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

Marti G. Subrahmanyam
Stern School of Business, New York University

Dragon Yongjun Tang
Faculty of Business and Economics, University of Hong Kong

Sarah Qian Wang
Warwick Business School, University of Warwick

We use credit default swaps (CDS) trading data to demonstrate that the credit risk of reference firms, reflected in rating downgrades and bankruptcies, increases significantly upon the inception of CDS trading, a finding that is robust after controlling for the endogeneity of CDS trading. Additionally, distressed firms are more likely to file for bankruptcy if they are linked to CDS trading. Furthermore, firms with more "no restructuring" contracts than other types of CDS contracts (i.e., contracts that include restructuring) are more adversely affected by CDS trading, and the number of creditors increases after CDS trading begins, exacerbating creditor coordination failure in the resolution of financial distress. (*JEL* G32, G33)

For their helpful comments on previous drafts of this paper, we thank Michael Weisbach (the editor), two anonymous referees, Viral Acharya, Edward Altman, Yakov Amihud, Sreedhar Bharath, Ekkehart Boehmer, Patrick Bolton, Dion Bongaerts, Stephen Brown, Jennifer Carpenter, Sudheer Chava, Peter DeMarzo, Mathijs van Dijk, Jin-Chuan Duan, Darrell Duffie, Alessandro Fontana, Andras Fulop, Iftekhar Hasan, Jean Helwege, Jingzhi Huang, Kose John, Stanley Kon, Lars-Alexander Kuehn, Anh Le, Jingyuan Li, Kai Li, Francis Longstaff, Ron Masulis, Robert McDonald, Lars Norden, Martin Oehmke, Frank Packer, Stylianos Perrakis, Xiaoling Pu, Talis Putnins, Anthony Saunders, Lukas Schmid, Ilhyock Shim, Marakani Srikant, Erik Stafford, Rene M. Stulz, Avanidhar Subrahmanyam, Heather Tookes, Hao Wang, Neng Wang, Wei Wang, John Wei, Andrew Winton, Pengfei Ye, David Yermack, Fan Yu, Gaiyan Zhang, Xinlei Zhao, Hao Zhou, Haibin Zhu, and the seminar and conference participants at CEMFI, Madrid, Cheung Kong Graduate School of Business, Beijing, City University of Hong Kong, European Central Bank, Erasmus University, Rotterdam, Hong Kong Institute for Monetary Research, Lingnan University, Hong Kong, Nanyang Technological University, National University of Singapore, NYU Stern School of Business, U.S. Office of the Comptroller of the Currency (OCC), Ozyegin University, PRMIA (Webinar), Rouen Business School, Singapore Management University, Standard & Poor's, Southwestern University of Finance and Economics, Chengdu, Tsinghua University, Beijing, University of Bristol, University of Hong Kong, University of New South Wales, University of Nottingham, Ningbo, University of the Thai Chamber of Commerce, Warwick Business School, Xiamen University, the 2014 AFA meetings, the 2013 American Economic Association (AEA) Annual Meetings, the 2012 European Finance Association Meetings, the 2012 China International Conference in Finance, the 2012 Risk Management Institute conference at NUS, the 2012 UBC Winter Finance Conference, the 2012 FMA Napa Conference, the 2012 Conference of the Paul Woolley Centre for Capital Market Dysfunctionality at UTS, the 2012 Multinational Finance Society Meetings, the 2012 International Risk Management Conference, the 2012 SFM Conference at National Sun Yat-sen University, and the 2011 Financial Management Association meetings in Denver. Dragon Tang acknowledges the support and hospitality of the Hong Kong Institute for Monetary Research (HKIMR), as part of the work was conducted when he was a HKIMR visiting research fellow. Supplementary data can be found on *The Review of Financial Studies* web site. Send correspondence to Dragon Yongjun Tang, Faculty of Business and Economics, University of Hong Kong, Pokfulam Road, Hong Kong; telephone: +852 221-943-21. E-mail: yjtang@hku.hk.

doi:10.1093/rfs/hhu038 Advance Access publication June 17, 2014

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

We empirically examine the effects of CDS trading on the credit risk of reference entities using a comprehensive dataset dating back to the broad inception of the CDS market for corporate names in 1997. It is difficult to obtain accurate data on CDS transactions from a single source because CDS trading does not occur on centralized exchanges. (Even the central clearing of CDS is a relatively recent phenomenon.) Hence, our identification of CDS inception and transactions relies on multiple leading data sources, including the GFI Group, CreditTrade, and Markit. Our dataset covers 901 North American firms with a CDS trading history during the period from 1997 to 2009. The list of bankruptcies for North American firms is comprehensively constructed from major data sources, covering 1,628 bankruptcy filings from 1997 to 2009.

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

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

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

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

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

One implication of the Bolton and Oehmke (2011) model is that, conditioning on financial distress, firms with CDS trading are more likely to file for bankruptcy. We find evidence consistent with this prediction. We further construct a more effective test of the tough creditor implications because our dataset includes details of the contract terms. Specifically, for each CDS contract, we know whether restructuring is covered as a credit event. Buyers of "no restructuring" CDS contracts will be paid only if the reference firm files for bankruptcy. However, buyers of CDS contracts that include restructuring as a credit event will be compensated even when the debt of the reference firm is restructured. Clearly, creditors with "no restructuring" CDS protection would have a stronger incentive to force the firm into bankruptcy than would those without this restrictive clause. Indeed, we find that the effects of CDS trading are stronger when a larger fraction of CDS contracts contains the "no restructuring" credit event clause.

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

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

1. Related Literature and Testable Hypotheses

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

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

Bolton and Oehmke (2011) model creditors' lending choices in the event that they can buy CDS after loan initiation. In their model, CDS protection increases banks' bargaining power in debt renegotiations and reduces borrowers' strategic defaults. Therefore, lenders are more willing to lend. However, lenders can become excessively tough with distressed borrowers if their CDS positions are sufficiently large, triggering bankruptcy. From a different perspective, Che and Sethi (2012) argue that lenders may opt to sell CDS contracts instead of lending to the respective borrowers.[2] Hence, it will be more difficult for distressed firms to roll over their debt if lenders choose to sell CDS protection instead of selling loans. Both the "tough creditor" and rollover risk concerns will exacerbate the credit risk of borrowers, particularly if the borrowers are financially distressed. Hence, the effect of CDS trading on the reference firms' credit risk may depend on market conditions and firm characteristics (Campello and Matta 2012). Therefore, the CDS effect is likely to be prominent when the borrower is already in financial distress.

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

The above hypothesis emphasizes the incentives of tough creditors, some of whom may be empty creditors.[3] One could alternatively examine the related issue that CDS trading may reduce the restructuring success rates of distressed firms. This latter question has been addressed in complementary studies with conflicting results: Danis (2012) finds a significant impact of CDS trading on restructuring, whereas Bedendo, Cathcart, and El-Jahel (2012) fail to find such effects. However, those two studies use relatively small samples, and our

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

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

empirical analysis applies to a large sample of both healthy and distressed firms. Moreover, bankruptcy provides a better testing context than does restructuring because bankruptcy events are more easily observed. Also, defining distressed firms based on restructuring is a subjective assessment, which may account for the mixed evidence in the aforementioned studies. Therefore, we focus on bankruptcy filings in our analysis.

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

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

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

The above hypotheses emphasize the *ex post* effects (after the loan and CDS positions are given) of CDS associated with lenders who are tougher in debt renegotiations. However, becoming an empty creditor is likely not the first goal of every lender when making lending decisions. Thus, from an *ex ante* perspective, lenders will consider their use of CDS along with other factors, such as reputation. Bolton and Oehmke (2011) predict that more banks will be willing to lend to a firm when CDS are available.[5] Such expansions in the lender base have two consequences. First, the likelihood of empty creditors is higher when there are more lenders. Second, because of the increased potential

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

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

for coordination failure, the probability of bankruptcy is higher when there are more lenders.

Hypothesis 4 (Lender coordination). (1) The number of (bank) lenders increases after the introduction of CDS trading. (2) Bankruptcy risk increases with the number of lenders.

