients of interest and omits an extensive set of control variables. "N" denotes number of observations; *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Term loans	Revolvers	Bonds
CDS trading	0.033	0.043	-0.123***
	[0.066]	[0.048]	[0.040]
Debt-level control variables	Yes	Yes	Yes
Firm-level control variables	Yes	Yes	Yes
Macroeconomic variables	Yes	Yes	Yes
Quarterly time fixed effects	Yes	Yes	Yes
N	241	237	892
Adjusted R^2	0.508	0.445	0.568

Table 11
CDS Trading and Bankruptcy Resolution Time

This table presents logistic regressions that examine the impacts of CDS trading on the resolution time of defaulted debts from bankruptcies. The estimation is based on a sample of defaulted debts of bankrupted firms over the period of 2002–2012. All variables are defined in Table 1. The dependent variable, "Resolution time longer than 1 year", is a dummy that equals one if the resolution time is longer than one year and zero otherwise. The key explanatory variable is "CDS trading", a dummy variable that equals one if the firm was quoted in CDS contracts both within the past three months before default and in the period of 12-24 months before default. This table consists of 5 specifications. Specification (1) includes "CDS trading" and debt-level variables as explanatory variables. Specification (2) adds firm-level variables. Specification (3) adds monthly macroeconomic variables. Specification (4) adds quarterly time fixed effects. Specification (5) excludes the "CDS trading" variable. "N" denotes number of observations; *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)
CDS trading	1.167***	2.103***	2.042***	2.102***	
	[0.208]	[0.300]	[0.327]	[0.432]	
Seniority index	0.511	0.402	1.010	1.063	0.938
	[0.404]	[0.634]	[0.632]	[0.877]	[0.622]
Senior secured bonds	-0.432	-1.112**	-1.301**	-1.958***	-1.133**
	[0.454]	[0.543]	[0.564]	[0.704]	[0.545]
Subordinated bonds	-0.381	-0.332	-0.304	0.035	-0.124
	[0.240]	[0.328]	[0.341]	[0.414]	[0.329]
Term loans	-0.393	-0.588	-0.683	-1.129*	-0.731
	[0.407]	[0.525]	[0.534]	[0.644]	[0.529]
Revolvers	-0.555	-1.023**	-1.124**	-1.618***	-1.143**
	[0.401]	[0.499]	[0.507]	[0.627]	[0.495]
Cash/receivable/inventory	1.075*	1.769**	1.492	1.984*	1.459
	[0.652]	[0.881]	[0.942]	[1.122]	[0.960]
Properties	2.343***	1.530**	1.224*	1.378	1.430**
	[0.601]	[0.658]	[0.705]	[0.994]	[0.659]
Capital stocks	0.670	0.796	0.624	0.290	0.955
	[0.637]	[0.742]	[0.714]	[0.828]	[0.714]
Other assets	-0.377	0.042	-0.146	0.533	0.057
	[0.387]	[0.569]	[0.594]	[0.730]	[0.558]
Maturity longer than 5 years	-0.374**	-0.348	-0.292	-0.229	-0.237
	[0.178]	[0.230]	[0.239]	[0.318]	[0.227]
Distance-to-default		0.335***	0.296***	0.227***	0.238***
		[0.068]	[0.071]	[0.081]	[0.071]
Leverage		-4.730***	-5.238***	-7.782***	-5.428***
		[0.582]	[0.628]	[1.169]	[0.657]
Earning-to-asset ratio		-3.228***	-3.825***	-6.384***	-3.268***
		[1.008]	[1.043]	[1.376]	[1.033]
Profitability		-1.968***	-2.276***	-1.357**	-2.486***
		[0.552]	[0.542]	[0.614]	[0.590]
Tangibility		1.126**	1.509***	1.456**	1.202***
		[0.456]	[0.447]	[0.691]	[0.441]

Current ratio		0.886***	0.864***	0.831***	0.799***
		[0.207]	[0.200]	[0.205]	[0.196]
Cash ratio		-11.462***	-12.017***	-12.518***	-10.921***
		[1.923]	[1.815]	[2.515]	[1.574]
Bonds debt ratio		0.198	0.301	0.417	0.461
		[0.509]	[0.507]	[0.679]	[0.489]
Utility dummy		-1.151***	-1.569***	-2.272***	-1.101***
		[0.386]	[0.430]	[0.529]	[0.346]
Coverage		-0.342***	-0.405***	-0.511***	-0.273**
		[0.107]	[0.107]	[0.146]	[0.107]
Tobin's Q		-0.488**	-0.461**	-0.790	-0.071
		[0.200]	[0.217]	[0.493]	[0.258]
Firm size		-0.022	0.142	0.372***	0.335***
		[0.081]	[0.095]	[0.143]	[0.084]
Aggregate default rate			39.775	-140.806	34.305
			[29.459]	[184.478]	[26.726]
Industry default rate			-29.654***	-40.219***	-32.717***
			[5.957]	[8.143]	[5.409]
T-bill rate			11.627	203.925	9.350
			[9.308]	[199.370]	[8.428]
Quarterly time fixed effects	No	No	No	Yes	No
N	1364	1364	1364	811	1364
Pseudo R^2	0.096	0.372	0.390	0.439	0.354