2. Dataset on CDS Trading and Bankruptcy

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

Our CreditTrade data cover the period from June 1997 to March 2006, and our GFI data cover the period from January 2002 to April 2009. Both datasets contain complete information on intraday quotes and trades, such as type of contract, time of transaction, order type, and CDS price. Because CDS contracts are traded over the counter rather than on exchanges, the first trading date for each firm's CDS is difficult to identify with a time stamp. Using overlapping samples from these two data sources between January 2002 and March 2006, we can cross-check the two records to confirm the reliability of our identification of CDS firms and starting dates. The dates of the first appearance of a particular CDS in the two data sources are typically within several months of each other. To ensure greater accuracy, we also cross-check trading-based CDS data with the Markit CDS database, a commonly used CDS dealer quote source, to confirm our identifications.[6]

There are two important advantages of using the complete set of CDS transaction data in our empirical analysis. First, our sample starts in 1997, which is generally acknowledged as the year of inception of the broad CDS market (Tett 2009). Therefore, our identified first CDS trading dates are not contaminated by censoring of the data series. Second, our CDS transaction data include detailed contractual terms, such as the specification of the credit event, maturity, and security terms, for each contract. Aggregate position or quote data obtained from broker-dealers or, more recently, clearing houses or

[6] 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 and binding quotes.

data aggregators, would generally not include such contract-level information. The credit event specification allows us to investigate the effect of restructuring clauses. Maturity information at the contract level allows us to calculate volumes of outstanding CDS positions at each point in time. Our sample of CDS introductions ends in April 2009 for an important institutional reason: the market practice in CDS changed significantly in April 2009 because of the "Big Bang" implemented by the International Swaps and Derivatives Association (ISDA), including, for example, the removal of restructuring as a standard credit event. In addition, an observation window of three years is required after the introduction of CDS trading to measure its potential effects, extending the study period to 2012.

Based on our merged dataset, there are 901 North American firms with CDS inception during the 1997–2009 sample period. The industry distribution of the CDS firms in our sample is rather diverse.[7] In our baseline analysis, we mainly utilize information about the first day of CDS trading, comparing changes in firm default risk upon the onset of CDS trading. We also use the volume of CDS outstanding and the fraction of CDS contracts with various restructuring clauses based on more detailed transaction information to further assess how CDS trading affects credit risk.

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

We link the bankruptcy dataset with our CDS sample so as to identify the bankrupt firms that had CDS trading prior to their bankruptcy filings. Table 1 presents the yearly summary of our sample, including the number of bankrupt firms, the number of firms on which CDS are traded, and the number of bankrupt firms with and without CDS trading. The row labeled "total" indicates that there were a total of 1,628 bankruptcy filings in the 1997–2009 sample period. Our bankruptcy sample is comprehensive and larger than those of prior studies, which have used various filters. Many bankruptcies were filed in the 1999–2003 and 2008–2009 periods, accounting for 1,214 (74.6%) of the 1,628 bankruptcy events occurring during the entire sample period. The fourth and fifth columns of the table report the number of *New CDS* firms and the number

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

Table 1
Credit default swaps trading and bankruptcies by year

(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
Final sample		57.7%	61.6%		70.0%	57.3%
Matched sample		3.1%	56.7%		56.7%	1.0%
Matched final		2.8%	53.3%		51.7%	0.9%

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

of firms with *Active CDS* trading firms across the years, respectively. More CDS contracts were introduced in the 2000–2003 period than in any earlier or later periods. Among the 901 distinct CDS trading firms, 60 (6.7%) subsequently filed for bankruptcy protection. Bankruptcies among CDS firms represent a small fraction of the total number of bankruptcies because only relatively large firms, in terms of asset size and debt outstanding, have CDS traded on them. However, the bankruptcy rate of 6.7% for CDS firms is similar to the four-year overall (or 11-year BBB-rated) cumulative default rate of U.S. firms (Standard & Poor's 2012). We further link the CDS and bankruptcy sample with relevant financial and accounting data in CRSP and Compustat. In our final sample used in the regressions, there are 940 distinct bankrupt firms (58% of the raw number of bankruptcies), 42 of which are CDS firms (70% of the raw number of CDS bankruptcies). Additionally, 898 bankruptcies in the final sample are non-CDS firms, representing 57% of the raw number of non-CDS bankruptcies. The last four rows of Table 1 (as well as Tables A1 and A2 in the Internet Appendix) indicate that our raw sample, final regression sample, and other samples used in our later analysis have similar distributions of bankruptcies and CDS firms.

3. CDS Trading and Credit Risk: Empirical Results

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

3.1 Credit ratings before and after the introduction of CDS

An ordinal measure of a firm's credit risk is its credit rating, a metric that is widely used in industry, regulations, and academia. Rating agencies are known to incorporate information on both bankruptcies and restructuring into their rating decisions (Moody's 2009). We first analyze the credit ratings of CDS firms around the time of CDS introduction. Changes in credit quality around the introduction of CDS trading may be reflected in credit rating changes. A credit rating downgrade is often the first step toward bankruptcy and is an indicator of an increase in bankruptcy risk.

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

Figure 1 displays a discernible shift to lower credit ratings after the introduction of CDS trading. Whereas the proportion of BBB-rated firms is approximately the same, both before and after CDS trading begins, the proportion of AA-rated and A-rated firms decreases. At the same time, the proportion of non-investment-grade and unrated firms increases. We examine the distributional differences before and after the introduction of CDS trading

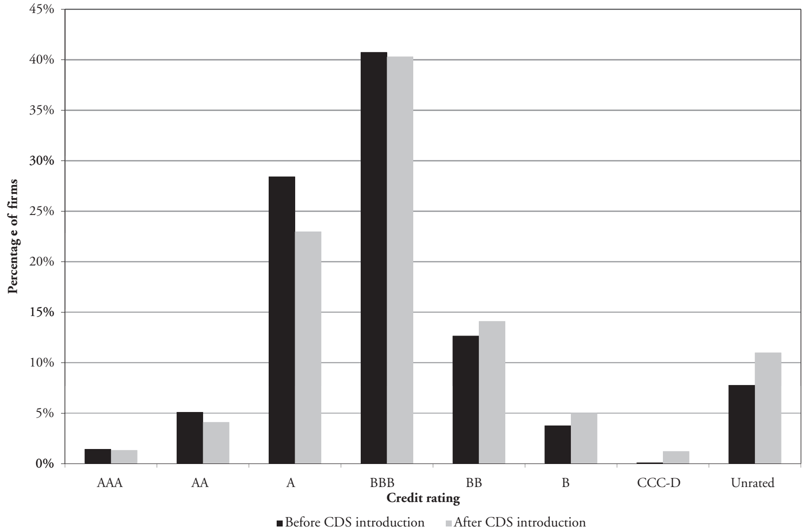

Figure 1
Rating distribution around the introduction of credit default swaps
This figure plots the credit rating distributions for firms with credit default swaps (CDS), before the inception of CDS trading and two years after the inception of CDS trading. The credit ratings are taken from S&P Credit 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.

using the Kolmogorov-Smirnov test.[8] We use the one-sided test for stochastic dominance. The *D*-statistic of the one-sided Kolmogorov-Smirnov test (the maximum difference between cumulative distributions) is significant at the 1% level, indicating that the credit rating distribution shifts to the right (lower rating quality) after CDS trading commences. In other words, the ratings before CDS trading is introduced stochastically dominate the ratings afterward.

At the firm level, 54% of firms maintain the same rating after as before the introduction of CDS trading, 37% of firms experience a rating downgrade, and only 9% of firms experience a rating improvement. We employ a difference-in-differences analysis to isolate the effect of the market trend using matched non-CDS firms with propensities for CDS trading similar to those of the CDS firms (the matching method is described in Section 3.3.2). We first compare the rating distribution for CDS firms and their non-CDS matched counterparts (see Figure A1 in the Internet Appendix). The distribution of the downgrades for CDS firms is similar to that for non-CDS firms. For both the CDS and non-CDS samples, the downgrades are mainly from the BBB category, which accounts for 50% and 76% of the downgrades in the two samples, respectively. We then regress rating changes, measured in terms of the number of notches, on firm

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

characteristics and the CDS indicator *CDS Active*. We convert letter ratings to numerical ratings (i.e., AAA=1, AA+=2) so that larger numbers indicate worse ratings. The regression results using 744 CDS and matched non-CDS firms with complete data are reported in Table A3 of the Internet Appendix, and indicate that downgrades for CDS firms after CDS trading commences are an average of 0.23 notches larger than those for non-CDS firms within the same time period. We also find that the downgrading frequency is 2.6% higher for CDS firms than for non-CDS firms of a similar size from the same industry. These rating results provide preliminary evidence that the credit quality of the reference entities deteriorates following the inception of CDS trading.

3.2 Baseline hazard model results on downgrading and bankruptcy

We next run multivariate analyses to obtain systematic statistical evidence regarding the effect of the inception of CDS trading on credit risk, while controlling for other credit risk determinants. Our baseline model predicts both credit rating downgrades and bankruptcy filings. We confine the discussion to bankruptcy for brevity. We adopt a proportional hazard model using firm-month panel data. Specifically, we assume that the marginal probability of bankruptcy over the next period follows a logistic distribution with parameters (α, β) and time-varying covariates X_{it-1}:

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

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 conduct several robustness checks on the model specification in the Internet Appendix.

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

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

We follow Bharath and Shumway (2008) by including five fundamental determinants of default risk in X_{it-1}, constructed from CRSP and Compustat

Table 2
Impact of credit default swaps trading on credit quality

	Probability of downgrade		Probability of bankruptcy	
	(1)	(2)	(3)	(4)
ln(E)	−0.735***	−0.736***	−0.713***	−0.710***
	(0.022)	(0.022)	(0.026)	(0.026)
ln(F)	0.507***	0.503***	0.711***	0.713***
	(0.024)	(0.024)	(0.026)	(0.026)
$1/\sigma_E$	−0.062*	−0.017	−1.626***	−1.675***
	(0.035)	(0.032)	(0.251)	(0.251)
$r_{it-1} - r_{mt-1}$	−0.281***	−0.252***	−1.320***	−1.331***
	(0.061)	(0.059)	(0.192)	(0.192)
NI/TA	−0.003	−0.000	−0.038***	−0.038***
	(0.008)	(0.008)	(0.009)	(0.009)
CDS Firm	0.755***		−2.009***	
	(0.088)		(0.720)	
CDS Active	0.691***	1.371***	2.373***	0.400**
	(0.096)	(0.067)	(0.736)	(0.179)
CDS Active Odds Ratio	1.925	3.939	10.730	1.492
CDS Active Marginal Effect	0.39%	0.78%	0.33%	0.06%
Time fixed effects	yes	yes	yes	yes
Industry fixed effects	yes	yes	yes	yes
Clustered standard error	yes	yes	yes	yes
Pseudo R^2	15.08%	14.75%	24.18%	24.06%
N	658,966	658,966	658,966	658,966
% of CDS observations	10.83%	10.83%	10.83%	10.83%
% of CDS downgrades (bankruptcies)	34.74%	34.74%	4.47%	4.47%
Sample probability of a downgrade (bankruptcy)	0.59%	0.59%	0.14%	0.14%

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

data: the logarithm of the firm's equity value *ln(E)*, the firm's stock return in excess of market returns over the past year $r_{it-1} - r_{mt-1}$, the logarithm of the book value of the firm's debt *ln(F)*, the inverse of the firm's equity volatility $1/\sigma_E$, and the firm's profitability measured by the ratio of net income to total assets *NI/TA*. We also control for year and industry fixed effects in the panel data analysis. Because we have autocorrelated observations from the same firms in our panel data, we follow Petersen's (2009) suggestion and cluster the standard errors within firms.

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

The positive coefficients for *CDS Active* in specifications 1 and 2 indicate that firms are more likely to be downgraded after the inception of CDS trading. In both specifications, the effect of CDS trading is statistically significant at the 1% level. The economic magnitude is also large: in specification 1, the marginal effect of CDS trading on the probability of a downgrade is 0.39%, whereas the average downgrading probability is 0.59%. Specification 3 reports similar findings for bankruptcy filings. Bankruptcies are relatively rare events—the likelihood of bankruptcy in our overall sample is 0.14%. However, bankruptcy risk increases substantially after CDS trading is initiated: the marginal effect of CDS trading on the likelihood of bankruptcy evaluated at the means is 0.33%, which is significant at the 1% level. Furthermore, in Specification 3, the odds ratio for *CDS Active* (the likelihood of bankruptcy after CDS trading divided by the likelihood of bankruptcy before CDS trading) for bankruptcy predictions is 10.73, indicating that bankruptcy is more likely to occur after CDS trading begins.[9]

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

Our baseline results are consistent with Hypothesis 1 that the credit quality of reference firms declines after CDS trading begins. Although this hypothesis specifically concerns the worsening of credit quality, one may wonder whether the effect is symmetric, that is, whether CDS trading may predict both a higher probability of credit quality deterioration and a lower probability of credit

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

quality improvement. We categorize rating changes into upgrades, no change, and downgrades. The results in Table A4 of the Internet Appendix indicate that *CDS Active* can predict rating downgrades but has no predictive power with respect to rating upgrades. In addition, the results demonstrate that we cannot distinguish an upgrade from no change in the credit rating. These findings justify our focus on downgrades. We note that CDS firms have more complete data and more often enter the final sample. Our main results also survive other robustness checks pertaining to sample period, sample selection, data frequency, model specification, and alternative measures, as reported in Tables A5–A14 of the Internet Appendix. For example, Table A6 shows that the effect of CDS trading is significant when we randomly select 200 or 300 CDS firms and an equal number of non-CDS firms to conduct our analysis.

3.3 Selection and endogeneity in CDS trading

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

$$Bankruptcy^{*} = \alpha + \beta CDSActive + \mu X + \varepsilon; \tag{2}$$

$$Bankruptcy = 1 \text{ if } Bankruptcy^{*} > 0; \text{ and } Bankruptcy = 0 \text{ otherwise,}$$

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

$$CDSActive^{*} = \gamma_0 + \gamma_1 X + \gamma_2 Z + \nu; \tag{3}$$

$$CDSActive = 1 \text{ if } CDSActive^{*} > 0; \text{ and } CDSActive = 0 \text{ otherwise,}$$

where Z is a vector of instrumental variables, and *CDS Active** and *CDS Active* are the CDS trading variables. Endogeneity concerns arise when the correlation between the residuals of the outcome and treatment equations, $corr(\varepsilon, \nu)$, is not zero. For example, there could be a feedback loop: the anticipated increase in bankruptcy risk induces CDS trading, and then CDS trading induces higher bankruptcy risk. This "binary outcome model with a binary endogenous explanatory variable" is also analyzed by Jiang, Li, and Wang (2012). They adopt the estimation method of Wooldridge (2002, chapter

15.7.3) using maximum likelihood estimation methods. We use a similar estimation approach.

We first select instrumental variables for CDS trading and then use two standard econometric approaches to address the selection issues (for detailed discussions, see Li and Prabhala 2007; Roberts and Whited 2013): propensity score matching and full-information maximum likelihood.

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

One way to uncover the true effect of CDS trading is by using an instrumental variable that has a direct effect on CDS trading but only affects bankruptcy via its effect on CDS trading. We employ two such instruments: foreign exchange hedging activities by banks and underwriters, *Lender FX Hedging*, and the Tier One capital ratio of lenders, *Lender Tier 1 Capital*.[10] We first identify lenders and bond underwriters for our sample firms based on DealScan data (for lenders) and FISD data (for bond underwriters). We then obtain Federal Reserve call report data for the FX derivative positions of these lenders and bond underwriters. For each firm in each quarter, *Lender FX Hedging* is constructed as the average of the notional volume of FX derivatives used for hedging purposes, relative to total assets, across the banks that have served as either lenders or bond underwriters for the firm over the previous five years. We use the Compustat Bank file containing lenders' Tier One capital ratio data to construct the second instrument, *Lender Tier 1 Capital*, defined as the average of the Tier One capital ratios across the banks that have served as either lenders or bond underwriters for a particular firm over the previous five years.[11]

In addition to these two instruments for CDS trading, we also include firm size and other characteristics as explanatory variables. The choice of these variables is dictated by their role in capturing hedging interest, credit risk, and

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

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

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

We use data from 1997 until the first month of CDS trading for CDS firms and all observations in our sample for non-CDS firms to estimate a model of the introduction of CDS trading for a firm. The model is estimated using a probit framework: the dependent variable equals one after the firm starts CDS trading and zero beforehand. The probit regression results are reported in Table 3. The results indicate that CDS contracts are more likely to be traded on larger firms than on smaller firms. CDS trading is more likely for firms with higher leverage but with investment-grade ratings, whereas CDS contracts are less likely to be traded on unrated firms. Firms with high profitability, tangibility, and large amounts of working capital are all more likely to have CDS trading. Overall, firms with relatively *high* credit quality and visibility (a stronger balance sheet and larger size) are more likely to be selected for CDS trading. Both of our instruments, *Lender FX Hedging* and *Lender Tier 1 Capital*, are significant predictors of CDS trading even after controlling for all other variables. After including bank size and bank credit derivative positions, our instrumental variables remain significant determinants of CDS trading. Moreover, the Sargan (1958) overidentification test fails to reject the null hypothesis that both instrumental variables are exogenous.[12]

Table 3 illustrates that CDS trading can be explained reasonably well by the chosen variables, with pseudo-R^2s of approximately 39% across the three model specifications (models 1 and 2 include one instrumental variable at a time, and model 3 includes both instrumental variables). We note that our findings are robust to the specification of the CDS prediction model (e.g., excluding ROA does not affect our results). In the following analysis, we use these CDS trading prediction models to control for endogeneity in CDS trading and re-examine the relationship between CDS trading and credit risk. In the remainder of the analysis, we focus on the likelihood of bankruptcy.

3.3.2 Propensity score matching. Because of the simplicity of its matching methodology, propensity score matching is among the most common

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

Table 3
Probability of credit default swaps trading

	Probability of CDS trading		
	CDS prediction model 1	CDS prediction model 2	CDS prediction model 3
Ln(Assets)	0.790***	0.804***	0.797***
	(0.006)	(0.006)	(0.006)
Leverage	0.429***	0.440***	0.431***
	(0.025)	(0.025)	(0.026)
ROA	−0.001	−0.001	−0.001
	(0.001)	(0.001)	(0.001)
$r_{it-1} - r_{mt-1}$	−0.104***	−0.104***	−0.104***
	(0.011)	(0.011)	(0.011)
Equity Volatility	0.063***	0.069***	0.067***
	(0.017)	(0.017)	(0.017)
PPENT/Total Asset	0.306***	0.321***	0.307***
	(0.031)	(0.031)	(0.031)
Sales/Total Asset	−0.026***	−0.027***	−0.026***
	(0.009)	(0.003)	(0.003)
EBIT/Total Asset	0.315***	0.375***	0.338***
	(0.064)	(0.064)	(0.064)
WCAP/Total Asset	0.142***	0.145***	0.143***
	(0.024)	(0.024)	(0.024)
RE/Total Asset	0.022***	0.023***	0.024***
	(0.005)	(0.005)	(0.005)
Cash/Total Asset	0.290***	0.302***	0.294***
	(0.023)	(0.023)	(0.023)
CAPX/Total Asset	−1.611***	−1.677***	−1.604***
	(0.122)	(0.122)	(0.122)
Rated	0.667***	0.645***	0.638***
	(0.203)	(0.205)	(0.205)
Senior Unsecured Debt	0.375***	0.377***	0.375***
	(0.014)	(0.014)	(0.014)
Lender Size	0.369***	0.378***	0.385***
	(0.011)	(0.011)	(0.011)
Lender Credit Derivatives	1.006***	1.013***	1.019***
	(0.024)	(0.024)	(0.025)
Lender FX Hedging	8.979***		9.104***
	(0.788)		(0.789)
Lender Tier 1 Capital		−3.865***	−4.000***
		(0.756)	(0.757)
F-statistic (instruments)	129.89	26.13	159.74
p-value (F-statistic)	0.000	0.000	0.000
Credit rating controls	yes	yes	yes
Time fixed effects	yes	yes	yes
Industry fixed effects	yes	yes	yes
Clustered standard error	yes	yes	yes
Pseudo R^2	38.96%	38.79%	38.99%
N	690,111	690,111	690,111
% of CDS observations	6.15%	6.15%	6.15%

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

techniques used to address endogeneity concerns, as noted by Roberts and Whited (2013) in their survey, due to the simplicity of its matching methodology. Once the matched sample has been determined, actual estimation involves only a one-equation system. The key advantage of the matching method is that it avoids specification of the functional form: matching methods do not rely on a clear source of exogenous variation for identification.

The propensity score matching approach conditions on the one-dimensional propensity score, defined as the probability of receiving treatment, conditional on the covariates. The potential outcomes are taken as independent of the treatment assignment, conditional on the propensity score. One disadvantage of this approach is that the latter assumption is strong and untestable. To quote Roberts and Whited (2013): "Matching will not solve a fundamental endogeneity problem. However, it can offer a nice robustness test." Therefore, we use propensity score matching as an alternative methodology to control for the expected increase in credit risk accompanying CDS trading.

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

We first compare the relevant characteristics of the CDS firms and the propensity score-matched non-CDS firms. There are no significant differences in the propensity scores between the CDS firms and the matched firms with the nearest propensity scores (see Table A15 in the Internet Appendix). The CDS firms have slightly better credit ratings but similar distances-to-default relative to the non-CDS matched firms. Nevertheless, the CDS firms are slightly larger than their matched counterparts. Therefore, we control for the size effect in the bankruptcy prediction model.

Table 4 presents the regression results for our CDS-trading propensity-matched sample. In all specifications, the coefficient estimates for *CDS Active* are significantly positive. We use "nearest one" matching as a benchmark case in the first specification. When we modify the matching criterion from "nearest one" to "nearest one with propensity score difference within 1%," the results are similar to those in Column 2 without the 1% restriction. As an alternative, we choose the two matching firms with the nearest propensity scores and continue to find a significant coefficient estimate for *CDS Active*. Therefore, the

Table 4
Credit default swaps trading and probability of bankruptcy: Propensity score matching

	Probability of bankruptcy		
	Nearest one matching	Nearest one PS diff.<1%	Nearest two matching
ln(E)	−1.206***	−1.350***	−0.993***
	(0.246)	(0.309)	(0.195)
ln(F)	1.274***	1.319***	1.008***
	(0.211)	(0.248)	(0.203)
$1/\sigma_E$	−0.078	0.048	−0.612
	(1.043)	(0.904)	(1.208)
$r_{it-1}-r_{mt-1}$	−2.054*	−1.655	−1.59
	(1.190)	(1.046)	(1.290)
NI/TA	−0.026	−2.919***	0.034
	(0.106)	(0.753)	(0.095)
CDS Firm	−0.262	−0.279	−0.555
	(1.050)	(1.261)	(0.879)
CDS Active	1.858**	2.261**	1.771**
	(0.910)	(1.082)	(0.802)
CDS Active Odds Ratio	6.411	9.593	5.877
CDS Active Marginal Effect	0.07%	0.07%	0.07%
Time fixed effects	yes	yes	yes
Industry fixed effects	yes	yes	yes
Clustered standard error	yes	yes	yes
Pseudo R^2	37.29%	38.53%	36.81%
N	119,710	108,401	168,600
% of CDS observations	57.49%	56.58%	40.82%
% of CDS bankruptcies	68.89%	71.43%	49.21%
Sample probability of a bankruptcy	0.03%	0.03%	0.03%

This table presents the estimates of the probability of bankruptcy, using a logistic model in a sample including firms with credit default swaps (CDS) and non-CDS propensity score-matched firms. Propensity score-matched firms are selected based on propensity scores estimated from the model of the probability of CDS trading presented in Table 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 begins. The coefficient of interest is *CDS Active*, which captures the impact of the inception of CDS trading on the probability of bankruptcy. The second column presents the analysis in the baseline-matched sample, that is the "nearest one" propensity score-matched firms, selected based on the CDS prediction model 3 in Table 3. The third column presents the same analysis, but for the "nearest one" with a propensity score difference within 1%. The fourth column uses the two matching firms with the nearest propensity scores. The sample period is 1997–2009, based on monthly observations. (*** significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level. The numbers in parentheses are standard errors.)

likelihood of bankruptcy increases after CDS trading begins even after adjusting for the propensity for CDS trading. *CDS Firm* is not significant in any of the specifications. Therefore, CDS firms are no longer statistically significantly different from non-CDS firms in terms of credit quality deterioration after matching by propensity for CDS trading, indicating the effectiveness of our matching procedure.

We also employ alternative CDS prediction models, using one of the two instruments at a time, with nearest-one propensity score matching. These models produce different matched samples because of variations in the data available to calculate propensity scores for each prediction model. *CDS Active* is significant in both of these specifications, as shown in Table A16 of the Internet Appendix.

3.3.3 Full-information maximum likelihood (FIML). Given the strong assumption in propensity score matching that the matching is based on observable information, we consider an alternative estimation approach that employs the full-information maximum likelihood (FIML) procedure, which is more efficient, provided that the model is correctly specified. FIML estimation considers all information regarding the joint distribution of the bankruptcy determination and CDS trading variables, $f(\varepsilon, \nu)$, in Equations 2 and 3 by using the conditional distribution, $f(\varepsilon|\nu)$, and the marginal distribution, $f(\nu)$, simultaneously. The FIML estimate is asymptotically efficient when the error terms are normally distributed.[13]

The estimation results are reported in Table 5. For brevity, we only present the estimation results for our main equation for bankruptcy prediction, and not for CDS trading, which is estimated simultaneously. The two specifications with and without the *CDS Firm* control yield positive and significant (at the 1% level) coefficient estimates for *CDS Active*. In addition, we provide the estimated correlation of the residuals from the selection equation and the outcome equation. The likelihood ratio test rejects the exogeneity of CDS trading at the 1% level. The coefficient estimates translate into economically large odds ratios for *CDS Active*.

We perform two robustness checks of our FIML estimation results. First, we remove the crisis period observations from our sample. The results are reported in the first column of Table A17 of the Internet Appendix, illustrating that the FIML estimate of the coefficient for *CDS Active* is similar to the full sample estimate in Table 5 in terms of economic magnitude and statistical significance. In our second robustness check, we consider an alternative but related estimation approach. Although the FIML estimator is efficient, it is computationally burdensome. Because of the lack of a closed-form expression for the likelihood function, the estimator and its derivatives must be estimated through numerical approximation. Moreover, the FIML estimates are sensitive to model specification. Any misspecification may lead to inconsistent estimates across all equations. Therefore, we also employ limited-information maximum likelihood (LIML) estimation.[14] The estimation results are reported in Table

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

[14] The LIML estimator is more efficient than the two-stage least squares estimator but is not as sensitive to model specification. In addition, LIML is a special case of FIML in which only a single equation is overidentified. LIML estimation is used and discussed in detail by Hochberg and Lindsey (2010). The Heckman two-stage analysis is also a LIML. The results reported in Table A18 of the Internet Appendix demonstrate that the effect of *CDS Active* is significant. However, the estimation results could be inconsistent because the outcome variable in our bankruptcy analysis is binary. Therefore, we focus on other econometric approaches.

Table 5
Credit default swaps trading and probability of bankruptcy: Full-information maximum likelihood

	Probability of bankruptcy	
	(1)	(2)
ln(E)	−0.581***	−0.580***
	(0.022)	(0.022)
ln(F)	0.628***	0.630***
	(0.024)	(0.024)
$1/\sigma_E$	−0.284***	−0.298***
	(0.044)	(0.044)
$r_{it-1} - r_{mt-1}$	−0.072**	−0.074***
	(0.028)	(0.028)
NI/TA	−0.288***	−0.288***
	(0.031)	(0.031)
CDS Firm	−0.340**	
	(0.147)	
CDS Active	0.864***	0.552***
	(0.175)	(0.111)
Time fixed effects	yes	yes
Industry fixed effects	yes	yes
Clustered standard error	yes	yes
N	558,376	558,376
% of CDS observations	11.98%	11.98%
% of CDS bankruptcies	4.47%	4.47%
Endogeneity test		
Rho	0.038***	0.035***

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

A17 of the Internet Appendix. The coefficient estimates for *CDS Active* are significant at the 1% level in both the full sample (Column 2) and the precrisis period subsample (third column). Therefore, the maximum likelihood estimates, which are more efficient than alternative approaches, support our previous finding that bankruptcy risk is greater following CDS trading, after considering the endogeneity of CDS trading.

3.4 Channels and mechanisms for the effect of CDS on credit risk

The baseline result that the reference firms' credit risk increases after the inception of CDS trading is not linked to any specific theory. In this section, we first demonstrate that, in addition to the mere presence of CDS trading, the volume of CDS trading affects credit risk. We then test the other three hypotheses stated in Section 1. We document that firms in financial distress are more likely to face bankruptcy if they are referenced in CDS trading. We demonstrate that the effect of CDS mainly arises from the "no restructuring" type of contract. Finally, the number of creditors increases after the initiation of CDS trading. Therefore, CDS firms become more susceptible to bankruptcy because it is more difficult for the creditors to coordinate and develop a restructuring plan if the firm gets into financial distress.

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

We calculate the ratio of the notional dollar amount of CDS contracts outstanding to the total dollar amount of debt outstanding at a given point in time, *CDS Notional Outstanding/Total Debt*, for each firm in each month.[15] We scale the CDS position by total debt to relate the dollar amount of CDS outstanding to the creditors' exposure. We conjecture that bankruptcy risk will be higher when *CDS Notional Outstanding/Total Debt* is larger. The estimation results, reported in Column 1 of Table 6, show that a firm is more likely to file for bankruptcy when the dollar amount of outstanding CDS contracts referencing its debt is large relative to its outstanding debt.

One possible objection to the use of *CDS Notional Outstanding/Total Debt* as an explanatory variable is that traders choose the amount of CDS they wish to buy or sell; therefore, the CDS exposure variable may itself be endogenous. To address this concern, we construct a two-stage model in which we first estimate the quantity of CDS outstanding. As shown in Table A19 of the Internet Appendix, the metric of CDS exposure, *CDS Notional Outstanding/Total Debt*, is smaller for investment-grade firms and for profitable firms. The model appears to be reasonably well specified, with an adjusted R^2 of 0.59 in specification 2. This analysis also suggests that CDS contracts are used, at least

[15] The outstanding positions include both buying and selling positions of all market participants. Ideally, we should use buying positions of the lenders, but our data do not distinguish those positions. The maximum value of *CDS Notional Outstanding/Total Debt* is 4.14, which is suggestive of overinsurance for such firms and the potential presence of "empty creditors." We thank an anonymous referee for observing that this measure could be contaminated by the positions of speculators in the CDS market. Unfortunately, we cannot consider this issue in this analysis because we do not have access to investor-level data.

Table 6
Credit default swaps outstanding and probability of bankruptcy

	Probability of bankruptcy	
	(1)	(2)
ln(E)	-0.689^{***}	-0.674^{***}
	(0.028)	(0.083)
ln(F)	0.652^{***}	0.631^{***}
	(0.028)	(0.085)
$1/\sigma_E$	-1.533^{***}	-2.027^{***}
	(0.121)	(0.371)
$r_{it-1}-r_{mt-1}$	-0.620^{***}	-0.830^{***}
	(0.102)	(0.237)
NI/TA	-0.076^{***}	-0.111^{***}
	(0.025)	(0.023)
CDS Firm	-0.582^{***}	-0.487
	(0.206)	(0.477)
CDS Notional Outstanding/Total Debt	0.071^{**}	
	(0.030)	
Instrumented CDS Notional Outstanding/Total Debt		0.946^{***}
		(0.213)
Time fixed effects	yes	yes
Industry fixed effects	yes	yes
Clustered standard error	yes	yes
Pseudo R^2	15.82%	15.25%
N	658,966	658,966
% of CDS observations	10.83%	10.83%
% of CDS bankruptcies	4.47%	4.47%
Sample probability of a bankruptcy	0.14%	0.14%

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

partially, for hedging purposes. We then use the instrumented *CDS Notional Outstanding/Total Debt* in the second stage, in specification 2 of Table 6, and continue to find a significant positive coefficient estimate for the instrumented variable, *Instrumented CDS Notional Outstanding/Total Debt*. The results are significant when *CDS Firm* is not included in the regression. The results are also significant when only CDS firms (in a within-CDS firm analysis) are included. Table A20 shows that for CDS firms, the larger number of CDS contracts outstanding, the higher likelihood of bankruptcy. These results, using an alternative quantitative measure of CDS exposure, suggest that the source of the *CDS Active* effect documented in the prior sections is indeed CDS trading.

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

We follow Gilson, John, and Lang (1990) and Demiroglu and James (2013) in identifying firms in financial distress. If a firm's stock return is in the bottom 5% of the market for two consecutive years, we classify it as financially distressed in the third year. According to this definition, there are 655 financially distressed firms in our sample period, providing sufficient information for our analysis. We perform a cross-sectional regression using CDS and non-CDS firms in financial distress. The estimation results are reported in Table 7. In line with Hypothesis 2, model 1 shows that, once a firm is in financial distress, it is more likely to file for bankruptcy if it is referenced by CDS trading. This effect is economically large. Compared to the default rate of 17.71% for all financially distressed firms, the marginal effect of CDS trading is 19.84%.

We select those firms that are in the bottom 10% of stock returns for two consecutive years as an alternative financial distress sample, as a robustness check, identifying 1,229 financially distressed firms based on this definition. The regression results for this alternative sample, presented in model 2, display a pattern similar to that observed above. In model 3, we remove the financial crisis period (using the 5% definition of financial distress) and demonstrate that the results are both quantitatively and qualitatively similar to the above results. Finally, adding variables for senior secured debt, the presence of bonds and loans (a measure of capital structure complexity), and tangibility does not alter the effect of *CDS Active*.[17] Overall, the conditional analysis using a different sample (distressed firms) supports Hypothesis 2 and the empty creditor model.

3.4.3 "No restructuring" CDS. In this section, we present an alternative test of the "empty creditor" model prediction. Empty creditors will clearly prefer firms to declare bankruptcy rather than restructure their debt only if their total payoffs are greater under bankruptcy than under restructuring. One such situation arises when bankruptcy, but not restructuring, triggers a credit event for CDS contracts and generates payments to the CDS buyers. In this case, as shown in Internet Appendix, creditors' incentives to encourage borrower

[16] CDS firms can also become more exposed to credit risk if they take on more debt after CDS trading begins. Indeed, Saretto and Tookes (2013) demonstrate that firm leverage increases following the inception of CDS trading. We also confirm that firms exhibit higher leverage after the start of CDS trading (see Table A21 of the Internet Appendix). We control for firm leverage before and after CDS trading begins in our regressions.

[17] We also find that firms are less likely to encounter financial distress after the inception of CDS trading (Table A22 of the Internet Appendix). However, this finding is not robust. Although the coefficient estimate for *CDS Active* is always negative, it becomes less significant when we cluster standard errors by firm or use an instrumented measure.

Table 7
Bankruptcy prediction for distressed firms

	Probability of bankruptcy			
	(1)	(2)	(3)	(4)
ln(E)	−0.492***	−0.398***	−0.495***	−0.430***
	(0.089)	(0.077)	(0.103)	(0.093)
ln(F)	0.504***	0.461***	0.506***	0.457***
	(0.089)	(0.071)	(0.103)	(0.092)
$1/\sigma_E$	−0.353	−1.072***	0.071	−0.462
	(0.532)	(0.376)	(0.654)	(0.542)
$r_{it-1} - r_{mt-1}$	−0.074	−0.085	−0.076	−0.100
	(0.224)	(0.088)	(0.271)	(0.223)
NI/TA	−0.046	0.002	−0.049	−0.043
	(0.033)	(0.026)	(0.033)	(0.033)
Senior Secured Debt				0.273
				(3.648)
Both Bond and Loan				0.690**
				(0.323)
PPENT/Total Asset				0.422
				(0.643)
CDS Active	1.626**	1.064**	1.655**	1.368**
	(0.663)	(0.484)	(0.821)	(0.671)
CDS Active Odds Ratio	5.083	2.898	5.233	3.927
CDS Active Marginal Effect	19.84%	9.99%	15.66%	16.51%
Time fixed effects	yes	yes	yes	yes
Industry fixed effects	yes	yes	yes	yes
Pseudo R^2	23.24%	19.91%	31.31%	24.33%
N	655	1,229	625	655
% of CDS observations	2.29%	3.25%	1.92%	2.29%
% of CDS bankruptcies	6.11%	5.96%	5.81%	6.11%
Sample probability of a bankruptcy	17.71%	12.29%	13.76%	17.71%

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

bankruptcy will be even stronger if restructuring is not covered by the CDS contracts. Empty creditors will not have this incentive to the same degree if their CDS contracts also cover restructuring as a credit event. Thus, the probability of bankruptcy will be positively associated with a no restructuring clause in a CDS contract if the empty creditor effect is present.

We investigate the effects of differences in contractual terms on the credit risk consequences of CDS trading. The Appendix describes the restructuring clauses used in CDS contracts and their historical evolution. There are four types of CDS contracts based on different definitions of credit events: full restructuring (FR), modified restructuring (MR), modified-modified restructuring (MMR), and no restructuring (NR). For FR contracts, any type of restructuring qualifies

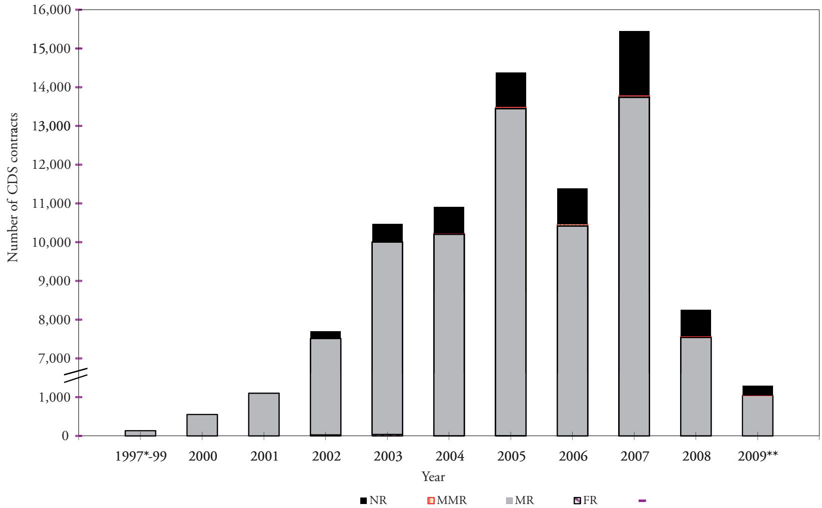

Figure 2
Credit default swaps' restructuring clauses by year
This figure plots the distribution of credit default swaps' (CDS') restructuring clauses, by year, in our sample, between 1997 and 2009. The CDS data are taken from CreditTrade and the GFI Group. There are four types of contract terms related 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, whereas for the other types, they do. MR and MMR contracts impose restrictions on the type of bond that can be delivered in the event of default.

as a trigger event, and any debt obligation with a maturity of up to 30 years can be delivered in that event. Any restructuring is considered a credit event under MR as well; however, in this type of contract, deliverable obligations are limited to those with maturities within 30 months of the CDS contract's maturity. For MMR contracts, the deliverable obligations are relaxed to include those with maturities within 60 months of the CDS contract's maturity for restructured debt and 30 months for other obligations. Restructuring is excluded as a credit event under NR. Firms with a greater proportion of NR contracts are more strongly subject to the empty creditor threat than those with other types of contracts. Similarly, FR contracts will not be as strongly influenced by empty creditor incentives.

Figure 2 plots the number of contracts of each type in each year, as observed in our CDS transaction records. The majority of firms in our sample have the MR type of clause in their CDS contracts. The FR and MMR contracts have a negligible presence in our sample, which is representative of the market as a whole, although there may be some variation at the firm level. Figure 2 illustrates that there were very few NR CDS contracts prior to 2002. Packer and Zhu (2005) demonstrate that, in their sample period, MR contracts were slightly more expensive than NR contracts. In such circumstances, CDS buyers would likely buy MR contracts rather than

Table 8
Restructuring clauses of credit default swaps and probability of bankruptcy

	Probability of bankruptcy				
	(1)	(2)	(3)	(4)	(5)
ln(E)	−0.716***	−0.713***	−0.714***	−0.710***	−1.379***
	(0.026)	(0.026)	(0.026)	(0.026)	(0.160)
ln(F)	0.715***	0.715***	0.713***	0.713***	1.381***
	(0.026)	(0.026)	(0.026)	(0.026)	(0.157)
$1/\sigma_E$	−1.636***	−1.656***	−1.642***	−1.678***	0.200
	(0.254)	(0.250)	(0.253)	(0.250)	(0.330)
$r_{it-1} - r_{mt-1}$	−1.327***	−1.330***	−1.330***	−1.335***	−2.126***
	(0.192)	(0.193)	(0.193)	(0.193)	(0.708)
NI/TA	−0.037***	−0.037***	−0.037***	−0.037***	−2.554***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.658)
CDS Firm	−0.206		−0.609**		
	(0.187)		(0.277)		
No Restructuring CDS	1.315**	1.023**			
	(0.517)	(0.438)			
Instrumented NR CDS			0.658***	0.324***	0.776**
			(0.192)	(0.110)	(0.363)
Time fixed effects	yes	yes	yes	yes	yes
Industry fixed effects	yes	yes	yes	yes	yes
Clustered standard error	yes	yes	yes	yes	yes
Pseudo R^2	24.06%	24.05%	24.11%	24.07%	39.67%
N	658,966	658,966	658,966	658,966	71,366
% of CDS observations	10.83%	10.83%	10.83%	10.83%	100%
% of CDS bankruptcies	4.47%	4.47%	4.47%	4.47%	100%
Sample probability of a bankruptcy	0.14%	0.14%	0.14%	0.14%	0.06%

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

NR contracts. The proportion of CDS contracts with NR specifications has increased dramatically in recent years, particularly in 2007. The median (mean) fraction of NR contracts out of all CDS contracts for a reference entity is 0.61 (0.55). There is wide variation across firms in terms of the proportions of NR contracts used.

We account for differences in contractual specifications in the estimations reported in Table 8, which include variables measuring the type of CDS contract. *No Restructuring CDS* is the fraction of CDS contracts with NR clauses among all CDS contracts on a given reference entity. This measure is zero for firms without CDS. The results in Table 8 indicate a significant positive relationship between CDS trading using NR contracts and bankruptcy risk. We include year dummies in our regressions to control for potential time series patterns in the composition of CDS contract types. The result is significant regardless of whether we include *CDS Firm* in the regression (the coefficient estimates for *CDS Firm* are insignificant).

Because CDS contract terms are chosen by traders, there may be concern over the choice of contract type, that is CDS buyers who believe bankruptcy is more likely than restructuring will buy CDS contracts that only cover bankruptcy. Table A23 of the Internet Appendix illustrates that firms with more tangible assets, low stock returns, and junk ratings are more likely to have NR CDS traded on them, as are all firms after the year 2003. We look at this finding more closely using *After January 2003* as an instrument. Our instrumented NR CDS continues to be significant, as shown in the third and fourth columns of Table 8. We present our results for the test of our specification for the NR CDS effect within the CDS sample in the final column of Table 8 (more results are in Table A24 of the Internet Appendix). The result is significant for this sample as well, supporting Hypothesis 3.

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

The results for *CDS Notional Outstanding/Total Debt*, bankruptcy conditioned on financial distress, and *No Restructuring CDS* are consistent with the empty creditor model. We repeated the analysis using distance-to-default and found similar results for instrumented CDS exposure and NR CDS, as reported in Table A25 of the Internet Appendix. Therefore, one source of the CDS effect on credit risk is creditors becoming tougher in debt renegotiations, thus causing firms to file for bankruptcy.

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

We investigate the impact of the introduction of CDS on the creditor relationships of a firm. The overall creditor relationship is represented in our analysis by the lending relationships available from DealScan LPC data.[18] We follow Acharya and Johnson (2007) and Bharath et al. (2007) in counting the number of lenders. For each firm in a given month, we examine the prior five-year period for any syndicated loan facilities in place for this firm. Summing over all such active facilities, we compute the number of unique banks lending to the firm. $\triangle$*Number of Banks* is the change in the number of bank relationships from one year before the inception of CDS trading to two years after its inception.

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

Second, we regress $\triangle$*Number of Banks* from the year before to two years after the start of CDS trading on a set of firm characteristics and the *CDS Active* variable. The sample includes 248 CDS firms and 248 matched non-CDS firms. These "event study" results are reported in Panel A of Table 9. In this cross-sectional regression, we find that CDS trading significantly increases the number of lenders for a firm. On average, controlling for the propensity for CDS trading, and for other factors that may affect the number of lenders, such as firm size and leverage, CDS firms have 2.4 more lenders than non-CDS firms two years following CDS introduction.

The relationship between the number of lenders and bankruptcy risk has previously been documented by Gilson, John, and Lang (1990) and Brunner and Krahnen (2008), among others. We present similar evidence using our sample, including the effect of CDS trading, in Panel B of Table 9. We include the *Number of Banks* as an additional explanatory variable in the hazard model of the firm's likelihood of bankruptcy. The results indicate that a firm's bankruptcy risk increases with the number of banking relationships, even after controlling for the direct impact of CDS trading. Model 2 in Panel B analyzes the effect of changes in the number of bank relationships of the 480 CDS firms with complete data: CDS firms with larger increases in the number of lenders around the time of CDS introduction are more likely to file for bankruptcy. Table A26 in the Internet Appendix shows that the effect of CDS Active on bankruptcy filing is significant after controlling for the change in number of banks and that the effect of change in number banks is significant only for CDS firms. Therefore, the results in Table 9 support Hypothesis 4, in that CDS trading increases the number of creditors, which in turn increases the bankruptcy risk of a reference firm.

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

Table 9
Credit default swaps trading, bank relationships, and probability of bankruptcy

Panel A: CDS and bank relationships

	△ Number of banks
△ *ln(Asset)*	6.291***
	(1.849)
△ *ROA*	−0.396
	(2.760)
△ *Leverage*	8.581*
	(5.201)
△ *PPENT/Total Asset*	−1.586
	(10.840)
CDS Active	2.432**
	(1.069)
Time fixed effects	yes
Industry fixed effects	yes
R^2	9.75%
N	496

Panel B: Bank relationships and bankruptcy risk

	Probability of bankruptcy (1)	(2)
ln(E)	−0.669***	−1.299***
	(0.029)	(0.324)
ln(F)	0.683***	1.445***
	(0.027)	(0.419)
$1/\sigma_E$	−1.763***	−0.974**
	(0.266)	(0.480)
$r_{it-1} - r_{mt-1}$	−1.339***	0.556
	(0.192)	(0.341)
NI/TA	−0.040***	−2.500
	(0.009)	(9.361)
CDS Firm	−2.210***	
	(0.722)	
CDS Active	2.378***	
	(0.736)	
Number of Banks	0.153***	
	(0.035)	
△ *Number of Banks*		0.043***
		(0.016)
CDS Active Odds Ratio	10.783	
CDS Active Marginal Effect	0.33%	
Time fixed effects	yes	yes
Industry fixed effects	yes	yes
Clustered standard error	yes	
Pseudo R^2	24.32%	33.54%
N	658,966	480
% of CDS observations	10.83%	100%
% of CDS bankruptcies	4.47%	100%
Sample probability of a bankruptcy	0.14%	5.83%

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

4. Conclusion

Using a comprehensive dataset of North American corporate CDS transaction records over the 1997–2009 period, we find strong evidence that the bankruptcy risk of reference firms increases after the inception of CDS trading. This effect of CDS trading on credit risk is economically significant: the likelihood of bankruptcy for the average firm more than doubles after the initiation of CDS trading. This finding is robust to the selection and endogeneity of CDS trading. Firms in financial distress are more likely to file for bankruptcy if they are referenced by CDS trading than if they are not. The effect of CDS trading on bankruptcy risk is more pronounced when CDS payments in the event of default do not cover restructuring. Moreover, the number of lenders increases after the initiation of CDS trading, exacerbating the problems of creditor coordination.

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

Appendix. Credit Default Swaps' Credit Event Definitions

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

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

However, the restructuring of Conseco Finance on September 22, 2000, highlighted the problems with the 1999 ISDA Credit Event Definitions. The bank debt of Conseco Finance was restructured to the benefit of the debt holders. Yet the restructuring event still triggered payments from outstanding CDS contracts. To settle the CDS position, CDS holders also utilized the cheapest-to-deliver option created by the broad definition of deliverable obligations and delivered long-maturity, deeply discounted bonds in exchange for the notional amount. To address this obvious lacuna, ISDA modified CDS contracts and defined a new structure known as modified restructuring (MR). Under this 2001 ISDA Supplement Definition, any restructuring is defined as a credit event. However, deliverable obligations are limited to those with maturities within 30 months of the CDS contract's maturity.

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

In sum, 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.

References

Acharya, V. V., and T. C. Johnson. 2007. Insider trading in credit derivatives. *Journal of Financial Economics* 84:110–41.

Allen, F., and E. Carletti. 2006. Credit risk transfer and contagion. *Journal of Monetary Economics* 53:89–111.

Ashcraft, A. B., and J. A. C. Santos. 2009. Has the CDS market lowered the cost of corporate debt? *Journal of Monetary Economics* 56:514–23.

Bedendo, M., L. Cathcart, and L. El-Jahel. 2012. Distressed debt restructuring in the presence of credit default swaps. Working Paper, Universita Bocconi and Imperial College Business School.

Bharath, S., S. Dahiya, A. Saunders, and A. Srinivasan. 2007. So what do I get? The bank's view of lending relationships. *Journal of Financial Economics* 85:368–419.

Bharath, S. T., V. Panchapagesan, and I. M. Werner. 2010. The changing nature of Chapter 11. Working Paper, Arizona State University, The Goldman Sachs Group, Inc., and The Ohio State University.

Bharath, S. T., and T. Shumway. 2008. Forecasting default with the Merton distance to default model. *Review of Financial Studies* 21:1339–69.

Bolton, P., and M. Oehmke. 2011. Credit default swaps and the empty creditor problem. *Review of Financial Studies* 24:2617–55.

Brunner, A., and J. P. Krahnen. 2008. Multiple lenders and corporate distress: Evidence on debt restucturing. *Review of Economic Studies* 75:415–42.

Busse, J. A., and T. C. Green. 2002. Market efficiency in real time. *Journal of Financial Economics* 65:415–37.

Campello, M., and R. A. Matta. 2012. Credit default swaps, firm financing and the economy. Working Paper, Cornell University and University of Illinois.

Chava, S., and R. A. Jarrow. 2004. Bankruptcy prediction with industry effects. *Review of Finance* 8:537–69.

Chava, S., and M. Roberts. 2008. How does financing impact investment? The role of debt covenants. *Journal of Finance* 63:2085–121.

Che, Y., and R. Sethi. 2012. Credit derivatives and the cost of capital. Working Paper, Columbia University.

Danis, A. 2012. Do empty creditors matter? Evidence from distressed exchange offers. Working Paper, Georgia Institute of Technology.

Demiroglu, C., and C. James. 2013. “Bank” loan ownership and troubled debt restructurings. Working Paper, Koc University and University of Florida.

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

Edmans, A., I. Goldstein, and W. Jiang. 2012. The real effects of financial markets: The impact of prices on takeovers. *Journal of Finance* 67:933–71.

Gilson, S. C., K. John, and L. H. Lang. 1990. Troubled debt restructurings: An empirical study of private reorganization of firms in default. *Journal of Financial Economics* 27:315–54.

Griffin, J., and D. Y. Tang. 2012. Did subjectivity play a role in CDO credit ratings? *Journal of Finance* 67:1293–328.

Hirtle, B. 2009. Credit derivatives and bank credit supply. *Journal of Financial Intermediation* 18:125–50.

Hochberg, Y. V., and L. Lindsey. 2010. Incentives, targeting, and firm performance: An analysis of non-executive stock options. *Review of Financial Studies* 23:4148–86.

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

Jensen, M. C., and W. H. Meckling. 1976. Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics* 3: 305–60.

Jiang, W., K. Li, and W. Wang. 2012. Hedge funds and Chapter 11. *Journal of Finance* 67:513–59.

Li, K., and N. R. Prabhala. 2007. Self-selection models in corporate finance. In *Handbook of corporate finance: Empirical corporate finance I*, chapter 2, pp. 37–86. Ed. B. Espen Eckbo. Amsterdam: Elsevier.

Minton, B. A., R. M. Stulz, and R. Williamson. 2009. How much do banks use credit derivatives to hedge loans? *Journal of Financial Services Research* 35:1–31.

Moody’s. 2009. Moody’s approach to evaluating distressed exchange.

Morrison, A. D. 2005. Credit derivatives, disintermediation, and investment decisions. *Journal of Business* 78:621–47.

Myers, S. 1977. Determinants of corporate borrowings. *Journal of Financial Economics* 5:147–75.

Packer, F., and H. Zhu. 2005. Contractual terms and CDS pricing. *BIS Quarterly Review* :89–100.

Parlour, C. A., and A. Winton. 2013. Laying off credit risk: Loan sales versus credit default swaps. *Journal of Financial Economics* 107:25–45.

Petersen, M. A. 2009. Estimating standard errors in finance panel data sets: Comparing approaches. *Review of Financial Studies* 22:435–80.

Roberts, M. R., and T. M. Whited. 2013. Endogeneity in empirical corporate finance. In *Handbook of the economics of finance* 2A:493–572. Eds. G. Constantinides, M. Harris, and R. Stulz. Amsterdam: Elsevier.

Saretto, A., and H. Tookes. 2013. Corporate leverage, debt maturity and credit supply: The role of credit default swaps. *Review of Financial Studies* 26:1190–247.

Sargan, J. D. 1958. The estimation of economic relationships using instrumental variables. *Econometrica* 26:393–415.

Shumway, T. 2001. Forecasting bankruptcy more accurately: A simple hazard model. *Journal of Business* 74:101–24.

Siegel, S., N. Castellan. 1988. *Nonparametric statistics for the behavioral sciences*. NY: McGraw Hill.

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

Tett, G. 2009. *Fool's gold: How the bold dream of a small tribe at J.P. Morgan was corrupted by Wall Street greed and unleashed a catastrophe*. NY: The Free Press.

Thompson, J. 2010. Counterparty risk in financial contracts: Should the insured worry about the insurer? *Quarterly Journal of Economics* 125:1195–252.

Wooldridge, J. M. 2002. *Econometric analysis of cross section and panel data*. Cambridge: MIT Press.